WORKING TOWARDS IMPROVED CONCEPTUALISATION AND IDENTIFICATION OF GAMING DISORDER AND CO-OCCURRING ADDICTIONS IN GAMERS

TYRONE L. BURLEIGH
School of Social Sciences

A thesis submitted in partial fulfilment of the requirements of the Nottingham Trent University for the degree of Doctor of Philosophy.

September 2022

Copyright Statement

Statement of Originality

I declare that the work presented in this thesis is, to the best of my knowledge and belief, original and my own work, except as acknowledged in the text. The material (presented as my own) has not been submitted previously, in whole or in part, for a degree at any other institution.

Statement of Contribution of Others

In those cases, in which the work presented in this thesis was the product of collaborative efforts I declare that my contribution was substantial and prominent, involving the development of original ideas, as well as the definition and implementation of subsequent work. Detailed information about my contribution to collaborative work in this thesis is outlined in Appendix I.

Dedication

I would like to dedicate this work to my loving family, especially my mum and dad, who have supported and celebrated my achievements from the other side of the world. I would not have been able to move to the other side of this planet and complete such a huge project without their love and support.

I would also like to dedicate this work to my amazing husband, David. I had started this PhD journey with a rule in mind not to date because it would be a distraction. Little did I know that I would meet the most amazing person, who would first become my *novio*, then my *prometido*, and now my *marido*. I feel truly blessed to have met you, David. Thank you for always supporting me and helping me through thick and thin. You are a guiding light in my life, and I will always be thankful to this PhD journey for leading me to you.

There is no doubt that all their love and dedication is what helped me thrive and kept me motivated to complete this PhD journey. From the bottom of my heart, thank you.

Acknowledgments

I would first like to give credit to my director of studies Daria Kuss for her unending encouragement, support, and feedback. It has been an absolute pleasure to be under her supervision and I am truly grateful for the help and guidance I have received. Daria always made me feel like I had a voice, that I was capable, that my mental health and wellbeing were always important, and that I was valued. Thank you so much for making this one of the best educational experiences of my life. I would also like to give a special thanks to Mark Griffiths for his invaluable feedback and insight to various aspects of writing, and the doors he has no doubt opened from being a part of my esteemed supervision team. I would also like to thank Alex Sumich, who has been immensely helpful and constructive in the process of learning brand new concepts around EEG technology, ML methods, and the NeuCube. These were challenging concepts, and I appreciated Alex's guidance immensely. I had the privilege of having an excellent supervision team, and I will be forever thankful for the dedication, attention, and guidance I received.

I would like to thank all my collaborators from around the world. Vasileous Stavropoulos from Victoria University and Lee Kannis-Dymand from the University of the Sunshine Coast in Australia for taking the time to distribute my survey at their universities. I would like to give a huge thank you to Grace Wang from the Auckland University of Technology in New Zealand (and now at the University of Southern Queensland in Australia) for helping me with data collection from multiple populations. Lastly, I would like to thank Zohreh Doborjeh from the University of Auckland for her invaluable help and guidance on the implementation and interpretation of the NeuCube architecture. Thank you all for your contributions to the research projects.

Another special aside to my first mentor and now dear friend Vasileous Stavropoulos. I will never forget that you are the reason I made it this far; it was your encouragement to apply for this PhD, and your willingness to help me succeed that made any of this possible. It is not an understatement to say that you changed the course of my life. I will be forever grateful to you and your support.

I would also like to thank my dear friend Dr. Brad Jessup. He was a huge support to me when going for this PhD scholarship and beyond. Brad has been such an inspiration in my life, and he has truly helped me become a better person. He has always afforded me opportunities to increase my skills and knowledge in academia and was invaluable in the lead up to leaving Australia and moving to England to make this journey possible. Thank you for believing in me and pushing me to put myself out there and spread my wings.

Moreover, I would like to thank Kristian and Tom, for opening up their home to me and allowing me to live with them while I attended Nottingham Trent University. To be able to live in such a lovely home and live with two beautiful dachshunds – Darcy & Cassie – was a dream come true. Thank you for giving me a home during my time in England.

Also, thank you to my PhD colleagues and especially those who were apart of (the fondly named) Doctors and Dragons – Chloe W., Chloe R., Isabelle, Lef, and our DM Ceci – it was such a pleasure to talk videogames, comics, and play dungeons and dragons. It was a wild ride and know I will always cherish our time together – I truly believe I have made friends for life! A special aside to Chloe W. (and her partner Rob) – thank you for always being there for a chat and to provide insight into various aspects of my life. Bouncing ideas off you during the PhD and being able to hash out ideas together was so helpful. You have made my life richer by being in it.

In tradition of saving the best for last, I would like to thank Lindsay Thurston, Adela Kratenova, and Liam Cahill who, like me, went into the doctoral office every single day without fail to work on their PhD. You all were a huge support to me. Being able to share our highs and lows truly helped me through this journey. Knowing we would be having lunch together, sharing stories, coming in early, or staying late always motivated me to come into the office and do the best I could do. On a day-to-day basis, it was you three that helped keep my spirits high and kept me sane. You are all *the best*.

To all I may have missed, thank you. You know who you are, and I am grateful for your contribution.

As demonstrated by this section, it takes a community to complete a PhD. It is no more my achievement than all those that were listed here, for without them none of this would have been possible.

Once again, thank you all so much.

It is done.

List of Publications

Peer-Reviewed Journal Papers

Burleigh, T. L., Griffiths, M. D., Sumich, A., Stavropoulos, V., & Kuss, D. J. (2019). A systematic review of the co-occurrence of gaming disorder and other potentially addictive behaviors. *Current Addiction Reports*, *6*(4), 383–401. https://doi.org/10.1007/s40429-019-00279-7

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

Burleigh, T. L., Griffiths, M. D., Sumich, A., Doborjeh, Z, & Kuss, D. J. (2022). Machine learning in gaming disorder: A systematic review. *Behavior & Information Technology*, *under review.*

Burleigh, T. L., Griffiths, M. D., Sumich, A., Wang, G., & Kuss, D. J. (2022). Coping and Co-occurrence of Gaming Disorder and Substance Use in Recovering Substance Users, *International Journal of Clinical Medicine, 11,* 7370. doi: 10.3390/jcm11247370

Burleigh, T. L., Griffiths, M. D., Sumich, A.,Wang, G., Stavropoulos, V., Kannis-Dymand, L., & Kuss, D. J. (2022). Co-Occurrence of Gaming Disorder and Other Potentially Addictive Behaviours Between Australia, New Zealand, and the United Kingdom, *International Journal of Environmental Research and Public Health*, *19*, 16078. doi: 10.3390/ijerph192316078

Conference Proceedings

Burleigh, T. L., Kuss, D. J., Sumich, A., & Griffiths, M. D. (2019). Exploring the implications of co-occurrence within internet addiction and gaming disorder. In Z. Demetrovics (Ed.), *6th International Conference on Behavioral Addictions* (ICBA 2019) (Vol. 8, Issue Supplement 1, pp. 1–220). *Journal of Behavioral Addictions*. https://doi.org/10.1556/JBA.8.2019.Suppl.1

Burleigh, T. L., Griffiths, M. D., Sumich, A., Yang, G. Y., & Kuss, D. J. (2022, May 12-15). *Co-occurrence in videogame players: Do videogames increase risk or improve resilience?* [Paper presentation]. 25th European Association of Substance Abuse Research (EASAR) Conference 2022, Gibraltar, Gibraltar. https://www.unigib.edu.gi/wp-content/uploads/2022/05/Book-of-Abstract-EASAR-2022.pdf

Burleigh, T. L., Griffiths, M. D., Sumich, A., Doborjeh, Z., & Kuss, D. J. (2022). Utilizing a brain inspired spiking neural network to better predict and identify gaming disorder using EEG data. In Z. Demetrovics (Ed.), 7th International Conference on Behavioral Addictions (ICBA 2022) (Vol. 11, Issue Supplement-1, pp. 1–329). *Journal of Behavioral Addictions*. https://doi.org/10.1556/2006.2022.00700

TABLE OF CONTENTS

List of Tables

List of Figures

Abstract

This doctoral research thesis investigated the neurophysiological underpinnings of gaming disorder (GD), and the way in which co-occurrence can influence and correlate with GD in a clinical and a multi-cultural context. The unique contribution of knowledge was (i) the assessment of the neurophysiological expression of gamers using a novel spiking neural network (SNN) methodology; (ii) exploring co-occurrence in gamers and substance abstinent gamers; and (iii) exploring co-occurrence in gamers across three different individualistic countries (i.e., Australia, New Zealand, and the United Kingdom). The conceptualisation of GD and related methodologies were explored using multiple systematic research methods. A number of methodologies were then employed, including the use of electroencephalographic (EEG) data, a machine learning (ML) approach which utilised a novel SNN architecture (i.e., the NeuCube), and the use of surveys to reach a clinical cohort and three cohorts spanning three different countries in an effort to investigate the way in which co-occurrence may influence gamers and at-risk gamers. The results of the empirical studies indicated that: (i) problematic gamers experience different neurophysiological expression than those who recreational game and that ML methodologies are an effective method of classifying recreational and problematic gamers when using EEG data; (ii) maladaptive coping strategies were significantly associated to gaming scores, and that gamers appeared to experience co-occurrence more so than their non-gamer counterparts; (iii) at-risk and high-risk gamers may utilise gaming as a maladaptive coping strategy and other accompanying potentially addictive behaviour, or substance use may be influenced as a result; (iv) the manifestation of maladaptive coping strategies and potentially addictive behaviours can be influenced by the country in which an individual resides. Taken together, the present doctoral project further clarified the conceptualisation of GD, utilising a neurophysiological underpinning, which is further supported with observed behaviour as suggested by the National Institute of Mental Health. In addition, it places an emphasis on the importance of understanding co-occurrence and specific at-risk factors (e.g., coping) which may contribute to the development and maintenance of problematic or disordered gaming in both a clinical sample and general population samples.

Part I: Introduction

Chapter 1

A Systematic Review of the Co-occurrence of Gaming Disorder and other Potentially Addictive Behaviours

Introduction

Research has begun to investigate the negative consequences of problematic video gaming in an effort to improve screening, assessment, definition and treatment of the disorder (Kuss et al., 2013; Tsitsika et al., 2014; Yau et al., 2012). Such work has contributed to the American Psychiatric Association (APA) (American Psychiatric Association, 2013) including Internet Gaming Disorder (IGD) as a form of behavioural addiction (warranting further investigation) in the latest (fifth) edition of the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5) in 'Section 3' ('Emerging measures and models'). The World Health Organization (2019) has also recognized 'Gaming Disorder' (GD) as an official disorder with addiction like properties in the eleventh revision of the International Classification of Diseases (ICD-11).

Prior to the inclusion of GD in the DSM-5 and ICD-11, several other terms were used to describe problematic video gaming including videogame addiction, pathological video gaming, gaming use disorder, and gaming use dependency (Estévez et al., 2017; Griffiths & Meredith, 2009; Grüsser et al., 2007; Lemmens et al., 2011a). Further confusing the issue, online problematic gaming has also been included within the umbrella terms of internet addiction, problematic internet use, and pathological internet use (Brand et al., 2014; Király et al., 2014; Yung et al., 2015). However, the internet addiction umbrella term encompasses several other problematic online activities, such as online gambling, online sex, social media use, and online shopping (Kuss & Billieux, 2017). In order to maintain consistency throughout the present review, the term 'disordered gaming' will be used to describe a range of similar and/or overlapping addictive, compulsive, and/or problematic gaming behaviours. When referring to clinically defined cases, the term 'GD' will be used, in line with DSM-5 and ICD-11. Furthermore, in relation to other potentially addictive behaviours, the term 'problematic' will be used to describe sub-clinical conditions that do not fully meet all the criteria in the DSM-5 or ICD-11 (e.g., problematic gambling), while the term 'disordered' will be used to describe clinical conditions that meet the requisite criteria in the DSM-5 and ICD-11.

There has been a growing body of research suggesting that disordered gaming is associated with a number of other mental health disorders, such as depression (King et al., 2013), anxiety (Adams et al., 2019), problematic substance use (Ko et al., 2008), and personality disorders (Schimmenti et al., 2017). However, an understudied area in this field is the co-occurrence of disordered gaming with other potentially addictive substances and behaviours. Within the present review, co-occurrence refers to when two or more potentially addictive behaviours (behavioural and/or substance) are engaged in concurrently. For example, in a systematic review on the prevalence of eleven different types of addictions, it was estimated that approximately 10% of adults with internet addiction may experience another concurrent problematic behaviour or substance use (e.g., alcohol use or dependence or gambling addiction (Sussman et al., 2011).

Evidence supports the co-occurrence of addiction for both substances and behaviours (i.e., the presence of a behavioural addiction increases the propensity for addiction to develop for other behaviours). Indeed, this may create a cycle of reciprocity, wherein mutual exacerbation occurs between two or more problematic behaviours (Gossop, 2001; Haylett et al., 2004; Martin et al., 2014). Moreover, those who do experience co-occurring problematic and addictive behaviours are at higher risk of poor mental health (e.g., depression) and physical health (Burleigh et al., 2018; Martin et al., 2014; Urbanoski et al., 2007).

In addition, co-occurring problematic behaviours interact to aggravate clinical symptoms, which can complicate accurate assessment and treatment of other psychiatric disorders (Najt et al., 2011). Likewise, disordered gaming may mask problematic substance use which could hinder diagnostic assessment. Alternatively, disordered gaming may aggravate problematic substance use, causing symptoms of both to alternate which can impact treatment efficacy (Freimuth et al., 2008). This highlights that the assessment and treatment of GD should have a broader focus by not only considering the presenting primary problematic behaviour or substance use and symptoms, but also any potential co-occurring addictive behaviours or substance use, which may enforce a cycle of reciprocity.

Consequently, clinicians need to be aware of how potentially addictive behaviours influence or enforce various aspects of a primary problematic behaviour (e.g., disordered gaming), and be aware of how co-occurring addictions may impact the onset, course, and outcomes of interventions. Previous literature has demonstrated that the prevalence of co-occurring addictions can be high (Sussman et al., 2011), suggesting that studies which consider addiction as only comprising one specific behaviour may be limited in ecological invalidity because individuals have more complex and varied histories of disordered behaviours and co-occurrence (Gossop, 2001).

Although there has been one previous comprehensive review investigating the co-occurrence of eleven behavioural and substance addictions, this mainly evaluated US studies, did not examine disordered gaming, and was written almost a decade ago (Sussman et al., 2011). Furthermore, this review was limited to clinical measures in relation to co-occurrence, and did not consider any proxy measures (e.g., time spent engaging in the activity as an indication of problematic or disordered behaviour). Consequently, given the large increase in research examining disordered gaming in the past decade, there is a need for a contemporary systematic review examining the co-occurrence of GD with other potentially addictive behaviours. While several studies have considered the impact of co-occurrence of neurodevelopmental and mood disorders on the onset, course, and maintenance of GD (Ko et al., 2012), there is limited integrative research examining addiction comorbidities. Furthermore, failure to integrate treatments which consider co-occurring addictions may lead to a ‘ping pong effect’, wherein an individual may bounce back and forth between problematic or disordered behaviours and/or substance use and treatment programs (Yakovenko & Hodgins, 2018).

There are several studies within the behavioural and substance addiction literature that support the efficacy and benefits of treating co-occurring addictions concurrently (Burdzovic Andreas et al., 2015; Morisano et al., 2014). Therefore, in order to integrate contemporary research, it is important to conduct a review highlighting extant findings concerning the co-occurrence of addictive behaviours, which specifically consider problematic and disordered gaming. This may aid in the development of effective models that identify and aid clinicians to treat disordered gaming alongside other co-occurring addictive behaviours.

The primary goal of the present study was to review empirical research over the past decade, providing up-to-date information that considers the impact of addiction to other behaviours on GD, and to provide recommendations for future research. More specifically, the aims of the present review were to: (i) determine the co-occurrence of potentially addictive behaviours with problematic and disordered gaming, and to (ii) elucidate the potential risk factors in the development and maintenance of co-occurrence within GD.

Methods

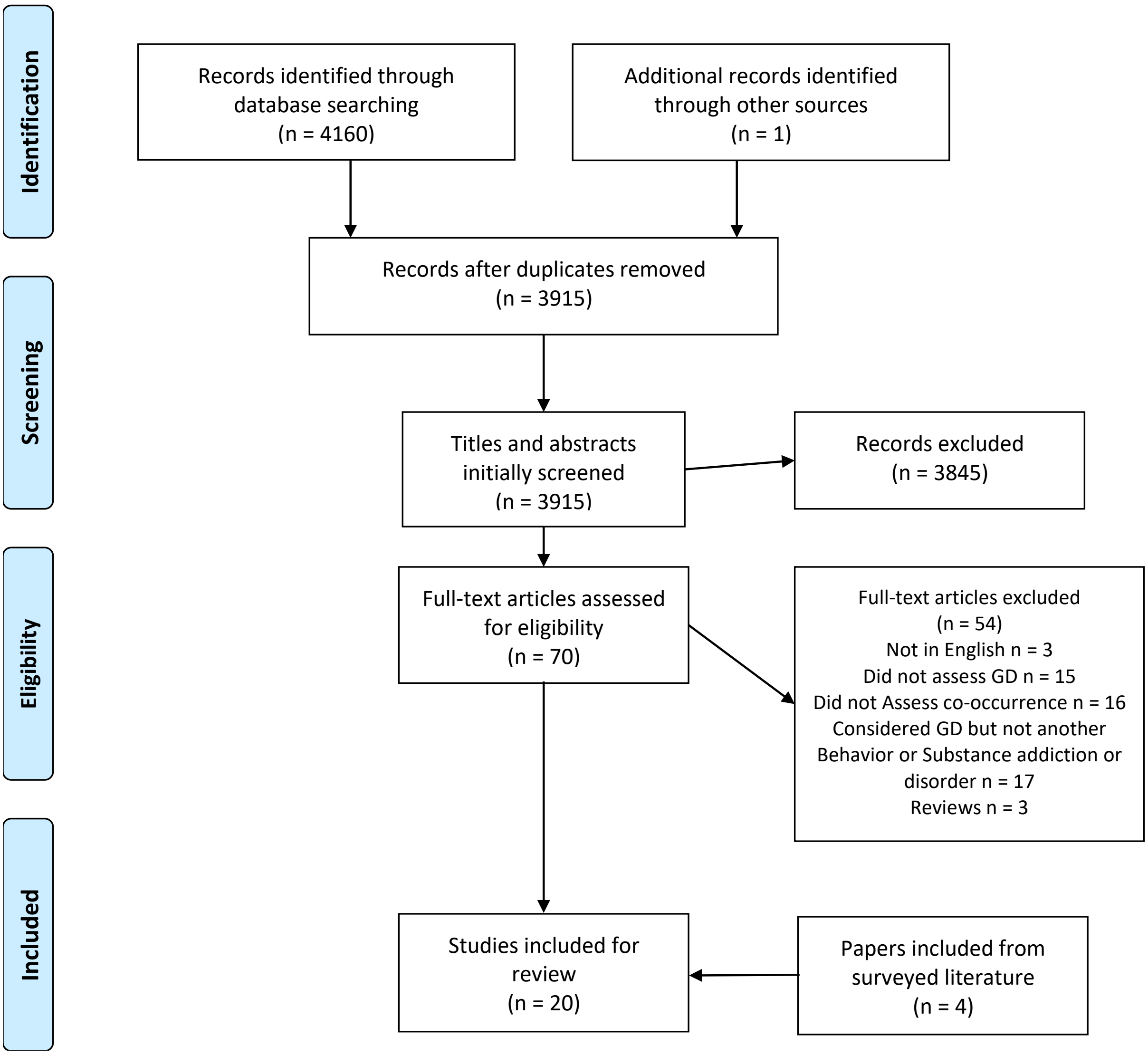
A systematic review was employed to examine the co-occurrence of potentially addictive behaviours with disordered gaming. A systematic review contains key elements, such as an overview of the literature, summary of the findings, dissemination of outcomes, and identification of gaps in the literature (Siddaway et al., 2019). The present review utilized a five-stage model of conducting a rigorous systematic review, which included (i) identifying the research question, (ii) identifying relevant studies, (iii) study selection, (iv) dissemination of outcomes, and (v) summarizing and reporting the results (Siddaway et al., 2019).

The inclusion criteria for the present review were as follows: (i) empirical studies containing primary data, (ii) studies that assessed the co-occurrence of and potential 'cross-addiction' or 'addiction hopping' within the problematic or disordered gaming literature; (iii) studies published in peer-reviewed journals, (iv) written in English, and (v) published within the past decade. *ProQuest, Scopus*, and *Web of Science* were searched, including the following databases*: PsychARTICLES, PsychINFO, Scopus, Web of Science Core Collection,* and *MEDLINE*. The search included a number of terms related to disordered gaming that have been used over the past decade. In addition to this, several terms were developed to explore cross-addiction and co-occurrence in the behavioural addiction literature, which led to the following search strategy: (patholog* OR problem* OR addict* OR compulsive OR dependen* OR disorder* OR excess*) AND (video gam* OR computer gam* OR internet gam* OR online gam*) AND ("cross addiction" OR "addiction hopping" OR "expression hopping" OR "substitution hypothesis" OR "switching hypothesis" OR "co-occur*" OR comorbid* OR "dual diagnosis"). Each study's title, abstract, and paper content were screened for eligibility. The full texts of potentially relevant studies were retrieved and screened for eligibility.

The literature search was conducted between November 2018 and January 2019. A total of 4160 papers were identified in the initial search. The *ProQuest* database contained 2507 papers (*PsychARTICLES n*=1749; *PsychINFO n*=799); *Scopus* contained 1271 papers; and *Web of Science* contained 341 papers. Duplicate studies were removed, leaving a total of 3915 papers. These papers had their journal of publication, titles, and abstracts screened, resulting in the exclusion of 3845 papers that were not relevant to the present review, leaving a total of 70 papers, which were eligible for further review. Of these, 54 were excluded as they were not written in English (n = 3), did not assess disordered gaming (n = 15), did not assess cross-addiction or co-occurrence (n = 16), did not consider disordered gaming in conjunction with another behavioural or substance addiction/disorder (n = 17), or were review papers (n = 3). The remaining 16 papers were considered eligible for further analysis as they met all the inclusion criteria. Furthermore, four additional relevant papers were included from the reference lists of the identified papers, bringing the total to 20 papers. The present paper followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines (PRISMA statement; Moher, et al. 2009), which includes the use of a PRISMA flow diagram (see Figure 1).

Figure 1

Flow Diagram of Paper Selection Process for the Systematic Review



Results

The 20 papers that met the inclusion criteria were divided into specific categories. A total of 16 papers were considered as papers that had assessed co-occurrence prevalence of problematic or disordered gaming with other addictive behaviours and had explored their commonalities with various related and/or unrelated risk and/or protective factors. Of these 16 papers, ten were categorized as 'prevalence of co-occurrence in GD and other potentially addictive behaviours.' The papers within this category each featured validated psychometric measures which provided an indication of severity risk for disordered gaming and other potentially addictive behaviours. The other six papers that assessed prevalence were categorized as 'proxy indicators of GD prevalence and other potentially addictive behaviours'. Unlike the papers in the first category, these papers did not use psychometric measures as a tool to assess severity for both problematic or disordered gaming and the co-occurring problematic or disordered behaviour and/or substance use. Instead, these studies assessed the frequency of the behaviour (e.g., sexual activity; 'how many times have you engaged in sexual activity in the last week?') or the consumption of substance (e.g., number of alcoholic drinks; 'How many alcoholic drinks have you had in the past week?') as an indicator of use and assessment. The remaining four papers were categorized as 'assessing the etiology of disordered gaming and other potentially addictive behaviours. These papers investigated specific relationships between GD and the mechanisms which may contribute to the understanding of the development, maintenance, or exacerbation of GDs with other potentially addictive behaviours (e.g., coping strategies and personality factors).

Prevalence of Gaming Disorder Co-occurrence with Other Addictive Behaviours

Of the ten studies examining prevalence (Andreassen et al., 2013; Erevik et al., 2019; Király et al., 2014; 2018; Mérelle et al., 2017; Monacis et al., 2017; Müller et al., 2015; 2017; Pontes, 2017; Ream et al., 2011), six examined adult populations (e.g., general populations), three examined adolescent populations (e.g., middle school students; see Table 1), and one examined both adolescents and adults. Six (Erevik et al., 2019; Lee et al., 2018; Mérelle et al., 2017; Müller et al., 2015; Na et al., 2017; Ream et al., 2011) of these studies focused on the co-occurrence of GD with problematic substance use (i.e., nicotine and cannabis use) and alcohol use. While there has been some exploration of other potentially addictive behaviours, such as buying, phone use, eating, gambling, exercise, sexual behaviour, and social media use, these were usually a part of a larger investigation of substance use or disordered substance use, which did not consider disordered gaming as the primary focus. Consequently, their findings lack nuanced consideration of disordered gaming and the wider implications within the gaming studies field. four studies (Andreassen et al., 2016; Király et al., 2014; Monacis et al., 2017; Pontes, 2017) investigated the co-occurrence of GD with other 'technological addictions' (e.g., social media addiction and internet addiction).

Prevalence was investigated in eight geographical locations, including Norway (*n*=2) (Andreassen et al., 2013; Erevik et al., 2019), Hungary (*n*=1) (Király et al., 2014), Netherlands (*n*=1) (Mérelle et al., 2017), USA (*n*=2) (Lee et al., 2018; Ream et al., 2011), Italy (*n*=1) (Monacis et al., 2017), Germany (*n*=1) (Müller et al., 2015), South Korea (*n*=1) (Na et al., 2017), and Portugal (*n*=1) (Pontes, 2017). Sample sizes ranged from 128 to 21,053 participants. However, the type of surveyed populations was relatively narrow, with the majority of the studies considering school students (*n*=5), and to a lesser degree the general population (*n*=3) (see Table 1).

Table 1

Prevalence Rates of Co-occurrence of Problematic and Disordered Gaming Using Psychometric Measures

Paper	Aims	Sample	Behaviour/ Substance	Instruments	Results/Outcomes
Andreassen et al., 2016 (Andreassen et al., 2016)	To investigate the associations between disordered use of technologies and comorbid psychiatric disorders	Norwegian Population; *n*= 23,533 (*M*=35.8; *SD*=13.3) 17 to 88 years of age.	- Social Networking Site (SNS) addiction -Videogame Addiction	**Bergen Facebook Addiction Scale** (Andreassen, Torsheim, et al., 2012) **(BFAS; 6 item); Game Addiction Scale for Adolescents** (Lemmens et al., 2009) **(GASA; 7 item);** The Adult ADHD Self-Report Scale (Kessler et al., 2005) (ASRS-Version 1.1; 18 items); The Obsession-Compulsive Inventory-Revised (Foa et al., 2002) (OCI-R; 18 item); Hospital Anxiety and Depression Scale (Bjelland et al., 2002) (HADS; 14 item)	- There was a weak interrelationship between SNS addiction and disordered gaming - Results suggest that internet use disorder as a unified concept is not warranted as there are enough differences and motivations between SNS addiction and disordered gaming to warrant separate classifications
Erevik et al., 2019 (Erevik et al., 2019)	To investigate the levels of problems associated with gaming/gaming investment and problematic alcohol use.	Norwegian university student population; *n*= 5217 (*M*=25.8)	- Problematic Gaming - Problematic Alcohol use	**Gaming Addiction Scale for Adolescents** (Lemmens et al., 2009) **(GASA; 7 item); Alcohol Use Disorder Identification Test** (Babor et al., 2001) **(AUDIT; 10 item);** Mini-International Personality Item Pool (Donnellan et al., 2006) (Mini-IPIP; 20 item); Hopskins Symptoms Checklist (Derogatis et al., 1974) (HSCL-25; 25 item)	- Low level gaming and problematic alcohol use co-occur - High levels of gaming act as a protective factor for problematic alcohol use
Kiraly et al., 2014 (Király et al., 2014)	To examine the interrelation and the overlap between problematic internet use (PIU) and problematic online gaming (POG) in terms of sex, school achievement, time spent using the Internet and/or online gaming, psychological well-being, and preferred online activities.	Hungarian nationally representative sample of adolescent gamers; *N*= 2,073 (*M*=16.4, *SD*=0.87)	- Problematic Internet Use - Problematic Online Gaming	**Problematic Online Gaming Questionnaire Short-Form** (Pápay et al., 2013) **(POGQ-SF; 12 item); adapted Internet Use Questionnaire** (Demetrovics et al., 2008) **(PIUQ-6; 6 items);** short-form Center of Epidemiological Studies Depression-Scale (Radloff, 1977) (CES-D; 6 item);	- 4.3% of the sample experienced problematic gaming; 8.8% experienced problematic internet use; and 6.7% experienced both problematic gaming and problematic internet use - Internet use was a common activity among adolescents;

				Rosenberg's Self-Esteem Scale (Winch & Rosenberg, 2006) (RSES; 10 items)	online gaming was engaged in by a much smaller group - POG and PIU appear to be two conceptually different behaviours, thus providing evidence that Internet addiction and IGD are separate nosological entities
Lee et al., 2018 (Lee et al., 2018)	To explore the relationship of various correlates of problematic and disordered gaming	Adult Sample, *n*=2801; 18-57 years (*M*=22.43, *SD*=4.70)	- Nicotine / Nicotine - Internet Addiction -Problem Videogame Playing (PVP)	**Internet Addiction Scale** (Young, 1998) **(20 items); Problem Videogame Playing Scale** (Tejeiro Salguero & Bersabé Morán, 2002) **(8 items);** Conners' Adult ADHD Rating Scale-Self-Report (Conners et al., 1999) (26 items); **Smoking Behaviour and Video Game Use (2 items)**	- ADHD symptomatology, smoking behaviour, and the amount of video game use have a significant effect on PVP - For every additional cigarette smoked, an individual's problematic gaming score increased by 0.022 (p<.05). - Smoking and PVP had a significant positive correlation
Mérelle et al., 2017 (Mérelle et al., 2017)	To identify which health related problems are most important for adolescents that are at risk for problematic gaming or social media use.	Dutch Adolescent Sample; *n*=21053 (*M*=14.4, *SD*=1.3).	- Smoking - Alcohol - Cannabis - Problematic gaming	**Problematic Video-gaming Use** (Meerkerk et al., 2008) **(6 items); Problematic Social Media Use** (van Rooij et al., 2015) **(6 items);** General Health (DeSalvo et al., 2006) (1 item); Strengths and Difficulties Questionnaire (Muris et al., 2003) (25 items); Life Events (2 items); Lifestyle Questionnaire (American Academy of Pediatrics. Committee on Public Education, 2001; Kemper et al., 2000; Martens et al., 2005) (13 items); **Substance Use (4 items)**	- Smoking is strongly associated with Problematic Video Gaming - A substantial number of adolescents reported some (addictive) problems with gaming (5.7%) or social media use (9.1%) - There is a weak association with substance use
Monacis et al., 2017 (Monacis et al., 2017)	To investigate the extent to which identity styles and attachment orientations account for three	Italian Students; n=712 (*M*=21.63; *SD*=3.90).	- Internet	**Italian Internet Addiction Test** (Fioravanti & Casale, 2015; Young, 1998) **(IAT; 20 items); Internet Gaming Disorder Scale-Short Form** (Monacis,	- Internet addiction, online gaming addiction, and social media addiction were interrelated

	types of disordered online behaviour	Split into two groups: Adolescent (*n*=267; *M*=18.22, *SD*=1.04) and Adults (*n*=445; *M*=23.67, *SD*=3.55)	- Internet Gaming Disorder - Social Media	Palo, et al., 2016; Pontes & Griffiths, 2015) **(IGDS9-SF; 9 items); Bergen Social Media Addiction Scale** (Andreassen, Torsheim, et al., 2012) **(BSMAS; 6 items);** Revised Identity Style Inventory (Monacis, de Palo, et al., 2016) (ISI-5; 36 items); Attachment Style Questionnaire (Fossati et al., 2003) (ASQ; 40 items)	and predicted by common underlying risk factors - Online gaming addiction was associated with two identity risk factors: informational and diffuse-avoidant identity style.
Müller et al., 2015 (Müller et al., 2015)	To assess how many participants were at risk for Exercise Dependence (EXD) and if the rates differ by gender. Also, to explore the correlations between symptoms of EXD and various correlates and the differences in behaviour in men and women.	German Sample; *n*=128; 18 years and over (*M*=26.5, *SD*=6.7)	- Exercise Dependence (EXD) - Eating Disorder - Pathological Buying - Hypersexual Behaviour - Alcohol Use Disorder - Pathological video gaming	**Exercise Dependence Scale** (Hausenblas & Downs, 2002; Müller et al., 2013) **(21 items); Eating Disorder Examination Questionnaire** (Fairburn & Beglin, 1994; Hilbert et al., 2012) **(28 items); Compulsive Buying Scale** (Faber & O'Guinn, 2002; Mueller et al., 2010) **(7 items); Assessment of Pathological Computer-Gaming** (Wölfling et al., 2011) **(15 items); Hypersexual Behaviour Inventory** (Klein et al., 2014; Reid, Li, Gilliland, et al., 2011) **(15 item); Alcohol Use Disorders Identification Test** (Babor et al., 2001; Dybek et al., 2006) **(10 items)**	- 7.8% of the sample were at-risk for EXD, 10.9% reported eating disorder pathology, 2.3% pathological buying, 3.1% hypersexual behaviour, and none of the participants suffered from pathological video gaming - EXD symptoms were positively correlated with both eating disorder pathology and pathological buying, but not with pathological video gaming - Eating Disorder pathology was found to be positively correlated with pathological video gaming
Na et al., 2017 (Na et al., 2017)	To investigate videogame usage patterns and clinical characteristics of Internet Gaming Disorder (IGD), Alcohol Use Disorder (AUD), and their comorbid status within a large sample size	South Korean Adults *n*=1819; 20s-40s	- Alcohol (AUD) - Internet Gaming Disorder	**DSM-5 Internet Gaming Disorder Criteria (9 items); Alcohol Use Disorders Identification Test** (So & Sung, 2013) **(10 items);** Dickman Impulsivity Scale (Dickman, 1990) (23 items); Brief Self-Control Scale (Won & Han, 2018) (13 items); Symptom Check-List 90 Items-Revised (Kim et al., 1984) (23 items [Depression 13 items, and Anxiety 10 items]); Behavioral Inhibition	- 14.1% of participants presented with problematic gaming - 37.9% of participants presented with problematic alcohol use - 21.2% of participants experienced both problematic alcohol use and internet game use

				System/Behavioral Approach System Scale (K. Kim & Kim, 2001) (20 items)	- The Comorbid group had higher smoking rates (44.8%) compared to the alcohol group (31.6%) or problematic gaming group (26%) - The comorbid group had significantly higher AUDIT-K scores than that of the AUD group
Pontes, 2017 (Pontes, 2017)	To investigate the interplay between SNS addiction and IGD and to ascertain how they can uniquely and distinctively contribute to increasing psychiatric distress when accounting for potential effects stemming from sociodemographic and technology-related variables.	Middle School Portuguese Sample *n*=700; 10-18 years (*M*=13.02, *SD*=1.64)	- Social Networking Sites Addiction (SNS) - Internet Gaming Disorder (IGD)	**Bergen Facebook Addiction Scale** (Andreassen et al., 2016) **(6 items); Internet Gaming Disorder Short-Form** (Pontes & Griffiths, 2015) **(9 items);** Depression, Anxiety, and Stress Scale (Lovibond & Lovibond, 1995) (21 items)	- SNS is correlated with the symptoms of IGD - IGD is correlated with the symptoms of SNS
Ream et al., 2011 (Ream et al., 2011)	To investigate if videogame engagement while using substances contributes to substance abuse problems	American Sample *n*=2885; Over 18 years and over (*M*=40.4, *SD*=15.7)	- Caffeine - Nicotine - Alcohol - Cannabis - Problem Videogame playing behaviour	**National Survey of Drug Use-based questionnaire (46 items)**; **Consumer Involvement in Video Games; Problem Video Game Play** (Tejeiro Salguero & Bersabé Morán, 2002) **(10 items)**	- Problem Play significantly correlated to problematic: Caffeine, Tabaco, alcohol, cannabis use. Males consumed more caffeine and alcohol, while females consumed more nicotine - There is a potential for "drug interaction" between self-reinforcing behaviours and addictive substances, with implications for the development of problem use. - Statistical models suggested that gaming an enthusiastic hobby (i.e., video game play frequency, enjoyment, and consumer involvement) could potentially be

	a third variable that was associated with co-occurring use of caffeine, nicotine, and alcohol and problematic gaming

Note. Items in bold represent relevant measures; SNS is Social Networking Site; POG is Problematic Online Gaming; PIU is Problematic Internet Use; EXD is Exercise Dependence; AUDIT-K is Alcohol Use Disorders Identification Test – Korea; AUD is Alcohol Use Disorder; IGD is Internet Gaming Disorder.

Six studies investigated the prevalence of problematic or disordered gaming within adult populations. Lee et al. (Lee et al., 2018) investigated the relationship between Attention Deficit Hyperactivity Disorder (ADHD), cigarette smoking, problematic gaming, and the frequency of playing videogames in an online American adult sample (*N*=2801). Their results suggested that ADHD, cigarette smoking, and frequency of playing videogames had a significant effect on problematic gaming. This finding was consistent with previous studies, such as Ream et al.'s study (2011), who found a significant correlation with nicotine, alcohol, caffeine, cannabis use, and problematic videogame use in a large American sample of adult gamers (*N*=2885). Furthermore, among gamers, 64% used caffeine and 41% of those caffeine users had consumed caffeine while gaming; 26% of their sample used nicotine and 61% of smokers had smoked cigarettes while gaming; 34% of participants consumed alcohol, and 38% of those had drank alcohol while gaming; and 5.6% of their sample smoked cannabis and 80% of those had smoked cannabis while gaming.

Similarly, Na et al. (2017), surveyed South Korean adults (*N*=1819) online, and found that 21% experienced both problematic alcohol use (i.e., scoring over 20 on the Korean version of Alcohol Use Disorders Identification test [AUDIT-K]) and problematic gaming. This group also had higher cigarette smoking rates (44.8%) than participants in the problematic alcohol group (31.6%) or problematic gaming group (26%), which is consistent with the American sample above. Furthermore, their results indicated that those participants who reported both drinking alcohol and gaming demonstrated higher scores on psychometric tests (which indicated poorer mental health outcomes) than any other group (i.e., control, alcohol group, and gaming group), lending support to the notion that co-occurring substance use and activities and potentially addictive behaviours are associated with maladaptive clinical outcomes (Na et al., 2017).

Müller et al. (2015) investigated Exercise Dependence (EXD) in a German sample of participants attending a fitness center (*N*=128). Their results found that out of the ten males (7.8%) who were at risk of developing EXD, two experienced problematic gaming. One participant was at risk of an eating disorder and at risk of problematic gaming, while the other had problematic alcohol use and problematic gaming, and at-risk pathological buying. While this example is not statistically significant, it does illustrate that problematic gaming can co-occur with other potentially addictive behaviours. Moreover, the research indicates that problematic or disordered gaming does not always co-occur with problematic substance use.

In a Norwegian university sample (*N*=5217), Erevik et al. (2019) reported that 44.9% of participants who had low engagement in gaming were more likely to experience the co-occurrence of problematic alcohol use than those who did not play video games (46.1%; however, this difference became non-significant when controlling for demographic variables, personality, and mental health); while the 4% of participants who experienced high levels of videogame engagement were found to be less likely to experience problematic alcohol use. A larger Norwegian online survey by Andreassen et al. (Andreassen et al., 2016) sampled 25,533 participants and found that 7% experienced problematic gaming and 13.5% experienced problematic social media use. Furthermore, there was a positive association between symptoms of problematic gaming and problematic social media use, demonstrating common risk factors (e.g., impulsive personality, comorbid psychopathology) and the potential for co-occurrence. This finding was corroborated in a study by Monacis et al. (Monacis et al., 2017) which considered the commonalities in shared identity styles in co-occurring online behaviours. In their sample of university students (*N*=445) aged over 20 years, they found that social media addiction and GD shared common identity styles (i.e., informational and diffuse-avoidant), further demonstrating the potential for these problematic behaviours to co-occur.

However, disordered gaming and problematic substance use are not limited to the adult population. Similar results have been found in adolescent populations. For example, in a large survey of 21,053 Dutch adolescents by Mérelle et al. (2017), 5.7% of the sample reported some problematic gaming (5.7%) and 9.1% reported problematic social media use. Smoking cigarettes was strongly associated with problematic gaming. Although their results suggested a high co-occurrence of problematic social media use and smoking cigarettes with problematic gaming, there was a weak association with other substance use.

Pontes (2017) investigated how disordered gaming and social media addiction uniquely contributed to psychological distress, and how these behaviours associated with distress when they co-occurred in a population of Portuguese middle school students (*N*=700). The results demonstrated that both disordered gaming and social media addiction appear to be associated with the symptoms of each other when they co-occur and contribute to deterioration of psychological health as indicated by increased scores on depression, anxiety, and stress scales. In Király et al.'s nationally representative study (Király et al., 2014), of 2,073 adolescents, 4.3% experienced problematic gaming, 8.8% experienced problematic internet use, and 6.7% experienced both problematic videogame use and internet use. Their results demonstrated an overlap in problematic internet use and problematic gaming but verified that these are two distinct problematic behaviours that have the potential to co-occur with one another, and which may influence problematic internet use and/or problematic gaming (Pontes, 2017).

Proxy Indicators of Prevalence of Gaming Disorder and Other Potentially Addictive Behaviours

Other studies have focused on prevalence of disordered gaming and other potentially addictive behaviours using proxy indicators (e.g., using number of alcoholic drinks consumed per day or per week to assess severity of alcohol use). Of the six studies that assessed proxy measures of potentially addictive behaviours (Gallimberti et al., 2016; Ivory et al., 2017; Konkolÿ Thege et al., 2016; McBride & Derevensky, 2017; Škařupová et al., 2018; van Rooij et al., 2014) (Table 2), two studies (Jiang & Shi, 2016; Konkolÿ Thege et al., 2016) examined general adult populations (e.g., national surveys) using proxy indictors of problematic use, two (McBride & Derevensky, 2017; Škařupová et al., 2018) considered both adolescents and adults, while the latter two (Gallimberti et al., 2016; van Rooij et al., 2014) examined adolescent populations (e.g., secondary school students). A total of five of six studies (Gallimberti et al., 2016; Ivory et al., 2017; Konkolÿ Thege et al., 2016; Škařupová et al., 2018; van Rooij et al., 2014) using proxy measures investigated alcohol use and substance use, while four considered smoking cigarettes (Gallimberti et al., 2016; Konkolÿ Thege et al., 2016; Škařupová et al., 2018; van Rooij et al., 2014), and one investigated gambling (McBride & Derevensky, 2017). The geographical locations also varied with papers based in the US (*n*=2) (Ivory et al., 2017; van Rooij et al., 2014), Italy (*n*=1) (Gallimberti et al., 2016), Canada (*n*=1) (Konkolÿ Thege et al., 2016), the Czech Republic (*n*=1) (Škařupová et al., 2018), and France (*n*=1) (McBride & Derevensky, 2017)

Table 2

Prevalence Rates of Co-occurrence of Problematic and Disordered Gaming Using Proxy Indicators

Paper	Aims	Sample	Behaviour/ Substance	Instruments	Results/Outcomes
Gallimberti et al., 2016 (Gallimberti et al., 2016)	The aim of the study was to investigate the association between problematic gaming and substance abuse in children and young adolescents	Italian Students; *n*=1156 (*M*= 12.03, *SD* =1.03)	- Alcohol - Smoking - Cannabis - Problematic Use of Video Games (PUVG)	Pinocchio Survey (136 items - Family, Peer, Personality, and behaviour domain factors ***[which included Smoking, Alcohol, Energy Drink [Caffeine], and Cannabis)***; **Problematic Use of Video Games scale (adapted from the DSM-5; 6 items)** (American Psychiatric Association, 2013)	- Smoking (nicotine & cannabis), alcohol, and energy drink consumption are associated with PUVG
Ivory et al., 2017 (Ivory et al., 2017)	To explore the potential role videogames may have on the unique health risk environment of college and university campuses. To predictions of the risk, incapacitation, and inconsequential approaches to the possible role of video games	US college students; *n*=533 (18 and over; *M* = 25.02, *SD* = 5.67)	- Alcohol - Substance use - Disordered eating - Exercise - Weekly videogame use	**Adapted and amalgamated version of the National College Health Risk Behaviour Survey and the National College Health Assessment (24 items)**	- Video game play was largely unrelated to disordered exercise, nicotine, and other substances - Video game play was related to higher weight, but reduced rates of disordered eating
Konkolÿ Thege et al., 2016 (Konkolÿ Thege et al., 2016)	To describe the prevalence of single versus multiple addiction problems in a large representative sample and to identify distinct	General Canadian Sample; *n*=6000 (18 and over; *M*=44.5, *SD*=15.1)	- Alcohol - Nicotine - Marijuana	**Alberta Addiction Survey** (Konkolÿ Thege et al., 2015) **(10 items);** Personal Wellbeing Index (8 Items)	- 29.8% reported a problem use with one substance or behaviour; 13.1% reported co-occurrence of two; 7.9% reported the co-occurrence of three or more.

	subgroups of people experiencing problematic or disordered behaviours.		- Cocaine - Gambling - Eating - Shopping - Sex - Video Gaming - Work		- Excessive video game playing frequently co-occurred with smoking, excessive eating and work - The highest co-occurring problem behaviours to the lowest (*n*=127): Work (37.2%), eating (36.6%), nicotine (31.1%), sex (14.1%), cannabis (13.5%), gambling (12.3%), shopping (4.9%), alcohol (1.2%), cocaine (0.6%)
McBride et al., 2017 (McBride & Derevensky, 2017)	To examine commonalities between gambling behaviour and problematic gambling among video game players and between video game playing and addicted playing among gamblers	French Canadian Student Sample; n=1229 (16-24 years old; *M*=18.69, *SD*=1,41)	- Problem Gambling - Game Addiction	**Gambling Activities Questionnaire** (McBride & Derevensky, 2009) **(12 items); Video Game Activities questionnaire (12 items); Problem Gambling** (American Psychiatric Association, 2000) **(12 items); Gaming Addiction Scale** (Lemmens et al., 2009) **(21 items)**	- Video gaming was associated with gambling - 11.4% (4) of addicted gamers (*n*=35) experienced problem gambling
Škařupová et al., 2018 (Škařupová et al., 2018)	To explore levels and patterns of online gaming while under the influence of various substances	Czech Online Gamers; *n*=3952 (11-59 years)	- Caffeine - Alcohol - Nicotine - Psychoactive pharmaceuticals - Illicit drugs	**Addiction Engagement Questionnaire** (Charlton & Danforth, 2007, 2010) **(24 items); Drug use while gaming (2 items)**	Caffeine was the most commonly co-occurring substance used by 74.2%, followed by alcohol 40.4%, nicotine 25.3%, and 14.5% used illicit substances while gaming - Substance use was positively associated with intensity of

			- Online Gaming Addiction		gaming and both addiction and engagement
van Rooij et al., 2014 (van Rooij et al., 2014)	The current study explored the nature of problematic video gaming (PVG) and the association with game type, psychosocial health, and substance use	Aggregated census data. Secondary School sample; *n*=8478	- Cannabis - Alcohol - Nicotine - Problematic Video Gaming (PVG)	**Video Game Addiction Test** (van Rooij et al., 2012) **(14 item); Psychoactive Substance Use/Non-Use;** Self-Esteem Scale (M. Rosenberg, 1965) (10 items); Loneliness Scale (Russell et al., 1980) (10 items); Depressive Mood List (Engels et al., 2001) (6 items); Revised Social Anxiety Scale for Children (La Greca & Stone, 2005) (Subscales: Social Avoidance & Distress [6 items] and Social Avoidance & Distress in General [4 items]); Self-Reported educational Performance (1 item)	- Higher scores on PVG indicated higher use of nicotine, alcohol and cannabis

Note. Items in bold represent relevant measures; PUVG is Problematic Use of Video Games; PVG is Problematic Video Game Use

In regard to prevalence within the adolescent populations, two studies showed a positive correlation between the frequency of video game use and substance use, demonstrating a strong association (Gallimberti et al., 2016; van Rooij et al., 2014). More specifically, Gallimberti et al. (2016) found in their adolescent sample (*N*=1156) that 16.4% experienced problematic gaming, and within this cohort, 41.2% had smoked cannabis, 23.2% had consumed an energy drink (i.e., caffeine), 21.7% had smoked a cigarette (i.e., nicotine), and 21.3% had drank alcohol (in their lifetime), demonstrating an association between gaming and use of these substances.

Van Rooij et al. (2014) also suggested that higher scores on the Video Game Addiction Test (VGAT; which assesses problematic videogame use) indicated an increase in frequency of substance use. Their research showed that 36.4% of online gamers in their sample (*n*=8478) consumed alcohol, 34% smoked cigarettes, and 44.6% smoked cannabis. This is in line with studies that exclusively used psychometric measures to assess use and severity of other potential addictions. A similar trend was found in a large sample of Czech online gamers (*N*=3952) (Škařupová et al., 2018) which investigated gamers and the influence of psychoactive substances. They found that while gaming, caffeine was the most frequently used substance (74.2%), followed by alcohol (40.4%), nicotine (25.3%), and illicit substances (14.5%).

Similarly, Konkolÿ Thege et al. (2016) surveyed 6000 adults and found that those who experienced problematic gaming (2.1%), 1.2% experienced problematic alcohol use, while 31.1% experienced problematic nicotine use, and 13.5% experienced problematic cannabis use. This was calculated using a single self-report question ‘Thinking back over your life, have you ever personally had a problem with [problematic behaviour or substance use]?’ with 3 possible responses – ‘No’, ‘Yes, but not in the past 12 months’, and ‘Yes, in the past 12 months.’ Using this question, the researchers also considered potentially addictive behaviours that co-occur with disordered gaming. Their results suggested that 37.2% of their participants had experienced the co-occurrence of problematic work, 36.6% had experienced problematic eating behaviours (i.e., eating too little or too much), 14.1% had experienced problematic sex (i.e., excessive sexual behaviour), and 12.3% had experienced problematic gambling. The latter finding was in line with a study by McBride et al. (2017), which reported that 11.4% of disordered gamers within in their sample experienced problem gambling, and which is consistent within the wider literature (Kessler et al., 2008; Mcbride & Derevensky, 2012). Finally, a study by Ivory et al. (Ivory et al., 2017) on US college students (*n*=533) suggested that gaming was not significantly associated with nicotine or substance use. However, taken as a whole, the aforementioned studies tend to indicate that disordered gaming appears to frequently co-occur alongside problematic substance use, and there are complex associations between the co-occurring problematic substance use and potential behavioural addictions.

Assessing the Etiology of Gaming Disorder and Co-occurring Potentially Addictive Behaviours

Four (Andreassen et al., 2013; Estévez et al., 2017; Schneider et al., 2018; Walther et al., 2012) out of the 20 eligible studies identified for review were classified as etiological papers and defined as papers that attempted to explore the underlying mechanisms that may contribute to co-occurrence of GD with other potentially addictive behaviours and possible etiological pathways (see Table 3). These papers also have diverse geographical locations, including Norway (Andreassen et al., 2013), Spain (Estévez et al., 2017), Australia (Schneider et al., 2018), and Germany (Walther et al., 2012).

Table 3

Cross-sectional Papers Assessing the Etiology of Disordered Gaming

Study	Aims	Sample	Behaviour/ Substance	Instruments	Results/Outcomes
Andreassen et al., 2013 (Andreassen et al., 2013)	To investigate behavioural addictions and how they relate to the main dimensions of the five-factor model of personality	Norwegian University Students; n=218 (*M*=20.7 years; *SD*=3)	- Facebook - Exercise - Mobile Phone Addiction - Compulsive Buying - Study Addiction - Videogame Addiction	**Bergen Facebook Addiction Scale** (Andreassen, Torsheim, et al., 2012) **(BFAS; 6 items); Game Addiction Scale for Adolescents** (Lemmens et al., 2009) **(GASA; 7 items); Young's Diagnostic Questionnaire** (Young, 1998) **(YDQ; 8 items); The Exercise Addiction Inventory** (Terry et al., 2004) **(EAI; 6 items); Mobile Phone Addiction Index** (Leung, 2008) **(MPAI; 8 items); Compulsive Buying Scale** (Faber & O'Guinn, 2002) **(CBS; 13 items); Study Addiction Scale** (Andreassen, Griffiths, et al., 2012) **(7 items; adapted from the Bergan Work Addiction Scale);** Revised NEO Five-Factor Inventory-Revised (McCrae & Costa, 2004) (60 items)	- Conscientiousness was negatively associated with video game addiction. - Conscientiousness seems to be a protective factor for unproductive behavioural addictions (i.e., Facebook use, video gaming, Internet use, compulsive buying) - The distinction between unproductive and productive behavioural addictions bears some resemblance to the distinction between impulsive control disorders and OCD
Estévez et al., 2017 (Estévez et al., 2017)	To examine the relationship of emotional regulation and attachment, with	Spanish high school students; *n*=472 (*M*=15.6, *SD*=1.33)	- Video Game Addiction - Gambling Disorder	Difficulties in Emotion Regulation Scale (Gratz & Roemer, 2004; Hervás, Gonzalo; Jódar, 2008) (28	- Emotional regulation is predictive of all addictive behaviours

	disordered substance use, disordered behaviours in adolescents and emerging adults		-Problematic Internet Use - Alcohol Abuse - Substance Abuse	items); Inventory of Parent and Peer Attachment (Armsden & Greenberg, 1987; Gallarin & Alonso-Arbiol, 2013) (Mother: 16 items Father: 16 items; Peer: 16 items); **Multicage CAD-4** (Pedrero Pérez et al., 2007) **(Alcohol [4 items] & Substance Abuse [4 items] Subscales); Problematic Internet Use** (Fargues et al., 2009) **(10 items); Video Game-related Experience Questionnaire** (Chamarro et al., 2014) **(17 items); South Oaks Gambling Screen for Adolescents** (Winters et al., 1993) **(12 items)**	- Attachment is predictive of non-substance-related addictions - Males scored significantly higher in gambling disorder and videogame addiction
Schneider et al., 2017 (Schneider et al., 2018)	To investigate Internet gaming disorder (IGD) in relation to coping, including emotion- and problem-focused coping styles	Australian Students 12-19 years; *n*=823 (*M*=14.2, *SD*=1.4)	- Internet Gaming Disorder - Substance abuse	**Internet Gaming Activities Survey**; **Internet Gaming Disorder Checklist** (Petry et al., 2014) **(12 items); Brief COPE** (Carver et al., 1989) **(28 items)**	- IGD was significantly correlated with denial and behavioural disengagement coping strategies - Age was positively associated with substance use coping
Walther et al., 2012 (Walther et al., 2012)	To investigate co-occurrence and shared personality characteristics of problematic computer gaming, problematic gambling and substance use	German Students: 12-25 years; *n*=2553	- Problematic gaming - Problematic Gambling - Alcohol, nicotine, and cannabis use (proxy indicator)	**Substance Use Frequencies (3 items)**; **South Oaks Gambling Screen - Revised for Adolescents** (Winters et al., 1993) **(12 items); Video Game Dependency Scale** (Rehbein et al., 2010) **(10 items);** Personality Factors (Kandel & Davies, 1982)	- Alcohol, nicotine, and cannabis were all positively correlated - Problematic gambling and problematic gaming were positively correlated

	(*Each original scale was reduced to 4 items)*; Adapted Depression scale; Inventory of Impulsivity, Risk Behaviour and Empathy (Stadler et al., 2002); Personality Questionnaire; Scale for General Self-Efficacy (Stadler et al., 2002); Scale for self-efficacy in Social Situations (Stadler et al., 2002); Social Anxiety Scale for Children Revised (Melfsen, 1999); Rating Scale for Attention-Deficit/Hyperactivity Disorder (Döpfner & Lehmkuhl, 1998); Rating Scale for Oppositional Defiant/Conduct Disorders (Döpfner & Lehmkuhl, 1998); Loneliness-Scale (Döring & Bortz, 1993); Rosenberg-Self-Esteem-Scale (von Collani & Herzberg, 2003); Satisfaction with Various Domains of Life (Schwarzer, 1999)	- Problematic gaming co-occurred with cannabis use - Problematic gambling co-occurred with alcohol, nicotine, and cannabis use - High impulsivity was associated with all five addictive behaviours

Note. Items in bold represent relevant measures; IGD is Internet Gaming Disorder

Dysfunctional coping strategies have been used to explore how underlying cognitive mechanisms contribute to the development and maintenance of co-occurring behavioural and substance addictions and understand aetiology. Schneider et al. (Schneider et al., 2018) utilized the Brief COPE (Carver, 1997) to assess different subdomains of coping styles (i.e., a range of cognitive and behavioural responses that are utilized in stressful situations) (McMahon et al., 2013). They surveyed 823 Australian high school students (*M*=14.3, *SD*=1.4) and found that coping may play a pivotal role when considering co-occurring risk behaviours. They highlighted a tendency toward denial and behavioural disengagement coping styles – which were positively correlated with substance use – within those who scored higher on disordered gaming, suggesting that adolescents may employ avoidant coping strategies.

In a sample of 472 Spanish students (aged 13-21 years), Estévez et al. (2017) assessed the relationship between emotional regulation and attachment in several addictive behaviours, including disordered gaming. The study found that attachment style was predictive of behavioural addictions, but not substance addictions. Poor peer attachment predicted gaming and gambling disorders, and poor maternal attachment predicted problematic internet use.

With regard to personality, Andreassen et al. (2016) found that social media addiction, internet addiction, and GD were all negatively associated with conscientiousness among a small sample of Norwegian university students (*n*=218). Walther, Morgenstern and Hanewinkel (2012) also proposed that co-occurrence between substance and behavioural addictions could be explained via personality traits. Their results indicated that impulsivity and social anxiety were associated with substance users, gamblers, and gamers. The high impulsiveness trait (i.e., doing things without thinking them through) characterized individuals who engage in problematic substance use, problematic gambling, and problematic gaming. However, while low social anxiety was predictive of problematic substance use and problematic gambling, the reverse was true for problematic gaming, where those with high social anxiety were at higher risk for problematic gaming behaviour. It should also be noted that social anxiety has been associated with dysfunctional coping strategies (Schneider et al., 2018), which in turn has been implicated in addiction (Buckner et al., 2014; Gregg et al., 2014). Furthermore, the researchers noted that while problematic substance users have high co-occurrence to other addictions, each addiction to one substance showed associations with personality traits (i.e., high impulsivity and high extraversion) and mental health problems (e.g., high depression, low social anxiety). Problem gamers showed overlap in some of these traits (i.e., impulsivity and social anxiety) with problematic gamblers.

Discussion

The aim of the present paper was to review and describe the literature on co-occurrence within the field of gaming disorder (GD) published over the past decade. The review considered the prevalence rates in empirical studies that investigated the potential co-occurrence of potential behavioural addictions and/or substance use in those with GD. It also described the use of psychometrically validated assessment instruments and proxy measures in assessing prevalence rates, as well as the etiological studies that investigated the development and maintenance of co-occurrence of potentially addictive behaviours among those with GD.

Ten papers considered GD and a co-occurring potential behavioural addiction and/or substance use and employed validated psychometric measures to assess the prevalence, frequency, and severity of the behaviours studied. Six papers investigated adult populations (Andreassen et al., 2016; Lee et al., 2018; Müller et al., 2015; Müller & Montag, 2017; Na et al., 2017; Ream et al., 2011), four papers investigated adolescents (Király et al., 2014; Mérelle et al., 2017; Pontes, 2017), and one considered both (Monacis et al., 2017).

Ream et al. (2011) investigated a North American sample and found that of those who consume psychoactive substances (e.g., nicotine and/or coffee) also engaged in concurrent use of gaming. The surveyed literature also suggested that smoking nicotine or drinking alcohol can have an impact on problematic gaming scores (Lee et al., 2018; Na et al., 2017). The broader literature suggests an overlap between various substance and behavioural addictions, suggesting it is a relatively common occurrence (Sussman et al., 2011) among adults. Collectively the reviewed literature also demonstrates that adults who play video games engage in concurrent use of psychoactive substances, which may result in co-occurring problematic use and engagement in potentially addictive behaviours.

The surveyed literature on adolescents also reflects a range of prevalence rates. In a nationally representative Hungarian sample, it was shown that 4.3% experienced problematic gaming, 8.8% experienced problematic internet use, and 6.7% experienced both problematic gaming and internet use (Konkolÿ Thege et al., 2016). Andreassen et al.'s (2016) results suggest that 7% of Norwegian adults reported problematic gaming. A similar result was found among a Dutch sample, which reported 5.7% of their sample experienced some problematic gaming and 9.1% reported problematic social media use, both of which were strongly associated with nicotine consumption (Mérelle et al., 2017). Pontes (2017) had a similar finding in Portuguese middle school students, which suggested that the co-occurrence of problematic gaming and problematic social media use can lead to the deterioration of psychological health more so than either problematic behaviour on its own. The studies also suggest that disordered gaming shares underlying risk factors (e.g., identity styles; Monacis et al., 2017) with problematic social media use and internet addition, suggesting that co-occurring problematic behaviours may share common identity styles, which act as risk factors in the co-occurrence of problematic online behaviours (i.e., gaming, social media, and internet use).

These results were consistent with the wider literature in regards to the association with potentially addictive behaviours and/or substance use (Smith et al., 2014; Tavolacci et al., 2013), while the findings concerning disordered gaming also showed parallels with other behavioural addictions and substance disorder fields (e.g., gambling; Griffiths et al., 2002; Griffiths & Sutherland, 1998). However, the variation in the consumption of substances or frequency of behaviours within the surveyed literature may indicate that traditional approaches in psychiatric comorbidities (Starcevic & Khazaal, 2017) and problem behaviour theory (Ko et al., 2008) may not be a viable approach when assessing disordered consumption of substances and resulting behaviours. Gamers may instead be making pragmatic choices involving their consumption of substances, which may not be an indication of uncontrolled behaviour (Škařupová et al., 2018). For example, having increased amounts of caffeine or using 'smart' drugs could be used to provide a competitive edge while gaming, which could be particularly true for those who play games professionally (Dance, 2016). This may explain why illicit substance use (as opposed to legal substance use) varies in the surveyed literature, because it may be a choice by gamers to prolong their gaming with stimulants such as caffeine or nicotine (Ivory et al., 2017). However, gamers may choose to consume substances irrespective of videogame participation (Škařupová et al., 2018), which would explain the high rate of nicotine use (Konkolÿ Thege et al., 2016) and alcohol use (Müller & Montag, 2017) in some samples of gamers. For example, if an individual is trying to quit smoking, they may increase their alcohol consumption (which has been associated with disordered gaming (Na et al., 2017)). In an attempt to offset their need for nicotine, they may engage in other potentially addictive behaviours (e.g., alcohol consumption), which may then co-occur with an addiction, such as GD. This suggests an underlying association with disordered substance use, which can be seen in other disordered behaviours, such as gambling disorder (Cunningham-Williams et al., 2000; Goudriaan et al., 2006).

Based on the empirical studies reviewed, problematic gamers consume a variety of substances while engaged in videogames. More specifically, while gaming, between 23.3%-74.2% of gamers consumed caffeine (Gallimberti et al., 2016; Škařupová et al., 2018), 21.7%-25.3% smoked cigarettes (Gallimberti et al., 2016; Škařupová et al., 2018), 41.2%-44.6% smoked cannabis (Gallimberti et al., 2016; Mérelle et al., 2017), 21.3%-40.4% consumed alcohol (Gallimberti et al., 2016; Škařupová et al., 2018), and 14.5% consumed illicit substances (Škařupová et al., 2018). In regard to problematic and disordered behaviour, the findings suggested that problematic gambling (McBride & Derevensky, 2017), problematic shopping, problematic sex, and problematic work (Konkolÿ Thege et al., 2016) were associated with disordered gaming, while disordered exercise was not related (Ivory et al., 2017; Müller et al., 2015).

Indeed, the presented evidence suggests that the co-occurrence of potentially addictive behaviours is not uncommon and is associated with a number of maladaptive outcomes for both adults (Lee et al., 2018) and adolescents (Bibbey et al., 2015; Pontes, 2017). There appears to be a clear divide between the experience of co-occurrence among adults and adolescents. The literature demonstrates that adults with disordered gaming frequently feature co-occurring problematic or disordered substance use (e.g., alcohol use; Erevik et al., 2019; Na et al., 2017; Ream et al., 2011), while disordered eating (Müller et al., 2015) appears less frequently. However, the opposite appears to be true for adolescents, who appear to experience co-occurring disordered behaviours, such as social media addiction or problematic internet use (Király et al., 2014; Pontes, 2017). The discrepancy between adults and adolescents may be explained due to the scarcity of available substances due to age-related factors (Tsai et al., 2016) because disordered substance use is seen to increase as adolescents get older (Schneider et al., 2018), allowing them to purchase alcohol or nicotine legally.

It is also worth noting that many of the problematic behaviours co-occurring with disordered gaming are ones that can be performed concurrently with gaming. For example, the surveyed literature shows that problematic exercise and problematic gaming co-occur. This may be attributed to the fact that gaming does not typically facilitate exercise, as gaming is largely a sedentary behaviour, whereas exercise requires vigorous physical activity (Müller et al., 2015), which acts as a protective factor in GD (Liew et al., 2018). This idea is also corroborated by the way the literature consistently shows that smoking and alcohol use co-occur with GD (Lee et al., 2018; Müller & Montag, 2017; Na et al., 2017; Ream et al., 2011). This may arise because the gaming context can facilitate the concurrent use of alcohol and smoking (i.e., nicotine or cannabis), especially if used as part of a coping strategy (Na et al., 2017).

Coping strategies were one of the three ways (i.e., (i) coping strategies, (ii) emotional regulation and attachment, and (iii) personality characteristics) in which the development and maintenance of co-occurrence was considered in behavioural and substance addictions. Schneider et al. (Schneider et al., 2018) considered coping strategies to be a key element in the development and maintenance of co-occurrence in an adolescent sample. Their results suggested that behavioural disengagement was a common coping strategy by those who experienced disordered gaming. One proposed reason of this resulting behaviour is the self-medication hypothesis. This hypothesis suggests that in addiction-related disorders, individuals use substances in order to overcome painful affective states as well as related mental disorders (Khantzian, 1985), and this has been a common area of interest in problematic internet use (Senormanci et al., 2014; Tang et al., 2014). It may also indicate that maladaptive coping strategies (i.e., denial and/or behavioural disengagement) may play a key role in the development of co-occurring behaviours within disordered gaming. Furthermore, when these coping strategies co-occur, it is evident that these strategies appear to worsen disordered gaming symptoms, more so than either one on their own (Kuss et al., 2017). However, while there has been some literature to suggest that coping strategies play an important role in problematic internet use (Brand et al., 2014; Kuss et al., 2017), further research is needed in the case of disordered gaming.

Estévez et al. (2017) suggested that gambling disorder and alcohol use disorder may be explained utilizing emotional regulation and attachment theory. Through lived experiences with attachment figures, minors learn how to cope with a variety of different negative emotions when facing distress or danger. Such experiences reinforce emotional regulation (i.e., the ability to modify emotions, as well as when and how such emotions are experienced and expressed (Gross, 2002; Mikulincer et al., 2009), and low levels of emotional regulation have been associated with an increase in risky behaviours, such as GD (Gutiérrez et al., 2014) and substance use (Schreiber et al., 2012). Emotional regulation is also predictive of addictive behaviours (but not substance addiction), suggesting that individuals with difficulty in emotional regulation may engage in addictive behaviours to avoid (i.e., behavioural disengage) or regulate negative feelings or emotions (i.e., the self-medication hypothesis (Aldao et al., 2010; Estévez et al., 2017; Kuss et al., 2017).

Attachment may also predict co-occurring use. Poor peer-attachment can predict GD and gambling disorder, and poor maternal attachment predicted problematic internet use. Individuals with a secure attachment are characterized by a self-acceptance of emotional needs. However, an individual with a non-secure attachment style may pay little attention to their emotional needs and feel they have a lack of support (Estévez et al., 2017). This may then cause them to avoid interpersonal relationships (Malik et al., 2015), lending support to the notion that behavioural addictions may be understood as a form of escape and compensation for poor relationships (Vollmer et al., 2014). Indeed, it could be suggested that individuals employ maladaptive behavioural coping strategies in response to poor emotional regulation or attachment, which may in turn aid in the development and maintenance of co-occurring at-risk behaviours.

Another dimension that has been considered in the development and maintenance of co-occurrence in GD is personality traits and factors. Low conscientiousness has been found to be associated with behavioural addictions (e.g., SNS addiction and GD; Andreassen et al., 2013). This suggests that people who experience problematic or disordered gaming may have low conscientiousness and may have a low priority of duties and obligations (Andreassen, Griffiths, et al., 2012), lack of planning ability (Lee et al., 2006), low self-control, weakness for temptations (Wang & Yang, 2008), and experience procrastination (Verplanken & Herabadi, 2001). This is in line with Walther et al. (Walther et al., 2012), whose results suggested that individuals that experience problematic or disordered gaming also have high impulsiveness (i.e., a lack of self-control), which has been associated with problematic or disordered behaviour, and/or substance use (Nicola et al., 2015). Furthermore, problematic gamers only shared a small overlap in personality factors with problem gambling (i.e., problematic behaviour), even though problematic gambling shares more of an overlap in personality factors with problematic substance use than problematic gaming. However, problematic gamers reported higher scores on ADHD symptoms, high irritability/aggression, high social anxiety and low self-esteem than any other addiction in Walther et al.'s paper (Walther et al., 2012), suggesting that gaming may take a unique dispositional position within the examined addictive behaviours here. The aforementioned studies indicate that personality traits or factors may influence the likelihood for co-occurrence to manifest in people experiencing problematic or disordered gaming.

The literature reviewed represents important examples of the next logical step in the progression of research beyond prevalence rates of co-occurrence. Each of the reviewed studies explored either specific psychological, sociological, and/or physiological factors. This in turn can guide future research into presenting a holistic representation of the specific risk factors (e.g., coping strategies and identity styles), which may contribute to developing, maintaining, or the exacerbation of co-occurring potentially addictive disorders. Furthermore, future research could help inform public policy and guide the development of treatment that encompasses the full clinical presentations of patients. However, only four recent studies (Andreassen et al., 2016; Estévez et al., 2017; Schneider et al., 2018; Walther et al., 2012) have taken the extra step to investigate the etiology and mechanisms of co-occurring disorders.

Understanding these processes is needed to further the understanding of addictive disorders. Nevertheless, the extant findings are beneficial in advancing the field and providing a framework for how to consider the mechanisms of co-occurring addictive behaviours in a multifaceted manner. Furthermore, the present review also highlights the potential for differing mechanisms of action, despite similar observed effects, suggesting that behavioural and substance addictions, and their co-occurrence involve complex processes. In understanding these factors, treatment efficacy may be increased by targeting common etiological mechanisms across multiple disorders (e.g. coping mechanisms; Schneider et al., 2018), or personality factors (Walther et al., 2012), much like the direction of the literature within the substance disorders field.

Co-occurrence within Disordered Gaming Compared to the Substance Disorder Literature

Arguably, GD is one of the newer behavioural disorders to be investigated. Nevertheless, more established substance use disorder literature can be used to provide a reference point on how to advance the co-occurrence research into disordered gaming. The drug and alcohol abuse literature appears to focus on the epidemiology of co-occurrence as it appears to be commonly studied (Kuss et al., 2014), a trend that the GD literature is following. Furthermore, within the substance abuse literature co-occurring behavioural and substance addictions appear to be commonly considered in both the general and clinical populations (Morisano et al., 2014; van Rooij et al., 2014), indicating that the GD literature should also mimic this global approach. In addition, individuals with co-occurring behavioural or substance use disorders (or problematic use) tend to have poorer functioning and treatment outcomes, much like individuals with disordered gaming (Kuss et al., 2014; Winkler et al., 2013; Yakovenko & Hodgins, 2018). These findings within the substance use literature are in part facilitated by the longitudinal research investigating the development, maintenance, and remission of each disorder, which the present field of co-occurrence in disordered gaming lacks.

While research on GD focuses on the prevalence and co-occurrence of psychiatric disorders (Ko et al., 2012), the substance use literature has gone much further by investigating and identifying the epidemiological factors of co-occurrence and the effect co-occurring disorders can have. For example, there have been a number of studies that have investigated a wide range of underlying mechanisms between co-occurring substance use and other disorders such as neurobiological commonalities, genetic markers, temporal changes, and qualitative research focusing on behavioural changes (Ruiz, 2017; Szerman et al., 2013). Furthermore, the substance use literature has also investigated whether treating one disorder causes the accompanying co-occurring disorder to go into remission, concluding that it can vary depending upon the disorders and individual presentation (Kalina & Vacha, 2013; Morisano et al., 2014). However, when looking to research concerning disordered gaming, this additional step has not yet been made, and the effects of co-occurrence and its impact on course of illness and by type of disorder is not yet known. Additionally, the substance abuse literature has also closely examined the links between multiple co-occurring disorders (Cleary et al., 2009; Winkler et al., 2013). While the research on disordered gaming has begun to move in this direction, research on substance use has attempted to separate various dimensions of co-occurrence (e.g., psychiatric disorders, mental health, and social functioning) by controlling for their effects on the primary disorder in question (Grant et al., 2015).

Finally, when considering treatments, the substance use literature has paved the way for behavioural disorders. There is a general agreement that co-occurring disorders may require an integrated approach (Carrà et al., 2015; Roncero et al., 2017) which consider not just the primary disorder, but also the co-occurring disorder. For example, in a systematic review on people who experiences severe mental illness and co-occurring substance use suggested that motivational interviewing in conjunction with Cognitive Behaviour Therapy (CBT; targeting both substance use, and mental health respectively) showed 'quality' evidence for reducing substance use and improving mental health than just CBT alone. However, this type of approach is not near the level of acceptance as more traditional treatments (such as CBT), although there are considerable efforts to evaluate its efficacy in the substance use field (Burdzovic Andreas et al., 2015; Cleary et al., 2009). In contrast, the research into integrative treatments that targets both disordered gaming and co-occurring addictive disorders is, to the best of authors' knowledge, notably absent from the literature.

Future Research

A majority of the surveyed literature does not go beyond measures of association and with measures of prevalence being questionable due to overwhelming lack of representativeness of samples. The published literature suggests that there are various behavioural and substance-related addiction disorders that have the potential to co-occur with GD. However, there is very little additional literature that continues to investigate this further. Regarding the co-occurrence of disordered gaming with other behavioural addictions, only a few studies exist, suggesting a co-occurrence with problematic gambling, shopping, and social media use. While there has not been an extensive amount of literature on the co-occurrence prevalence rates of disordered gaming with other addictive behaviours, it has been explored across several geographical locations and cultures, indicating that it is moving in a similar direction of other addiction-related literature (e.g., gambling; Yakovenko & Hodgins, 2018). However, while it is important that this line of enquiry is followed, it is also important to investigate the etiological aspects of co-occurrence within GD because it is experienced differently across culturally diverse groups of people.

There is a significant gap in the literature when it comes to longitudinal surveys that focus on the changes of co-occurring addictive disorders over time. The current literature establishes that co-occurrences between disordered gaming and other addictive-related disorders are common. Furthermore, no paper to the authors' knowledge has investigated whether disordered gaming preceded the onset of another co-occurring addictive disorder or vice versa. It is imperative to understand how co-occurring disorders interact over time in order to develop appropriate treatment methods. Moreover, models for hypothesizing potential treatment frameworks and outcomes, which consider onset or remission of other co-occurring problematic or disordered behaviour, would be instrumental in improving potential effectiveness of treatment methods. For example, having confidence that disordered gaming symptoms typically occur within specific substance abuse disorders (e.g., alcohol or cannabis abuse) may allow for a more tailored approach that targets both disordered gaming and the co-occurring use of other behaviours or substances. Future studies should also consider investigating the time of onset in relation to disordered gaming because this would also provide more robust data and allow for more significant conclusions to be drawn.

Substance Use Literature May Act as a Model to Guide Future Research

A finding that was consistent across both adults and adolescents was that those who presented with problematic or disordered gaming and a co-occurring addiction-related condition consistently reported more severe experiences as assessed using clinical measures (Lee et al., 2018; Na et al., 2017; Pontes, 2017), which is mirrored within the substance abuse literature (Gossop et al., 2002; Morisano et al., 2014). Another way in which the reviewed literature mirrored the substance use literature is the calls for the early intervention for individuals experiencing co-occurring disorders (Staiger et al., 2013), with a number of studies calling for additional early intervention screening measures (Na et al., 2017), providing psychoeducation on the co-occurring disorder (Lee et al., 2018), or considering shared clinical features (e.g., personality factors; Andreassen et al., 2013). These suggestions highlight the need for careful clinical assessment of co-occurring problematic behaviours that may have developed on a subclinical level and, thus, might contribute to the primary disorder.

The momentum of research examining GD more generally has increased and those in the field are engaging in effective efforts to understand the impact of co-occurring addictive behaviours. The substance use literature provides various research frameworks and designs that could be utilized in the future to bring gaming research in line with the wider field of addictive disorders. For example, investigating the nuances between different co-occurring disordered use in clinical samples (Morisano et al., 2014), continuing investigations into prevalence, but expanding and evaluating the epidemiological data of such impacts as onset and remission (Freimuth et al., 2008), and establishing clinical trials and protocols that are tailored towards individuals presenting with co-occurring disorders (Morisano et al., 2014; Ruiz, 2017).

Limitations

Although the present review identified several important trends within the disordered gaming co-occurrence literature, it is subject to limitations. Firstly, methodology used in the review was descriptive and does not quantitatively synthesize data. Although the authors followed a rigorous and transparent review methodology, it still investigates the breadth of literature, rather than its depth, and as such, no statistical conclusions can be drawn from the results. Secondly, the study excluded literature that was not peer-reviewed (i.e., grey literature), this is in direct conflict with the suggested approach by Siddaway et al. (2019) which specifically states that unpublished work should meet the inclusion criteria to reduce the effects of publication bias, which is important when conducting systematic reviews and meta-analyses (Siddaway et a., 2019). The present review chose only to use high-quality peer-reviewed work, as to ensure the quality and reliability of the literature reviewed. Nevertheless, the present review is not representative of both grey and peer-reviewed literature and thus may contain publication bias. Furthermore, the inclusion criteria meant that only English language papers were reviewed, limited by a specific set of databases and search terms. As a result, the authors may have missed relevant studies in other languages or databases. As with any review, screening and selection is always a subjective process and is thus prone to biases. Despite capturing a wide range of research terms in several databases, it is possible that relevant studies may have been missed due to a lack of fit with the inclusion criteria. In addition, due to the nature of a long-term project, the present review may be missing additional papers which were released after the initial search and screening. Thus, the present review may be considered a comprehensive search of information up to the and including the search date, but not after. Moreover, considering only the use of papers that were published in the last several years may have also contributed the small number of papers on co-occurrence and gaming disorder. Finally, the present literature review does not contain literature after the COVID-19 pandemic, as it occurred after the final literature search. The way in which the COVID-19 pandemic may have influenced co-occurrence within gaming disorder and problematic behaviours this limitation should be considered when interpreting the results within the present review.

Conclusion

The evidence in the present review suggests an increase in research interest on co-occurrence of other addiction-related behaviours with disordered gaming. However, currently, most research investigates the prevalence rates of co-occurring addiction-related disorders with disordered gaming and frequently demonstrated the potential for co-occurrence between problematic and disordered behaviours and substance use. Various reviewed papers considered novel ways to investigate the potential development and maintenance of problematic and disordered gaming and its co-occurrence, which could be improved further by considering the frameworks and study designs used in the substance addiction disorder literature. Indeed, the research indicates that co-occurrence in problematic and/or disordered gaming is common, and when examining the substance use field as a guide, outcomes may be improved when separate treatment modalities for these co-occurring disorders are offered in combination. While it is not certain how well these treatment models may work in a diverse population, current research consistently calls for trials of multimodal treatment (i.e., using tailored treatments that consider co-occurring behaviour or substance use) to take place. As such, there are a number of different ways to investigate and explore the expression of disordered behaviour. The following chapter will investigate the use of EEG and neurophysiology in the conceptualisation and identification of gaming disorder.

Chapter 2

Gaming Disorder and Internet Addiction: A Systematic Review of Resting-State EEG Studies

Introduction

Negative consequences associated with the rising use of digital technology and technology-related disorders (e.g., Gaming Disorder [GD]) have been investigated in an effort to improve screening, assessment, definition, and treatment (Kuss & Billieux, 2017; Yau et al., 2012). Consequently, in the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5), Internet Gaming Disorder (IGD) was included as a tentative behavioural addiction warranting further investigation (American Psychiatric Association [APA], 2013). Furthermore, the World Health Organization (WHO) officially recognized GD in the latest International Classification of Diseases (ICD-11; WHO, 2018).

IGD and GD have undergone conceptual evolution prior to inclusion in diagnostic manuals (DSM-5, ICD-11), with several other terms used to describe disordered gaming (e.g., pathological video gaming; Lemmens et al., 2011). These terms also fall under the broad umbrella of 'Internet Addiction' (IA), containing several descriptive terms (e.g., problematic internet use; Kuss et al,, 2014). The present review evaluates both clinically defined GD as well as the less defined IA. To maintain consistency, the term 'GD' here refers to the clinically defined measures of IGD/GD as defined by DSM-5/ICD-11.

Research indicates associations between disordered gaming (and/or problematic gaming) and psychiatric disorders, including anxiety (Adams et al., 2019) and depression (Burleigh et al., 2018) – and substance use disorders (e.g., Alcohol Use Disorder [AUD], Na et al., 2017). Several studies have considered psychopathological aspects of GD (Bishop et al., 2015) and IA (Kuss et al., 2014) and their co-occurrence with other behavioural disorders, substance use, and psychiatric disorders (Burleigh, Griffiths, et al., 2019). Furthermore, empirical evidence suggests that GD and IA are distinctly different disorders (Király et al., 2014), despite the terms being used interchangeably. Consequently, research examining the neurophysiological aspects of GD and IA has emerged, providing contributions to studying psychopathological dimensions of behavioural addiction disorders (Kuss et al., 2018; Sharifat et al., 2018).

The US National Institute of Mental Health (NIMH) advocates using Research Domain Criteria (RDoC) and a multidimensional approach that includes observable behaviour and neurophysiological measurements to understand complex human behaviours and the mental disorder continuum (Clark et al., 2017). Therefore, GD/IA research should also consider underpinnings of neurophysiological mechanisms.

This review focuses on EEG which has several advantages relative to other neuroimaging techniques (e.g., high temporal resolution, non-invasive scanning, mobility, accessibility and low financial cost; Wang et al., 2013). EEG data is the recording of electrical activity across the scalp which is produced by the brain; thus, the recorded waveforms reflect cortical electrical activity (Houston & Ceballos, 2013). Quantitatively measured EEG (QEEG) has been used to investigate various disorders, of which spectral and coherence analyses have been used to investigate addiction (Houston & Ceballos, 2013). Power spectral analysis quantifies power and/or voltage within bandwidths: delta (1–4 Hz), theta (5–7 Hz), alpha (8–13 Hz), beta (14–30 Hz), and gamma (>31 Hz; Houston & Ceballos, 2013). Power is typically measured as either relative or absolute (Houston & Caballos, (2013). Relative power is a proportion of power in the entire spectrum and minimizes the individual differences across participants, whereas absolute power is the entire spectrum and may be obscured with group differences. Coherence analysis quantifies the interdependence or statistical correlation between scalp recording sites, as an estimate of functional connectivity between cortical areas in the time domain (Gonzalez et al., 2015). Each method can be used to measure baseline brain states ('at rest'), spontaneous activity, and/or that induced during information-processing (Barry et al., 2010; Kounios et al., 2008).

Resting-state (i.e., 'at rest') brain activity has been associated with different aspects of behaviour and event-related cognitive processes comprising attention, memory, and thinking, and demonstrates high test–retest reliability, as well as producing stable trait-like indices of brain function (Massar et al., 2014). During resting-state EEG, data are recorded using Eyes-Closed (EC) or Eyes-Open (EO) conditions. During the EC-condition, there are no external task demands, providing a functional baseline (Barry et al., 2007). The EO-condition allows passive engagement with visual input, without any specific task requirements (Barry et al., 2007; Wang et al., 2015). Resting-state EEG has been used to investigate substance and behavioural addictions. For example, studies consistently show raised absolute beta power in AUD, which is positively correlated with clinical severity, suggesting higher absolute beta may be a neurophysiological marker of AUD (Coutin-Churchman et al., 2006; Rangaswamy et al., 2004). However, whether this represents a vulnerability-marker or response to the illness remains unclear.

Consolidating knowledge on the underpinning neurobiological mechanisms would benefit the conceptual development of GD/IA, and carry practical implications for understanding aetiology, establishing diagnostic criteria, and improving intervention. Whilst previous reviews span a range of neurophysiological methods (Kuss & Griffiths, 2012; Kuss et al., 2018), resting-state EEG studies in GD/IA have not been systematically evaluated.

Consequently, this paper presents a systematic review of resting-state EEG studies in GD/IA, to direct further work in the field. The primary goal is to review empirical research over the past decade, providing contemporary information on resting-state EEG findings concerning GD/IA. It therefore aims to: (i) investigate resting-state EEG within GD/IA, and to (ii) determine potential for neurophysiological markers.

Methods

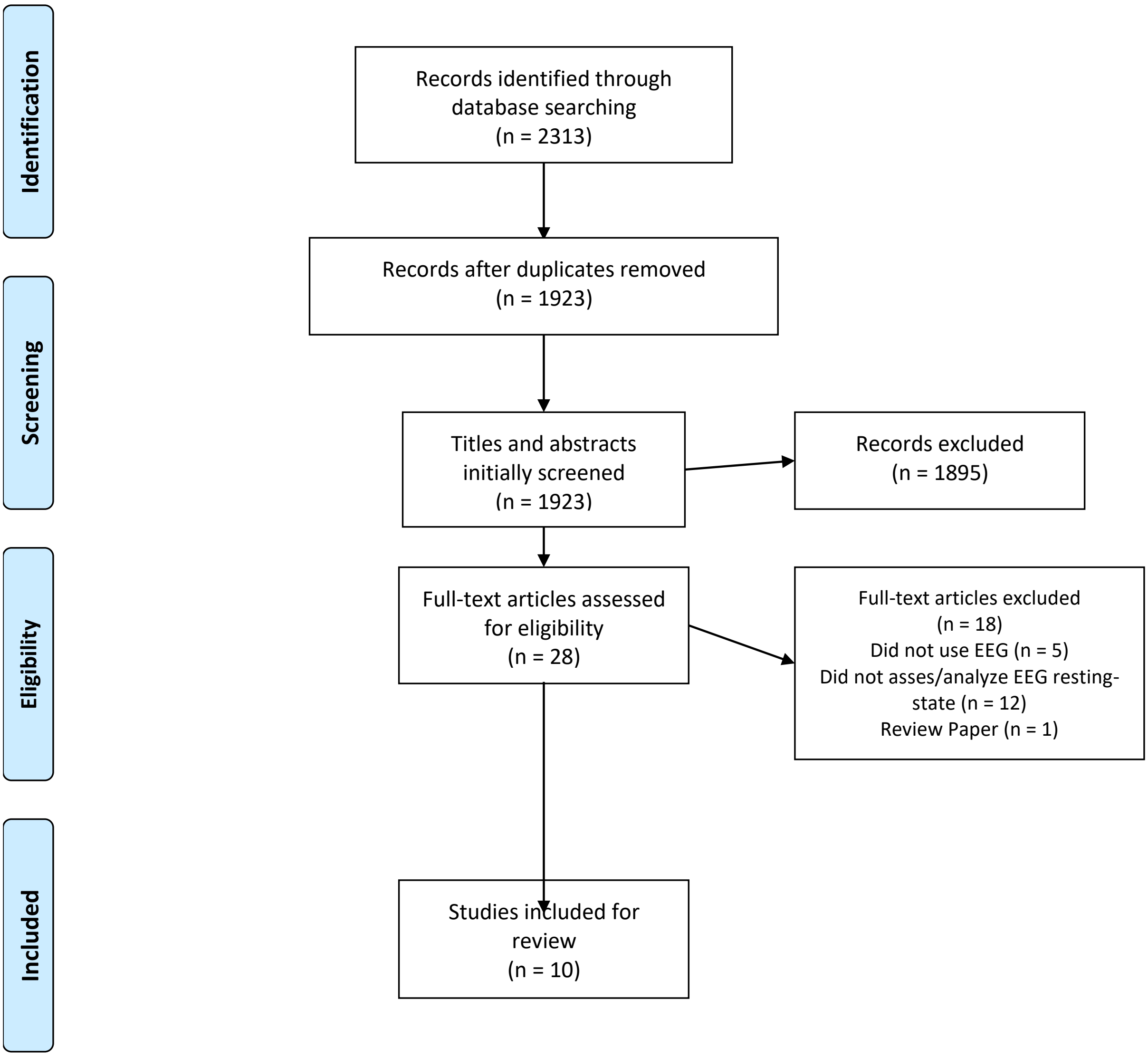
The five-stage model of conducting a rigorous systematic review was used: (i) identifying the research question, (ii) identifying relevant studies, (iii) study selection, (iv) dissemination of outcomes, and (v) summarizing and reporting the results (Siddaway et al., 2019). Inclusion criteria for review were as follows. Studies had to be (i) empirical and contain primary data, (ii) using resting state quantitative EEG techniques in GD and/or IA; (iii) published in peer-reviewed journals, (iv) written in English, and (v) be published within the past decade. The database searches included: *PsychARTICLES, PsychINFO, Scopus,* and *PubMed*.

Search terms related to GD and IA used over the past decade. Additionally, other terms identified specific neuroimaging techniques and analysis in the behavioural addiction literature, leading to the following search-strategy: (patholog* OR problem* OR addict* OR compulsive OR dependen* OR disorder*) AND (video OR computer OR internet) gam* OR internet AND ("resting stat*" OR "default mod*" OR Quantitative) AND (neuroimaging OR electroencephalogr* OR EEG OR QEEG) NOT gambling. Paper title, abstract, and content were screened for eligibility. Then, full texts of potentially relevant papers were retrieved and screened for eligibility.

The literature search was conducted between February 2019 and March 2019. A total of 2313 papers were initially identified. Duplicate papers were removed. Papers not relevant to the present review or non-English were removed, leaving 28 papers. Of these, a number were excluded because they (i) did not utilize EEG neuroimaging techniques (*n* = 5), (ii) utilized EEG but did not assess/analyse resting state (*n* = 12), or (iii) were review papers (*n* = 1). The remaining ten papers met all the inclusion criteria. This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines (PRISMA statement; Moher, et al. 2009), which includes a PRISMA flow diagram (see Figure 1).

Figure 1

Flow Diagram of Paper Selection Process for the Systematic Review



Results

The ten papers meeting the inclusion criteria were separated into two groups – GD and IA. Seven papers investigated GD. Participants were diagnosed with GD by an experienced psychiatrist/clinician based on the DSM-5 criteria for IGD; symptom severity was assessed using either the Internet Addiction Scale (IAS; Young, 1998) (*n*=2) (Park, Hong et al., 2017; Youh et al., 2017) or Internet Addiction Test (IAT; Beard & Wolf, 2001) (*n*=5) (Kim et al., 2017; Lee, Choi, & Kwon, 2019; Park, Lee et al., 2017; Park et al., 2018; Son et al., 2015). Three studies investigated IA and utilized the IAS as a diagnostic tool and severity measure. However, two of these studies noted that participants reported online gaming as their primary internet use (Choi et al., 2013; Lee et al., 2014); the third paper did not report specific internet use (Son et al., 2019).

Gaming Disorder

Seven studies investigated GD (Kim et al., 2017; Lee, Choi, & Kwon, 2019; Park, Hong et al., 2017; Park, Lee et al., 2017; Park et al., 2018; Son et al., 2015; Youh et al., 2017), and all conducted in South Korea. Five studies recruited participants from the SMG-SNU Boramae Medical Center, Seoul (Kim et al., 2017; Lee et al., 2019; Park, Lee et al., 2017; Park et al., 2018; Son et al., 2015), while the remaining two recruited participants from the Department of Psychiatry, Chung-Ang University Medical Center (Park, Hong et al., 2017; Youh et al., 2017). Each study recruited male-only participants. The selected papers reported power spectral analysis and/or coherence analysis (see Table 1).

Table 1

Summary of Findings from Gaming Disorder Studies

Paper	Aims	Sample	EEG Method	Behaviour /Substance /Psychiatric Diagnosis	Results
Kim et al. (2017)	To identify neurophysiological markers (i.e., brain waves) through associated symptom changes in GD patients who have undergone pharmacotherapy with selective serotonin reuptake inhibitors (SSRIs*).	South Korea: SMG-SNU Boramae Medical Center 49 Male Participants. GD: *n*=20 (*M*age: 22.71/*SD*: 5.47); HC: *n*=29 (*M*age: 23.97/*SD*: 4.36).	Power Spectral Analysis	GD	Patients who experienced comorbid depression and anxiety symptoms had increased resting-state Delta and Theta activity. Delta-band activity normalized after 6 months of pharmacotherapy. The findings suggest that slow wave activity may be a neurophysiological marker with changes in addiction symptoms following treatments.
Lee et al. (2019)	To determine the effects of resilience on neurophysiological correlates within GD patients compared to HCs.	South Korea: SMG-SNU Boramae Medical Center 71 (reduced from 76) Male Participants. HR: n=19 (*M*age: 25.47/*SD*: 5.04);	Coherence Analysis	GD	GD patients with low resilience had increased coherence, especially in the right hemisphere when compared to GD patients with high resilience and the HCs.

		LR: n=16 (*M*age:22.13/*SD*: 5.56); HC: n=36 (*M*age: 25.14/*SD*: 3.60).			There were conditional indirect effects of GD on alpha coherence in the right hemisphere through depressive symptoms.
Park, Hong et al. (2017)	To identify the potential of differing neurophysiological features in individuals experiencing GD and individuals with comorbid ADHD.	South Korea: Chung-Ang University Medical Center 45 Male Participants. ADHD & GD: *n*=16 (*M*age: 14.6/*SD*: 1.9); ADHD: *n*=15 (*M*age: 13.7/*SD*: 0.8); HC: *n*=14 (*M*age: 14.4/*SD*: 1.7).	Power Spectral Analysis / Coherence Analysis	GD/ADHD	GD/ADHD showed lower relative delta band power and higher relative beta-band power in temporal regions compared to the ADHD group. Relative beta-band power between GD/ADHD and HCs was not significant. Internet games may enhance attentional ability, creating a similar relative beta power in attention deficit in GD/ADHD and HCs. The continuous activation of the brain reward and working memory systems while gaming may increase neuronal connectivity for the GD/ADHD group.

Park, Lee et al. (2017)	To compare and detail the difference in neurophysiological features of GD and AUD patients with HCs using coherence analysis.	South Korea: SMG-SNU Boramae Medical Center 96 Male Participants. GD: n=30 (*M*age: 23.26/*SD*: 5.15); AUD: n=30 (*M*age: 29.86/*SD*: 7.13); HC: *n*=32 (*M*age: 24.96/*SD*: 3.70).	Coherence Analysis	GD/AUD	GD group has significantly greater high frequency coherence – especially in gamma activity– compared to AUD and HCs. Increased gamma activity was independent of psychological comorbidity. Gamma coherence positively predicted the degree of GD tendency in all three groups. GD and AUD display different neural activity patterns. Heightened phasic synchrony in the gamma-band may be a neurophysiological marker of GD.
Park et al. (2018)	To investigate the treatment response (to SSRIs*) in relation to cortical activity in patients with GD and to determine if altered phasic synchrony is a state or trait-marker.	South Korea: SMG-SNU Boramae Medical Center 62 Male Participants. GD: *n*=30 (*M*age: 23.27/*SD*: 5.15);	Coherence Analysis	GD	GD group has increased beta, gamma, and delta coherence at baseline, signifying abnormal phasic synchrony.

		HC: *n*=32 (*M*age: 24.97/*SD*: 3.70).			Post 6 months of pharmacotherapy (SSRIs*) showed no change in phasic synchrony despite significant improvements in GD symptoms. Heightened phasic synchrony may be a neurophysiological marker for GD.
Son et al. (2015)	To compare and detail the difference in neurophysiological features of GD and AUD patients with HCs using power spectral analysis.	South Korea: Chung-Ang University Medical Center 76 Male Participants. GD: *n*=34 (*M*age: 22.71/*SD*: 5.47); AUD: *n*=17 (*M*age:29.71/*SD*: 4.88); HC: *n*=25 (*M*age: 23.88/*SD*: 4.66).	Power Spectral Analysis	GD/AUD	GD group showed significantly lower absolute beta power than AUD and HCs. GD and AUD displayed different spectral power analyses in resting-state. Lower absolute beta-power may be a neurophysiological marker for GD.
Youh et al. (2017)	To identify the potential of differing neurophysiological features in individuals experiencing MDD and individuals with comorbid GD.	South Korea: SMG-SNU Boramae Medical Center 29 Male Participants. MDD+GD: *n*=14 (*M*age: 20.00/ *SD*: 5.00);	Coherence Analysis	GD/MDD	Inter-hemispheric coherence value for the alpha-band between right and left frontal regions was significantly lower in MDD/GD than MDD.

	MDD: n=15 (*M*age: 20.30/*SD*: 5.50).		Increased intra-hemispheric coherence for the alpha-band within the left parietal-occipital area was observed in MDD/GD compared with MDD.
			MDD/GD showed increased intra-hemispheric coherence values for the beta-band within the right frontal-temporal, temporal-occipital, and parietal-occipital areas compared with MDD.
			Decreased inter-hemispheric connectivity in the frontal region is associated with attention problems in MDD/GD.
			Excessive gaming may result in increased intra-hemispheric connectivity in the fronto-temporo-parieto-occipital areas.

Note. GD is Internet Gaming Disorder; HC is Healthy Control; HR is High Resilience; LR is Low Resilience; ADHD is Attention Deficit Hyperactivity Disorder; AUD is Alcohol Use Disorder; MDD is Major Depressive Disorder; *Escitalopram, Fluxetine, and Paroxetine.

Gaming Disorder Studies Using Power Spectral Analysis

Three studies used power spectral analysis across several frequency bands (Kim et al., 2017; Park, Hong, et al., 2017; Son et al., 2015). Kim et al. (2017) compared GD patients with healthy controls (HCs) over a six-month period on delta and theta bands. GD participants were scanned prior to and following pharmacotherapy with selective serotonin reuptake inhibitors (SSRIs). At baseline, GD was associated with higher delta-band power across the whole scalp and higher theta-band activity centrally. Compared to baseline, following treatment, the GD group showed reduced frontal delta wave activity, and reduction in IAT scores. Furthermore, high-baseline theta activity predicted greater improvement in GD symptoms post-treatment. The authors suggested that raised slow-wave activity may represent a state neurophysiological GD marker.

Son et al. (2015) investigated resting state QEEG of individuals with GD and AUD, compared to HCs without these disorders. The GD group had lower absolute beta-power than either the AUD group or HCs, while the AUD group had higher absolute delta power than the GD group and HCs. However, there were no significant correlations between GD severity and EEG activity. The authors concluded that lower absolute beta-power may be a neurophysiological GD marker.

Park, Hong et al. (2017) noted GD is commonly comorbid with ADHD, and presence of ADHD may increase vulnerability to loss of control, which is associated with excessive gaming (Bioulac et al., 2008). They found individuals with comorbid ADHD/GD had lower relative delta wave power and higher relative beta-power restricted to temporal regions, compared to those with ADHD. The researchers conservatively suggested individuals vulnerable to ADHD appear to engage in continuous videogame play to subconsciously enhance attentional ability. They concluded that differences in QEEG profiles between groups provide clues to understanding neurophysiological mechanisms of GD and its ADHD comorbidity.

Gaming Disorder Studies Using Coherence Analysis

Park, Hong et al. (2017) applied coherence analysis in conjunction with power spectral analysis, while the remaining four studies used coherence analysis only (Lee et al., 2019; Park, Lee et al., 2017; Park et al., 2018; Youh et al., 2017). Park, Hong et al. (2017) investigated both inter-hemispheric and intra-hemispheric coherence (i.e., between the two hemispheres and within either of the two hemispheres). They found that intra-hemispheric coherence values in the delta-wave band were higher for the ADHD/GD group compared to the ADHD group. Furthermore, they found raised intra-hemispheric coherence (theta, alpha, beta) in the ADHD/GD group compared to ADHD-only and HCs. Inter-hemispheric coherence in the theta-band was higher in the ADHD/GD group compared to HCs. IAS scores in the ADHD/GD group positively correlated with intra-hemispheric (but not inter-hemispheric) coherence in the delta, theta, alpha, and beta bands between parietal and occipital (i.e., P4-O2) electrodes.

Lee et al. (2019) investigated the role of resilience (i.e., personal qualities empowering individuals to thrive in the face of hardship) and relationship to neurophysiological measurements, and how it acted as a protective factor among GD individuals, using the Connor-Davidson Resilience Scale (Connor & Davidson, 2003). Association between resilience and resting-state EEG was only observed in alpha-band activity. Resilience was negatively associated with alpha inter-hemispheric and intra-hemispheric coherence. The authors concluded that participants with low resilience exhibit impaired EEG features relative to HCs, while participants with high resilience exhibited less impaired EEG features relative to HCs.

Park, Lee et al. (2017) found no differences in inter-hemispheric coherence, but found raised intra-hemispheric coherence among GD participants for higher frequencies: gamma (compared to AUD participants and HCs) and beta (compared to AUD group). Furthermore, gamma (but not beta) coherence positively correlated with IAT scores for all groups. However, EEG variables were not significantly correlated with GD severity among the GD group. These results suggest AUD and GD display different neurophysiological characteristics, and that increased gamma coherence may be a GD trait-marker.

Park et al. (2018) considered longitudinal changes that may occur in neural connectivity among GD patients before and after pharmacotherapy treatment with SSRIs. At baseline, raised intra-hemispheric coherence in the beta and gamma bands were observed in the GD group when compared with HCs. Additionally, raised right delta intra-hemispheric coherence was seen in GD compared to HCs. Six-month SSRI treatment lowered GD symptoms in the GD group. However, there were no significant changes in EEG coherence following treatment compared to HCs. It was concluded that greater intra-hemispheric activity in beta and gamma bands may be a neurophysiological trait-marker of GD individuals.

Finally, Youh et al. (2017) investigated EEG features of individuals with co-occurring GD and major depressive disorder (MDD). Inter-hemispheric coherence of the alpha-band between left and right fronto-polar (Fp1, Fp2) electrodes was lower in the MDD/GD group than MDD-only. However, the GD/MMD had higher intra-hemispheric coherence between left parietal-occipital (P3-O1) electrodes in the alpha-band and between right fronto-temporal (F8-T4), temporo-occipital (T6-O2), and parieto-occipital (P4-O2) electrode in the beta-band. Results suggested that the GD/MMD group experienced an association between decreased inter-hemispheric coherence in the frontal region of the brain and demonstrated a vulnerability to attention problems. Moreover, increased intra-hemispheric coherence in the GD/MDD group may be a result of high gaming engagement.

Internet Addiction

Three studies examined resting-state EEG among individuals with internet addiction (IA). Two of the studies were conducted at the SMG-SNU Boramae Medical Center, South Korea (Choi et al., 2013; Lee et al., 2014), while the third was conducted in China (Sun et al., 2019). All studies recruited males and females (see Table 2).

Table 2

Summary of Findings from Internet Addiction Studies

Paper	Aims	Sample	EEG Method	Behaviour /Substance	Results
Choi et al. (2013)	To investigate resting-state EEG activity in beta- and gamma-bands and how they relate to impulsiveness in IA patients.	South Korea: SMG-SNU Boramae Medical Center 41 Participants. IA: *n*=20 (M:12/F:9; *M*age: 23.33/*SD*: 3.50); HC: *n*=29 (M:11/F:9; *M*age: 22.40/*SD*: 2.33).	Power Spectral Analysis	IA	IA group demonstrated higher impulsive behaviour and impaired inhibitory control. IA group showed decreased absolute beta-band activity when compared to the HCs. IA group showed increased gamma-band activity when compared to HCs. Decreased beta activity was correlated with both impulsivity and IA severity. Increased gamma activity was correlated with both impulsivity and IA severity.

Lee et al. (2014)	To compare and contrast the resting-state EEG activity of treatment seeking IA patients with co-morbid depression, IA patients without co-morbid depression, and HCs in an effort to identify neurophysiological differences in IA and depression.	South Korea: SMG-SNU Boramae Medical Center 69 Participants. IA/Dp: *n*=18 (M:15/F:4; *M*age: 21.25/*SD*: 4.71); IA: *n*=17 (M:12/F:5; *M*age: 23.44/*SD*: 4.82). HC: n=34 (M:25/F:9; *M*age: 23.59/*SD*: 4.34).	Power Spectral Analysis	IA	IA group showed decreased absolute delta and beta-power in all brain regions when compared to IA/Dp group. IA/Dp group showed increased relative theta and beta-power in all regions of the brain when compared to the IA/Dp group and HCs. The neurophysiological changes were not correlated to the clinical variables.
Sun et al. (2019)	To investigate the differences in brain networks when considering resting-state EEG between IA and HCs.	China 52 Participants. IA: *n*=25 (M:6/F:19; *M*age: 20.19/*SD*: 1.83); HC: *n*=27 (M:4/F:23; *M*age: 20/*SD*: 1.74).	Functional Connectivity Analysis / Network Analysis	IA	There were no significant differences in functional connectivity between IA and HC. Individuals with IA exhibit a more random network organization in beta- and gamma-band activity compared to HCs. There were no significant correlations between EEG

	graph measures and clinical measures.

Note. IA is Internet Addiction; HC is Healthy Control; Dp is Depression

Internet Addition Studies Using Power Spectral Analysis

Two of the three IA studies used spectral power analysis (Choi et al., 2013; Lee et al., 2014) and one used connectivity analysis and network analysis (Sun et al., 2019). Choi et al. (2013) investigated the relationship between impulsiveness and fast frequency (beta, gamma) activity among internet addicts. Results showed that compared to the HC group, IA participants had significantly lower absolute power in beta- and gamma-band activity in all brain regions. Moreover, both beta- and gamma-power in the frontal region significantly correlated with IA severity.

Lee et al. (2014) investigated the neurophysiology among internet addicts and comorbid depression (IA/Dp), with IA only, and HCs (without IA/Dp). The IA group showed lower absolute delta-power (widespread compared to both other groups) and beta-power (compared to HCs). In the comorbid group, relative theta-activity was higher and relative alpha-activity was lower across the scalp compared to other groups. However, there was no correlation between any EEG measure and clinical variables for IA/Dp or IA groups.

Internet Addiction Study Using Functional Connectivity Analysis and Network Analysis

In Sun et al.'s study (2019), an IA group (compared to HCs) exhibited a more random network organization, with decreased clustering coefficients and characteristic path length, demonstrating an alteration in the typical balance of network function. However, functional analysis did not demonstrate any significant differences in connectivity strength between the groups. However, there was a trend for increased global connectivity among internet addicts compared to HCs. Additionally, there was no significant correlation between EEG and clinical measures. The authors concluded that internet addicts demonstrate altered topological organization which shifts towards a more random state, which suggests that the associated connection paths may be reflecting alterations in the ability of information processing in IA. Thus, providing additional evidence supporting an IA neurophysiological component.

Discussion

This systematic review is the first to focus on resting-state EEG studies of GD and IA. Both spectral and coherence analysis were investigated. Findings demonstrate that disordered gamers have raised slower frequency (delta, theta; Kim et al., 2017; Son et al., 2015), and reduced higher frequency (beta) activity (Son et al., 2015). Furthermore, coherence analysis findings suggest that disordered gamers demonstrate altered synchronised brain activity (Lee et al., 2019; Park et al., 2017; Park et al., 2018; Park et al., 2017; Youh et al., 2017). Internet addicts appear to have raised gamma activity and reduced beta and delta activity (Choi et al., 2013; Lee et al., 2014). Multiple neurotransmitters are involved in the modulation of EEG, such as dopamine, glutamate, noradrenaline, acetylcholine, N-methyl-D-aspartate (NMDA) and γ-aminobutyric acid (GABA; Watson et al., 2009; Hansenne et al., 1995). In the context of addictive behaviours, it is well established that the mesocorticolimbic dopamine and brain stress systems are critically involved in reward function and psychomotor performance. Observed EEG changes among disordered gamers and internet addicts may reflect neuroadaptive changes in these systems associated with addictive behaviours. While current knowledge of addictive behaviours has been predominantly built on substance use research, assessing the neurophysiological aspects of GD/IA provides an important contribution in understanding the psychopathological mechanisms of behavioural addiction disorders.

Power Spectral Analysis

When considering the power spectral analysis, the studies reviewed suggest that disordered gamers demonstrate specific trait-like markers when compared to HCs (Park, Lee et al., 2017; Son et al., 2015). For example, Kim et al. (2017) demonstrated prior to pharmacotherapy (i.e., at baseline) disordered gamers showed increased delta- and theta-wave activity compared to HCs. However, at the completion of (SSRI) pharmacotherapy, there was a significant decrease in delta-wave activity, while theta showed no significant changes despite the significant reduction in GD severity measures. The decreased delta-activity significantly correlated with a reduction in GD severity scores, while theta-activity remained high when compared to HCs. Slow-wave activity (i.e., delta and theta) has been associated with a range of cognitive processes, such as attention, and higher-order control processes (Thatcher et al., 2005), an increase of which has been related to impairments in attention, control processes, and inhibitory control (Schiller et al., 2013), which have been found to be psychometrically correlated with GD (Şalvarlı & Griffiths, 2019). This suggests these neurophysiological differences may be GD trait-markers, a method which has been used to indicate possible trait-markers in other fields, such as substance use addiction (e.g., AUD; Porjesz et al., 2005).

Additional findings were reported among internet addicts who experienced higher gamma-activity (Choi et al., 2013), but lower beta- and delta-activity compared to HCs (Choi et al., 2013; Lee et al., 2014). Gamma-wave activity has been understood to represent local neural communication and have been associated and binding of perceptual and conceptual information, while decreased beta-activity has been related to inattention and impulsivity (Abhang et al., 2016; Park et al., 2017; von Stein & Sarnthein, 2000). Given that dysfunctional resting-state gamma-activity is present without external stimuli, it may suggest anomalous connectivity and neural asynchrony while in a resting-state (Tallon-Baudry, 2003; Tallon-Baudry et al., 2005). Similarly, aberrant gamma activity may suggest dysfunctional activity in the dopaminergic system, which can be related to excitatory activation of the brain and seeking-behaviours related to addiction (Buzsáki & Wang, 2012; Yordanova et al., 2002). Furthermore, decreased beta activity suggests that internet addicts experience low impulse-control and therefore use increased cognitive resources, which has been associated with psychometric findings (D’Hondt et al., 2015). Taken together, it could be that increased gamma-activity among internet addicts, coupled with low beta-activity demonstrate a trait-like marker for internet addicts (Choi et al., 2013; Lee et al., 2014).

GD and IA each show lower beta-activity (Park, Hong et al., 2017; Son et al., 2015; Choi et al., 2013; Lee et al., 2014). Lower beta-activity has frequently been found among individuals with ADHD, and reported to be associated with poor cognition, inattention, and impulsiveness in ADHD (Snyder & Hall, 2006), which was also related to impulsivity trait and severity in a resting-state gambling EEG study by Lee et al. (2017). Similarly, decreased beta-activity among disordered gamers and internet addicts may implicate higher levels of impulsiveness, which is corroborated by psychometric literature (Şalvarlı & Griffiths, 2019; Zhang et al., 2015). However, unlike disordered gamers, internet addicts experienced significantly lower delta-activity compared to HCs, similar to AUD patients (Ehlers et al., 1989). This is suggestive of dysfunctional information processing, which has been related with slow-wave changes (Howland et al., 2011; Saletu-Zyhlarz, 2004). Overall, these results suggest that although IA and GA share similar cognitive and behavioural characteristics, they can be differentiated by their distinct neurophysiological features.

Coherence Analysis

When considering coherence analysis, findings suggest altered synchronised brain activity between spatially separated scalp electrodes among disordered gamers. The severity of this alteration may be related to clinical variables, including resilience and co-existing conditions. Disordered gamers with low resilience exhibited increased alpha coherence in the right hemisphere and reported severe depressive symptoms and high stress levels (Lee et al., 2019). Increased alpha coherence has been associated with poor emotional regulation (Kautz et al., 2017), which has been theorized as a mechanism in the development and maintenance of GD (Burleigh, Griffiths, et al., 2019). Furthermore, Park et al. (2018) found that fast-frequency coherence activity was also present pre- and post-SSRI treatment and concluded that increased gamma and beta coherence may act as neurophysiological GD marker. Distinctive gamma, alpha, and beta coherence were also found when disordered gamers were compared with AUD patients (Park, Lee et al., 2017), comorbid GD/ADHD patients (Park, Hong et al., 2017), and GD/MDD patients (Youh et al., 2017).

Taken together, disordered gamers may have specific neurophysiological states when compared to HCs and other SUDs and psychiatric disorders. The consistent findings of mid- to high-frequency bands can be explained as a possible risk factor and a secondary change derived from repetitive gaming (Dong et al., 2012; Jeong et al., 2016). The increased beta and alpha coherence activity within the right hemisphere may also be associated with the repeated activation of the visuospatial working memory and executive function that is accompanied by frequent gaming (De Benedictis et al., 2014; Jeong et al., 2016).

Limitations and Future Directions

Despite neuroimaging studies on GD offering important contributions, there are limitations and future directions that should be considered. Firstly, the reviewed studies of GD contained all male participants. This may have created a neurophysiological bias within the data. The reviewed studies were also exclusively conducted and recruited in South Korea and China, which may compromise the generalizability of the results. Moreover, eight studies recruited participants from the same clinic, which may also compromise the generalizability of the results to a larger demographic. Furthermore, there were no studies in this review investigating other cultural populations, which may produce different results. Additionally, a majority of the reviewed studies used cross-sectional methods and therefore it is not possible to ascertain any causal relationships between GD and altered neurophysiological traits. Future research should utilise both men and women from other countries and cultures and employ longitudinal designs with male and female samples to overcome these shortcomings. Multi-cultural studies are necessary to understand the neurophysiological and potential GD trait-markers.

Additionally, there are limitations regarding the veracity of the psychometric-related conclusions drawn within the GD and IA studies. More specifically, each GD study used an IA severity measure (i.e., IAS or IAT) to assess GD, despite other measures specific to IGD or GD being available. Furthermore, two of the three IA studies reported predominantly online gamers as participants. The use of IA tools to assess GD, is a trend that has continually been observed, and scholars have debated the detrimental effect it has had on both fields (see King et al. [2020] and Pontes et al. [2017] for reviews). This issue is also present in the current review because the samples used in the IA studies (Choi et al., 2013; Lee et al., 2014) were reported as problematic online gamers. This suggests the findings may reflect problematic gaming more so than IA. However, given these studies explored IA themes and theoretical underpinnings, it is important to collate and contrast the data in the context of which they were collected. Moreover, it is important to consider that these IA studies were published before the DSM-5's IGD diagnostic criteria were conceived, further supporting the decision to present the findings in their original contexts. Finally, it is important to note that the reviewed studies employed an experienced psychiatrist/clinician to assess GD and IA (excluding Sun et al. [2019]), lending validity to the overall neurophysiological results and the behavioural constructs they explored. Future research in this area should endeavour to use psychometrically validated constructs that are specific to GD when evaluating neurophysiological data.

The present review is also subject to some limitations. Firstly, the methodology used was descriptive in nature and not quantitatively synthesized. While the review followed rigorous and transparent methods, it considered the breadth of the literature, and as such, no statistical conclusions can be drawn from the results. Secondly, due to the inclusion criteria, only peer-reviewed papers published in English were used. Therefore, no non-peer-reviewed literature was present, which conflicts with the recommended approach by Siddaway et al. (2019) for reducing the effects of publication bias in systematic reviews and meta-analyses. Thus, the exclusion of non-peer-reviewed literature in the present review implies lack of representation of both grey and peer-reviewed literature, which must be considered as a limitation of the study. In addition, given that the entirety of the papers reviewed were from south-east Asian countries, it could be that important findings published were overlooked because they may have been available in other languages or databases. Moreover, despite including broad research terms in several databases, it is possible a number of studies were missed due to a lack of fit with the inclusion criteria. In that line, the present review may be missing additional papers which were released after the initial search and screening. Thus, the present review may be considered a comprehensive search of information up to the and including the search date, but not after. Finally, the current literature review does not include literature published after the COVID-19 pandemic, as the final literature search was conducted prior to its onset. This limitation is particularly relevant in terms of how the pandemic may have impacted or influenced increased gaming, which may have affected the neurophysiological behavior of individuals. Therefore, it is important to take this limitation into account when interpreting the findings of the review.

Conclusion

The evidence in this review suggests that there are distinct neurophysiological features associated with GD and IA. Although both share some neurophysiological similarities to substance use disorders, the results suggest that internet addicts have higher gamma-activity and lower delta-activity, while disordered gamers show higher theta-activity and higher gamma and beta coherence than HCs. Taken together, the findings indicate possible impairments in attention and inhibitory control (i.e., impulsivity), and dysfunctional dopaminergic activity. These distinct pairings may help improve diagnosis by objectively highlighting an individual's neurophysiological state, and in conjunction with correlated psychometric scales could allow clinicians to provide tailored interventions. Therefore, the findings support the NIMH's suggestions of using the RDoC criteria for mental disorder diagnosis (Clark et al., 2017). Future research should focus on replicating the findings in a wider variety of cultural contexts to support the neurophysiological basis of classifying GD and related behavioural addictions. In that line, the next chapter will explore novel machine learning methods which may help provide additional insight into the identification of GD using a wide range of different techniques.

Chapter 3

Exploring Problematic Gaming through Machine Learning: A Systematic Review

Introduction

As gaming technology advances, there has been an increasing need to understand associated disorders (e.g., gaming disorder [GD]) through improved conceptualisation, assessment, and treatment (Kuss & Billieux, 2017). As a result, the American Psychiatric Association (APA) included Internet Gaming Disorder (IGD) as a tentative behavioural addiction in the fifth edition of the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5) which warranted further investigation (American Psychiatric Association, 2013). Subsequently, the World Health Organization (WHO) officially recognised GD in the 11th revision of the *International Classification of Diseases* (ICD-11; World Health Organization, 2019).

Prior to the inclusion in the diagnostic manuals, IGD and GD had been described in other ways and with other terms (e.g., problematic online gaming; Király et al., 2014). A large number of these gaming-related terms have also fallen under the broader category of internet addiction (IA), which has also been referred to using various terms (e.g., problematic internet use; Kuss et al., 2014). The present review incorporates research relating to both the clinically defined GD as well as problematic use of videogames. To maintain consistency, the term 'gaming disorder' will be used when referring to the clinically defined IGD/GD constructs as included in the DSM-5/ICD-11.

Disordered gaming (and/or problematic gaming) has been associated with several negative outcomes, such as anxiety (Adams et al., 2019), depression (Burleigh et al., 2018), and substance use (Škařupová et al., 2018). Furthermore, it has been suggested that GD frequently co-occurs with psychiatric and substance use disorders (Burleigh, Griffiths, et al., 2019). Due to the multifaceted nature of GD, several assessment techniques have been used to identify problems, predict adverse outcomes, and inform treatment (Kuss & Billieux, 2017). Some methods include psychometric self-report (King et al., 2017), clinical assessment and intervention (Yau et al., 2012) and brain imaging methods (e.g., electroencephalography, EEG; Burleigh et al., 2020) functional magnetic resonance imaging, (*f*MRI; Kuss et al., 2018). Indeed, the topic of assessment and prediction has long been explored by data analysts, experimental scientists, and psychologists. In recent years, the advent of artificial intelligence (AI) technology has brought new insights into the discussions regarding analysis and assessment (Orrù et al., 2020).

In the past decade, AI has emerged as a fast-growing field of study when modelling complex sets of data across multiple disciplines (Orrù et al., 2020). The term 'artificial intelligence' is used to describe machines that emulate human mind-related cognitive functions, such as learning and problem solving (Elliott, 2021). The rapid expansion of AI-related methodologies has seen researchers employ various related techniques ranging from hypothesis generation to experimentation (Lin et al., 2020; May, 2021). Indeed, when presented with large and complex data sets, AI has demonstrated an aptitude at extracting meaningful patterns for the purposes of regression, prediction, and classification (Lin et al., 2020). For example, AI has contributed to the diagnostic and therapeutic approach for treatment, prognosis, diagnosis prediction, and the detection of potential biomarkers in an individual-specific and treatment-specific manner in psychiatric disorders (Lin et al., 2020). Thus, AI can then use these data to aid in the optimisation of procedures and parameters, offering unique insights into decision-making and support (Lin et al., 2020; May, 2021). Therefore, AI implements a predictive model to forecast future events, whereas traditional data analytics is focused on data pre-processing, interpretation, visualisation, and prediction. Therefore, in making sense of data with diverse features, researchers have moved beyond conventional data analyses, and there is a growing use of machine learning (ML) technology to identify predictors and outcomes for at-risk groups (Hastie et al., 2009).

ML emerged as a computer science field, but is now becoming increasingly used across multiple disciplines (Orrù et al., 2020). It involves the construction of complex algorithms that can learn and make predictions based on various data inputs (i.e., historical data; Hastie et al., 2009). There are four types of prominent ML techniques: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning (Vieira et al., 2020). Supervised learning requires the use of a labelled dataset, wherein each datapoint is labelled with the appropriate answer (Vieira et al., 2020). Based on this information, when new unlabelled data are presented, the algorithm then uses the key features (i.e., predictor variables) from the labelled datapoints to apply the correct classification for the new data (Vieira et al., 2020). Consequently, supervised learning allows for dependent or outcome variables to be predicted by independent or predictor variables (i.e., features) through classification using ML techniques (Hastie et al., 2009).

Unsupervised learning works with unlabelled datasets. When given data, the algorithm seeks to identify trends and clusters of distinctive characteristics, and will then seek to place new data within these trends or clusters (Vieira et al., 2020). Semi-supervised learning is an amalgamation of the two aforementioned techniques and uses a dataset in which only a select number of datapoints are labelled (Vieira et al., 2020). The algorithm then uses clustering techniques (i.e., unsupervised learning) to identify groups within the dataset and then uses the labelled datapoints to label the other unlabelled datapoints in the same cluster or group (Vieira et al., 2020). Finally, there is reinforcement learning which uses goal-orientated algorithms which place an emphasis on the interactive environment and learn through trial and error (Vieira et al., 2020). It is through these techniques that ML is able to make accurate predictions concerning data with (comparatively) very few assumptions (Bishop, 2006; Breiman, 2001) – unlike more traditional methods of data analysis which require specific assumptions about the data to enable prediction, such as analysis of variance and regression (Mak et al., 2019).

ML has emerged in various fields relating to psychology. It has been utilized to improve classification of depressive disorders with neurophysiological data (Drysdale et al., 2017), and to improve prognosis and diagnosis in other mental health disorders, such as anxiety (McGinnis et al., 2018; Tekin Erguzel et al., 2015). Furthermore, ML techniques have been utilized to screen (Mumtaz et al., 2017), predict treatment efficacy (Acion et al., 2017), and assist in clinical decision-making within the substance-use disorder field (Connor et al., 2007). Indeed, there have been several reviews on ML within the addiction literature (e.g., Mak et al., 2019) and within the substance use literature (Zulkifli et al., 2020). However, to the best of the authors' knowledge, there has never been any previous review of ML and GD. Given ML techniques are being utilized with increased frequency in the addiction literature, consolidating the knowledge on the use of ML learning within GD will benefit future implementations of these techniques. Moreover, the use of ML techniques may help better understand aetiology, relevant diagnostic criteria, and the potential to improve interventions (Ferreri et al., 2018). In the present review, ML is considered to be a statistical process which is used as a predictive modeling tool to make predictions about future data based on past observations. More specifically, ML in the present context focuses on optimizing a model's performance on new data rather than on understanding the underlying relationships between variables. For example, logistic regression can be used through the lens of both traditional and ML statistics. In traditional statistics, logistic regression is often used to test hypotheses and make inferences about the relationships between predictor variables and an outcome variable. While in a ML context logistic regression may be used in conjunction with other machine learning techniques, such as regularization or feature selection, to improve model performance and generalization to new data. Thus, within the present review, ML is considered to be statistical methodologies which employ, and have an emphasis on, predictive modelling and/or optimization within a defined ML scope as set out by each reviewed paper.

Given the increasing use of ML in the GD literature, the present paper presents a systematic review of ML studies within GD to inform and direct further work in the field. The primary goal is to review empirical research over the past decade, providing contemporary information on the use of ML techniques and findings in relation to GD. More specifically, the review provides an up-to-date summary of ML techniques currently employed and the subsequent findings within the scope of GD.

Methods

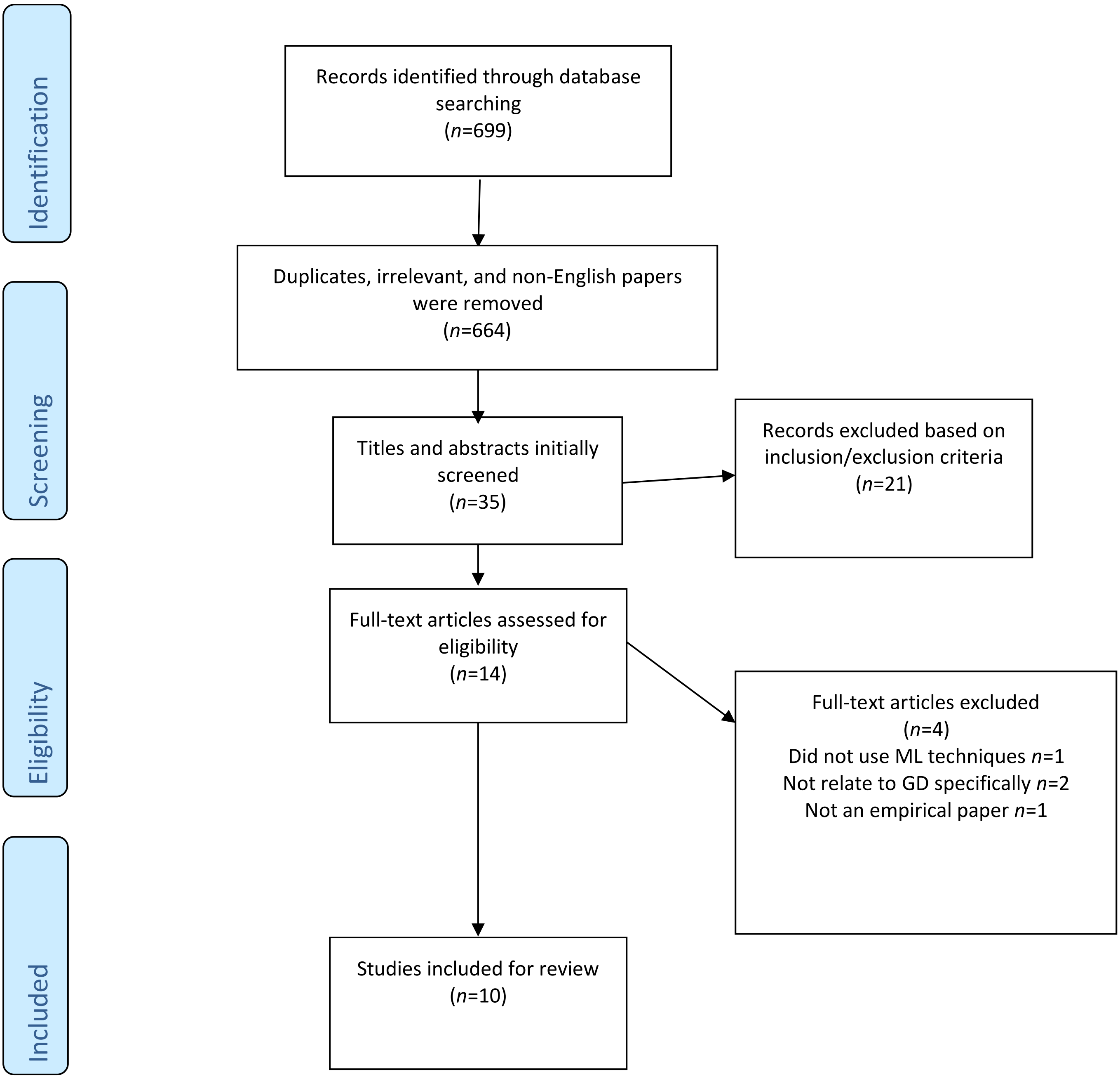
The best practice five-stage model of conducting a rigorous systematic review was used as follows: (i) identifying the research question, (ii) identifying relevant studies, (iii) study selection, (iv) dissemination of outcomes, and (v) summarizing and reporting the results (Siddaway et al., 2019). Inclusion criteria for the review were as follows. Studies had to (i) be published in English; (ii) use gaming or problematic/disordered gaming as an outcome measure or another related measure which considers gaming (e.g., internet addiction); (iii) use ML to classify, identify, or predict individuals with problematic gaming or gaming disorder; (iv) use ML in problematic or disordered gaming treatment, and (v) be published in peer-reviewed journals in the past decade. Studies were excluded if they (i) used simulation of addictive behaviours; (ii) used statistical models which were utilized exclusively as statistical models, rather than extended models used in machine learning; (iii) were review papers with no new empirical data; and (iv) were conference proceedings. The database searches included *PsychARTICLES*, *PsychINFO*, *Scopus*, and *Web of Science*.

Keyword combinations of various ML techniques and terms relating to GD and associated fields were used. ML keywords included: machine OR supervised OR unsupervised OR reinforcement OR ensemble learning; support vector machine; SVM; linear discriminant analysis; LDA; Naïve Bayes; NB; k-nearest neighbours; KNN; learning vector quantization; LVQ; decision trees; random forests; chi-square automatic interaction detection; CHAID; iterative dichotomizer 3; least angle regression; ridge regression; least absolute shrinkage and selection operator; LASSO; k-means clustering, k-medians clustering, kmedoids clustering, hierarchical clustering, fuzzy clustering, hidden Markov model, model-based, model-free. Gaming disorder keywords included: patholog* OR problem* OR addict* OR compulsive OR dependen* OR disorder*; video OR computer OR internet gam*.

The literature search was conducted between January 2021 and February 2021. A total of 699 papers were initially identified. Duplicate papers were removed. Papers not relevant to the present review or non-English were removed, leaving a total of 35 papers. The abstracts of these papers were screened, and a some were excluded because the studies (i) were not in English (n=3); (ii) were published in conference proceedings (n=1); and (iii) did not meet the inclusion/exclusion criteria (n=17). The remaining 14 papers were screened based on full text with a further four papers being excluded due to not using ML techniques (n=1), not relating to GD specifically (n=2), and not being an empirical paper (n=1). The remaining ten papers met all the inclusion criteria. The present review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines (PRISMA statement; Page et al., 2021, which includes a PRISMA flow diagram [see Figure 1]).

Figure 1

Flow Diagram of Paper Selection Process for the Systematic Review



Results

The ten papers meeting the inclusion criteria utilized supervised ML techniques. The papers were classified into three groups based on the type of data collected: psychometric data (n=4; Aggarwal et al., 2020; Ioannidis et al., 2016, 2018; Rho et al., 2016), neurophysiological data (n=4; Dong et al., 2020; Song et al., 2021; Wang et al., 2022; Wang et al., 2020), and physiological data (n=2; Kim et al., 2018, 2019).

Studies Utilizing Psychometric Data

Four studies primarily utilized psychometric data within their ML analyses (Aggarwal et al., 2020; Ioannidis et al., 2016, 2018; Rho et al., 2016). The samples contained both males and females, and data were collected in India (Aggarwal et al., 2020), North America and South Africa (Ioannidis et al., 2016, 2018), and South Korea (Rho et al., 2016). The selected papers utilized a range of ML analyses, which are shown in Table 1.

Table 1

Psychometric Data Utilized in Machine Learning

Paper	Aims	Sample	Behaviour	ML Method/Analysis	Key findings
Aggarwal et al., 2020	To identify predictors of GD, ADHD, and GAD using a gamers' videogame related statistics in conjunction with demographic data.	Indian 44 participants (42 Male; 2 Female). M_{age}: 21.7 years.	IGD	***Supervised ML*** Logistic Regression, K Nearest Neighbour, Naive Bayes, Decision Tree, Decision Tree with Adaboost	The authors were able to predict IGD with an accuracy of 93.18% using Logistic Regression classifier. Logistic Regression classifier resulted in a maximum AUC of 0.60 for predicting IGD.
Ioannidis et al., 2016	To investigate the predictive power of impulsive and compulsive trats in relations to problematic internet use.	North American and South African n= 2006 HC: n=1852 (M_{age}: 29.8 years; SD=13.3) PIU: n=181 (M_{age}: 33.2 years; SD=14.3)	Problematic Internet Use (including Gaming)	***Supervised ML*** Logistic Regression, Random Forests, Naïve Bayes	Impulsivity and compulsivity significantly increased predictability of PIU compared to baseline (*note*. baseline is the model which excluded impulsivity and compulsivity measures). Logistic Regression could distinguish PIU from non-PIU with an AUC of 0.83 (SD 0.03) compared to baseline AUC 0.73 (SD 0.03). Random Forests had an AUC of 0.84 (SD 0.03) compared to baseline AUC 0.69 (SD 0.03). Naïve Bayes had an AUC of 0.83 (SD 0.03) compared to baseline AUC 0.74 (SD 0.04).

Ioannidis et al., 2018	To investigate the moderating relationship of age and gender on problematic internet use.	North American and South African *n*= 1749 NA: *n=686* (M_{age}: 36.3 years; Female: 27%; Male: 73%) SA: *n*=1063 (M_{age}: 36.3 years; Female: 42%; Male: 58%)	Problematic Internet Use (including Gaming)	***Supervised ML*** Linear Regression, Ridge Regression, Elastic-net, LASSO, Random Forests, Naïve Bayes	LASSO and elastic-net were superior to ridge regression and linear regression and not statistically different between each other. LASSO was utilized as the main ML algorithm. Higher PIU scores were significantly related to internet gaming. Age moderated the relationship between PIU and role-playing games. There was inconclusive evidence for gender and its moderating effect on activities being associated with PIU scores.
Rho et al., 2016	To investigate patterns and potential predictors of problematic internet game use.	South Korean *n= 1022* HC: *n*= 511 IGD: *n*= 511	Problematic Internet Game Use (IGD)	***Supervised ML*** Decision Tree: CHAID	Six important predictors of problematic internet game use were found: gaming costs, average weekday gaming time, offline Internet gaming community meeting attendance, average weekend and holiday gaming time, marital status, and self-perceptions of addiction to Internet game use. Using these six predictors, three types of gamer were found: Cost-consuming

gamer, socializing gamer, and solitary gamer.

Note. IGD is Internet Gaming Disorder; HC is Healthy Control; ADHD is Attention Deficit Hyperactivity Disorder; ML is Machine Learning; PIU is Problematic Internet Use; ROC is Receiver-Operating Characteristic; AUC is Area Under Curve; PR-AUC is Precision-Recall Area Under Curve; NA is North America; SA is South African; LASSO is Least Absolute Shrinkage and Selection Operator; CHAID is Chi-square Automatic Interaction Detector

A cross-sectional study from India used gamers' in-game statistics - from *PlayerUnknown's Battlegrounds* (PUBG) - in conjunction with self-esteem to predict GD, attention deficit hyperactivity disorder (ADHD), and generalized anxiety disorder (GAD). The aim was to investigate the feasibility of detecting the early onset of GD, ADHD, and GAD using basic demographic information (i.e., age and gender), self-reported self-esteem, and gaming statistics. The gaming statistics which were used as features (i.e., predictor variables) in the ML model were: headshots (i.e., number of enemy players killed with headshots), kills (i.e., number of enemy players killed), longest time survived (i.e., longest time survived in a match), rounds played (i.e., number of matches played), round most kills (i.e., highest number of kills in a single match), top 10s (i.e., number of times this player made it to the top 10 in a match), wins (i.e., number of matches won), average time survived (i.e., average time survived in a match), top 10s percentage (i.e., percentage of times this player made it to the top 10 in a match), win ratio (i.e., percentage of times this player has won a match; Aggarwal et al., 2020).

Data were processed in a *Python 3* environment using Spyder, Jupyter-Notebook, NumPy (Harris et al., 2020), and pandas (McKinney, 2011), while the ML framework utilized was Scikit-learn (Pedregosa et al., 2011). Leave One Out Cross Validation (LOOCV) was used in conjunction with a Synthetic Minority Oversampling Technique (SMOTE) due to a small imbalanced data set. The LOOCV technique is a special case of k-fold cross validation wherein the model is trained on N-1 datapoints and tested on one left out sample. SMOTE aids to avoid overfitting by creating additional samples along the line between the supplied data and its neighbours. Therefore, oversampling balances the dataset which results in an effective training model (Aggarwal et al., 2020). The results indicated that a logistic regression classifier held a maximum prediction accuracy of 93.18% for GD, followed by decision tree with adaboost (adaptive boosting) (90.90%), decision tree (88.65%), naïve Bayes (79.94%), and K nearest neighbour (79.54%). Moreover, multiple models were run removing gender, age, and self-esteem which resulted in an 8%-15% reduction in prediction accuracy, suggesting that these factors are important when considering GD. Performance of the model was evaluated using the Receiver Operating Characteristics (ROC) curves and the Area Under the Curve (AUC) was used as a performance metric. Briefly, the ROC is a tool which evaluates how successful the classifier (i.e., the ML algorithm) can discriminate between positive and negative cases (Streiner & Cairney, 2007). The ROC is visualised as a plot containing a true positive rate (sensitivity) with a false positive rate (specificity) for various threshold points (Aggarwal et al., 2020). The area under the ROC curve (i.e., the AUC) is calculated to measure the performance of the classifier used; this metric falls between 1.0 (ideal) and 0 (poor), with 0.5 being comparable to guess at random (Streiner & Cairney, 2007). In regard to GD, the logistic regression classifier model had an AUC of 0.6.

Similar results were found when using a logistic regression ML technique in a cross-sectional paper by Ioannidis et al. (2016). Their aim was to investigate whether problematic internet use (PIU) could be predicted from impulsive and compulsive traits and related symptomology. It is worth noting that PIU was broadly defined and included a number of different internet activities (e.g., general surfing, social networking), but also included online gaming. The full model included 20 features, such as: age, sex, race, education, clinical variables (diagnoses of ADHD, GAD, social anxiety and obsessive-compulsive disorder [OCD]), impulsivity, and compulsivity variables (for a full list of variables, see Ioannidis et al. [2016]). In addition, the full model was compared against a baseline model which excluded impulsivity and compulsivity variables.

The data were processed using *R Studio*, with the ML framework applied through the caret (classification and regression training) package (Kuhn, 2008). The analysis used cross-validation with 50 replications and the results were then averaged. Three ML techniques were utilized in this study: logistic regression, random forest, and naïve Bayes. Briefly, the random forest algorithm is a combination of multiple binary decision trees. As the model receives new data, each tree produces a response – therefore, the overall output is determined by a majority vote (Ioannidis et al., 2016). Naïve Bayes is an algorithm that applies the Bayes rule to select the optimal classification based on the posterior probability of the classification labels given in the dataset (Ioannidis et al., 2016). The results found that random forest algorithms (AUC 0.84) were able to classify PIU and non-PIU participants with the greatest accuracy, followed by naïve Bayes (AUC 0.83) and logistic regression (AUC 0.83). This indicated that these ML techniques were able to predict PIU based on the given features. However, there were no specific scores for internet gaming or what it contributed to the overall classification of PIU. However, this was explored in a follow-up study by Ioannidis et al. (Ioannidis et al., 2018).

The follow-up study by Ioannidis et al. (2018) also investigated PIU. The aim was to identify specific internet-related activities that were statistically associated to PIU, and whether age and gender moderated these associations. The final model contained a total of 51 variables. This included six demographic variables (e.g., age, gender), two behavioural variables (e.g., impulsiveness), four diagnostic variables (e.g., generalized anxiety disorder), 13 internet activity variables (e.g., internet gaming), and 26 interaction variables (i.e., the interaction of each internet activity with age and gender). The large number of variables was used in an attempt to create a more accurate model that captured the complexity within the demographic and internet use variables. In order to address the potential of over-fitting the data, the authors chose to use ML techniques to address this limitation, namely least absolute shrinkage, and selection operator (LASSO), ridge regression, elastic-net, and random forests.

Briefly, the LASSO regression is a regularization technique. It is well-suited to models with high multicollinearity and can provide more accurate predictions when compared to other ML techniques (Ioannidis et al., 2018). More specifically, data values are shrunk towards a central point (i.e., penalised), and therefore encourages simple, sparse models which reduce over-fitting (Huys et al., 2016). As a result, LASSO can aid in feature selection because it can lead to zero coefficients (i.e., variables that do not contribute to the model are not used). Ridge regression works in a similar way to LASSO. However, unlike LASSO (which uses an L1 penalty), ridge regression does not aid in feature selection and uses an L2 penalty (Huys et al., 2016). Elastic-net is a statistical model which sits between LASSO and ridge regression. Unlike LASSO and ridge regression, the elastic-net penalty is controlled by α, bridging the gap between LASSO (α=1) and ridge (α=0; Zou & Hastie, 2005). Moreover, elastic-net can perform feature selection and has the ability of selecting 'grouped' features, the latter being a property that LASSO does not share (Zou & Hastie, 2005). Therefore, each of these techniques are useful when considering models that contain many highly related variables.

Ioannidis et al. (2018) found that LASSO and elastic-net performed more favourably than ridge regression, linear regression, and random forests. Furthermore, all models performed significantly better than the naïve baseline. While elastic-net has the potential to give a more powerful and complex model, it did not perform significantly better than LASSO. Consequently, LASSO was chosen as it increases interpretability due to shrinking the coefficients to zero (therefore removing the features) as opposed to grouping multiple features (Ioannidis et al., 2018). Within PIU, two gaming-related measures were considered, internet gaming and role-playing game (RPG). Each of these features had a significant LASSO coefficient, indicating that they significantly contributed to the PIU classification. More specifically, internet gaming was significant in the full sample (β: 0.60) and with participants aged 18-25 years (β: 0.45) and 26-55 years (β: 0.11) years, while RPGs were strongly associated with participants aged 26-55 years (β: 0.71). This demonstrates that gaming (and playing RPGs) contributed to the classification within the ML algorithm, and therefore to the PIU construct.

Finally, Rho et al. (2016) conducted a cross-sectional survey in Korea to investigate potential predictors of GD. They included 14 features in their model which included demographic data (e.g., age, marital status) and game style factors (e.g., gaming costs, time spent gaming). They employed a decision tree ML technique with a chi-square automatic interaction detector (CHAID) algorithm. A decision tree is similar to the random forest technique explained above. However, instead of using multiple 'trees', it has one tree in which the data are split into branch-like divisions. The CHAID algorithm uses adjusted significance testing in addition to the classification of patterns, and uses a similar prediction method to regression (Rho et al., 2016). Moreover, it is useful for data that are inappropriate for regression analysis due to violated assumptions (Murphy & Comiskey, 2013). Their model found six important predictors for GD: gaming cost (50%), average weekday gaming time (23%), offline internet gaming community meeting attendance (13%), average weekend and holiday gaming time (7%), marital status (4%), and self-perceptions of addiction to internet game use (3%). Based on these six predictors, the researchers suggested that there were three problematic gamer types (i.e., cost-consuming, socializing, and solitary players) which could successfully classify GD participants with an accuracy of 70.41% (Rho et al., 2016).

Studies Utilizing Brain Function Data

Four studies utilized *f*MRI data within the ML analyses (Dong et al., 2020; Song et al., 2020; Wang et al., 2020; Wang et al., 2020). The samples all comprised Chinese populations with two samples being exclusively male (Song et al., 2020; Wang et al., 2020). Each study utilized varying ML techniques as shown in Table 2.

Table 2

Neurophysiological Data Utilized in Machine Learning

Paper	Aims	Sample	Behaviour	ML Analysis/Method	Key findings
Dong et al., 2020	To investigate if regional brain features and functional connectivity could be utilized in MVPA to distinguish recreational gamers from gamers experiencing IGD based on IGD diagnostic criteria.	Chinese RGU: *n*= 226 (M_{age}: 21.60 years; SD=2.48; Female: 85; Male: 141) IGD: *n*= 148 (M_{age}: 21.25 years; SD= 2.45; Female: 63; Male: 86)	IGD	Multivariate Pattern Analysis: Support Vector Machine	MVPA could not discriminate between RGU and IGD when using IGD scores ≥5 as the inclusion criteria for IGD subjects. IGD scores ≥5 and ReHo yielded an accuracy rate of 73.8% (43.92% for IGD; 93.36% for RGU) with an AUC of 0.74. IGD scores ≥5 and FC yielded an accuracy rate of 60.42% (41.33% for IGD; 72.16% for RGU) with an AUC of 0.28 MVPA could discriminate between RGU and IGD when using IGD scores ≥6 as the inclusion criteria for IGD subjects. IGD scores ≥6 and ReHo yielded an accuracy rate of 89.84% (63.44% for IGD; 98.58% for RGU) with an AUC of 0.95. IGD scores ≥6 and FC yielded an accuracy rate of 75.31% (59.16% for IGD; 82.73% for RGU) with an AUC of 0.67. Using a IGD score of ≥6 and ReHo, the brain regions with high

					discriminative powers were the bilateral inferior cerebellum; orbitofrontal cortex; cuneus; inferior temporal gyrus; middle frontal gyrus; and the parahippocampal. Using a IGD score of ≥6 and FC, the brain networks with high discriminative power included regions in the default-mode network (praecuneus and middle temporal gyrus) and the executive-control network (anterior cingulate cortex and middle frontal cortex).
Song et al., 2020	To investigate the predictive power resting-state functional connectivity to assess severity of IGD when utilising connectome-based predictive modelling.	Chinese males *n*= 113 HC: *n*=41 (M_{age}: 23.02 years; SD=2.09) IGD: *n*=72 (M_{age}: 22.32 years; SD=1.96)	IGD	Connectome-based Predictive Modelling: Support Vector Machine	The default-mode network is the most informative network in predicting IGD both in classification (78.76%) and regression (association between predicted and actual psychometric scale score: r=0.44, P < 0.001). The dorsal medial prefrontal cortical default-mode network appears to significantly contribute to the prediction of IGD scores and severity.
Wang, Dong et al., 2020	To investigate if MVPA can classify IGD participants from RGUs and finding which brain regions contribute most to the classification of IGD.	Chinese *n*= 202 RGU: *n*=99 (M_{age}: 36.3 years; Female: *n=48*; Male: *n*=51)	IGD	Multi-voxel Pattern Analysis: Support Vector Machine	Image-based ML techniques can be utilized to distinguish IGD using ReHo maps. Discrimination between the two groups held an AUC of 0.92, with an accuracy rate of 82.67%.

		IGD: n=103 (M_{age}: 36.3 years; Female: n=46; Male: n=57)			The brain regions which contributed most to the classification between IGD subjects and RGUs included the bilateral parahippocampal gyrus, right anterior cingulate cortex, middle frontal gyrus, and left cerebellum posterior lobe.
Wang, Potenza et al., 2020	To investigate the if MVPA can correctly identify IGD participants using cue-reactive data. To examine the potential of MVPA in predicting treatment responses using baseline beta values in IGD subjects receiving craving behavioural intervention treatment.	Chinese males n= 59 HC: n=*19* (M_{age}: 22.89 years; SD=2.23) IGD: n=40 (M_{age}: 22.05 years; SD=1.78)	IGD	Multi-voxel Pattern Analysis: Support Vector Machine	Classification of the two groups had an AUC of 0.94, with an accuracy of rate of 92.37%. The most discriminative brain regions that contribute to classification were the bilateral middle frontal gyrus, praecuneus, and posterior lobe of the right cerebellum. MVPA statistically predicted clinical outcomes in the craving behavioural intervention group. The most strongly implicated brain regions in the prediction model were the right middle frontal gyrus, superior frontal gyrus, supramarginal gyrus, anterior/posterior lobes of the cerebellum and left postcentral gyrus.

Note. MVPA is Multivariate/Multi-voxel Pattern Analysis; IGD is Internet Gaming Disorder; RGU is Recreational Game Use; HC is Healthy Control; SVM is Support Vector machine; ReHo is Regional Homogeneity; ROC is Receiver-Operating Characteristic; AUC is Area Under Curve

Dong et al. (2020) conducted a cross-sectional study that investigated whether multivariate pattern analysis using a support vector machine (SVM; i.e., ML technique) could distinguish recreational game users (RGUs) from disordered gamers using resting-state *f*MRI data in conjunction with the DSM-5 classification criteria (American Psychiatric Association, 2013). Multivariate pattern analysis is an approach that is used to identify disordered brain activity which is manifested as spatially distributed patterns across multiple brain regions (Linn et al., 2016). A popular ML technique utilized in multivariate pattern analysis is a SVM, which is trained to predict disordered activity from the vectorized set of voxels within *f*MRI data (Linn et al., 2016). The SVM training algorithm then builds a model that assigns new examples to one category or the other using weights to decide the contribution of each voxel in the classification process, therefore, making it a non-probabilistic binary linear classifier (Linn et al., 2016). The researchers collected *f*MRI data and analysed them via two methods: (i) regional homogeneity (ReHo) which measures temporal synchronization of the time series of nearest neighbours and can be used to map local spontaneous neural activity (Peng et al., 2016); and (ii) functional connectivity (FC) which can be used to map short or long-distance connectivity patterns within the brain and provides additional information which cannot be found in ReHo (Peng et al., 2016).

The SVM algorithm was applied using the pattern recognition for neuroimaging toolbox (PRoNTo; Acion et al., 2017) and *LibSVM* (Chang & Lin, 2011), respectively. The PRoNTo utilized a LOOCV method during ReHo classifier validation. In order to obtain a corrected *p*-value that could determine significance of accuracy, sensitivity, and specificity, a 1000 times non-parametric permutation test was conducted. In regard to FC, feature selection was conducted using scripts within *LibSVM* and a Kendall tau rank correlation coefficient was used to estimate the discriminative power of the selected features. A LOOCV method was then used to estimate the generalization ability of the classifiers chosen. The results demonstrated that multivariate pattern analysis using ReHo data was able to predict disordered gamers better than FC data, especially when GD scores were ≥6 (out of 9 utilizing DSM-5 criteria). Indeed, when using a GD score of ≥6 in conjunction with ReHo data, multiple brain regions achieved high discriminative power in the prediction of GD. Furthermore, the FC data suggested that the default-mode network (DMN) and the executive-control network also appeared to have high discriminative power (Dong, Wang, Dong, et al., 2020). These findings suggest that disease-related resting-state network alterations may contribute to some mood and executive-control disturbances seen in GD. The authors concluded that ML could discriminate between RGUs and disordered gamers, and that GD appeared to have a legitimate neurophysiological basis. The researchers suggested that the DSM-5 diagnostic threshold should be further investigated, especially when related to resting-state neural functioning.

Song et al. (2021) conducted a cross-sectional study to investigate the predictive power of FC utilising a connectome-based predictive model in conjunction with a SVM. More specifically, they examined the predictive power of resting state FC in the assessment of the GD severity. Briefly, connectome-based predictive modelling is a method that is optimized for FC analysis (Shen et al., 2017). This modelling technique uses cross-validation methods and can protect against overfitting by testing identified connectivity in independent samples, which can enhance the replicability of findings (Song et al., 2021). The authors used the statistics and ML toolbox in *MATLAB*, adjusting the scripts to create connectome-based predictive models that utilized SVM for classification and feature selection. In order to obtain null distributions for significance testing, a 1000 times non-parametric permutation was conducted. The *p*-values for leave-one-out predictions were then calculated based on the null distributions. The results suggested that DMN was the most informative brain network when predicting GD in both classification and regression analyses. Three subsystems within the DMN appeared to contribute to the prediction of GD. More specifically, Song et al. (2021) found that the dorsal medial prefrontal cortical DMN contributed the most to the prediction of GD, followed by the midline core DMN, and medial temporal DMN subsystems. The dorsal medial prefrontal cortical DMN has been associated with impairments with social functioning, and addictions (Zhang & Volkow, 2019) – which is a notable feature as social impairment is one of the diagnostic criteria in the DSM-5 and is encountered in clinical contexts (American Psychiatric Association, 2013; King & Delfabbro, 2014).

The midline core DMN has shown that atypical resting state functional connectivity may be an indicator of impaired self-awareness, emotional dysregulation, and contributes to an increase in self-related thoughts during abstinence (Zhang & Volkow, 2019). The resulting impaired cognitive and affective processes may be associated with compulsivity and tolerance, which has been implicated in craving and relapse (Yao et al., 2017; Zhang & Volkow, 2019). Lastly, the medial temporal DMN is often found to be coactive with the midline core DMN and is involved in memory retrieval in reference to personal experience (Zhang & Volkow, 2019). The resulting activation may reflect memories of previous gaming experiences. Therefore, an increased and consistent activation may represent a preoccupation with gaming. Consequently, the authors concluded by suggesting that individual differences within the resting state DMN may further the understanding of GD and its severity.

Wang, Dong et al. (2020) also conducted a cross-sectional study and collected resting-state *f*MRI data. They investigated if multi-voxel pattern analysis could successfully classify RGUs from disordered gamers using SVM and spectral dynamic causal modelling. Additionally, they attempted to identify which brain regions contributed significantly to the classification of GD. Multi-voxel pattern analysis considers the interrelationship between voxels and as a result can be sensitive in detecting subtle and spatially distributed alterations within the data (Wang et al., 2020). Furthermore, it can allow for single-participant statistical inferences to be drawn, therefore aiding in diagnostic decisions on an individual level (Vieira et al., 2017). The SVM algorithm was applied using the PRoNTo (Schrouff et al., 2013) and utilized a LOOCV method during classifier validation.

Following this, a 1000 times non-parametric permutation test was conducted to supply corrected *p*-values that could determine the significance of accuracy, sensitivity, and specificity of the SVM. The results suggest that image-based ML techniques can be utilized to distinguish disordered gamers from RGUs. More specifically, the classification between the two groups had an AUC of 0.92, an accuracy of 82.67%, a sensitivity of 83.50%, and specificity of 81.82%. They found that the brain regions which significantly aided in the GD gyrus classification were the bilateral parahippocampal, right anterior cingulate cortex, middle frontal gyrus, and left cerebellum posterior lobe. The results of the spectral dynamic causal model showed that disordered gamers demonstrated a weakened connection between the bilateral parahippocampal gyrus and the prefrontal cortex, which included right anterior cingulate cortex and the middle frontal gyrus. It has been suggested that each of these brain areas contribute to memory recall through the representation and retrieval of contextual information (Eichenbaum et al., 2007; Weible, 2013), while the anterior cingulate cortex and middle frontal gyrus have also been implicated in mood regulation (Caetano et al., 2006) and emotional modulation (Drabant et al., 2009), respectively.

These findings are in line with previous research which suggests that disordered gamers exhibit a significant blunted neural reaction in the anterior cingulate cortex and the middle frontal gyrus when responding to negative affective cues and during emotion regulation (Yip et al., 2018). Therefore, the generation and regulation of negative emotions are not only affected by one brain area. Therefore, Wang, Dong et al. (2020) concluded that the weakened connections between these brain areas may be an underlying mechanism of GD.

Finally, Wang, Potenza et al. (2022) conducted a cross-sectional study that investigated whether multi-voxel pattern analysis could identify disordered gamers using cue-reactive *f*MRI data. They also examined the potential of multi-voxel pattern analysis in regard to treatment response among disordered gamers. The SVM algorithm was applied using the PRoNTo (Schrouff et al., 2013) and utilized a LOOCV method during classifier validation. Following this, a 5000 times non-parametric permutation test was conducted to supply corrected *p*-values determining the significance of accuracy, sensitivity, and specificity. The results demonstrated that the classification between disordered gamers and gamers had an AUC of 0.94, an accuracy of 92.37%, a sensitivity of 90.00%, and specificity of 94.74%. They found that the brain regions which aided GD classification the most were the bilateral middle frontal gyrus, praecuneus, and posterior lobe of the right cerebellum. Moreover, the multi-voxel pattern analysis was able to statistically predict clinical outcomes in the craving behavioural intervention (CBI) group (r=0.48, p=0.0032).

The most discriminate brain regions in the prediction model were the right middle frontal gyrus, superior frontal gyrus, supramarginal gyrus, anterior/posterior lobes of the cerebellum and left postcentral gyrus. The prefrontal cortex, which include the middle frontal gyrus and superior frontal gyrus, have been associated with craving processes in disordered gamers (Dong, Wang, et al., 2018; Dong, Zheng, et al., 2018; Dong, Liu, et al., 2019), while the prefrontal activations have been implicated in recovery (without formal intervention) in GD (Dong, Liu, et al., 2019; Dong, Wang, et al., 2019). The cerebellum has been linked to a number of functions relating to GD, such as visual, emotional, and cognition-related processes (Tirapu-Ustarroz et al., 2011). Lastly, the supramarginal and postcentral gyri are main sensory receptive regions for touch (Carlson & Birkett, 2017). Wang, Potenza et al. (2022) concluded that findings suggest that craving responses, emotion and cognitive processes can aid in identifying disordered gamers and aid in the prediction of treatment outcomes.

Studies Utilizing Physiological Data

Physiological data were utilized in two studies based in Korea, each using all-male samples (Kim et al., 2018, 2019; see Table 3).

Table 3

Physiological Data Utilized in Machine Learning

Paper	Aims	Sample	Behaviour	ML Analysis/Method	Results
Kim, Ha et al., 2018	To investigate if craving could be detected in IGD participants using multi-modal physiological data in order to aid future intervention strategies.	Korean males n= 57 (M_{age}: 19.19 years; SD: 2.49)	IGD	Support Vector Machine	Craving was detected in IGD participants with an average classification accuracy of 87.04%, and an average sensitivity and specificity of 87.71% and 86.37%, respectively. Results suggest that ML classification between craving and the IGD measure were not significant – suggesting that classification of craving is not significantly altered by severity of IGD symptomology. Participants with higher IGD scores generally report higher craving scores – suggesting IGD participants feel stronger cravings than those with lower scores.
Kim, Kim et al., 2019	To confirm test-retest reliability of the physiological-signal-based craving detection method from the previous study using multi-modal physiological data.	Korean males n= 9 (M_{age}: 20.60 years; SD= 1.14)	IGD	Support Vector Machine, K-nearest Neighbours, Centroid Displacement-based, Linear Discriminant Analysis, Random Forest	A SVM was utilized in the final analysis as it had the most consistent results when compared to other ML techniques. The present study provided evidence for good test-retest performance, even when conducted over a three-day period. The greatest classification accuracy was 72.77% and was achieved

	through using day one and day two data for training the SVM.

Note. IGD is Internet Gaming Disorder; ML is Machine Learning; RGU is Recreational Game Use; HC is Healthy Control; SVM is Support Vector machine; ReHo is Regional Homogeneity; ROC is Receiver-Operating Characteristic; AUC is Area Under Curve

The overall aim in the studies was to detect craving among disordered gamers using physiological data in order to inform treatment interventions (Kim et al., 2018). This was then followed up in validation of test-retest reliability in a practical setting (Kim et al., 2019). The physiological measurements taken in each study were photoplethysmogram (PPG), galvanic skin response (GSR), and electrooculogram (EOG) signals. Each study used the *LibSVM* software package (Chang & Lin, 2011), and therefore the SVM technique, to classify high and low craving states. The SVM classifications were validated using a ten-fold cross-validation individually for each participant. The first study (Kim et al., 2018) used a total of 14 variables (e.g., heart rate, respiratory rate, eye-blinks) within their model and found that the average classification accuracy was 87.04%, with the average sensitivity and specificity being 87.71% and 86.37%, respectively.

The correlations between classification performance and GD scores were not significant, suggesting that classification is not affected by the severity of GD symptoms. The authors also noted that reduced saccadic movements were the most selected feature in the ML-based classification process and were also correlated with GD scores. Similar results have been found among smokers, where craving for smoking caused participants to fixate their attention on smoking cues (Mogg et al., 2003). Therefore, the reduction in the number of eye blinks and saccadic movement may be associated with the increased attention and increased cravings for gaming. This suggests that EOG-based physiological features may better reflect characteristics of GD than autonomic nervous system responses. The authors concluded that ML was able to successfully discriminate between craving and non-craving states, although each trial was too long to feasibly implement in a practical setting.

The authors' second study (Kim et al., 2019) attempted to mitigate the 'tediousness' of data collection by reducing the long training stages required. This was done by splitting the data collection over three days, resulting in much smaller sessions. On the first day, the two features with the highest Fisher score (i.e., the Fisher score algorithm which selects the most discriminant features; Duda et al., 2000) were chosen (only two features were selected due to the small sample size and therefore controlling the potential risk of over-fitting) to be included in the ML model of classifiers. The second day was then used as training data. The third (final) session was used to evaluate the classification accuracy of the binary craving states using the previously collected data. In addition, a six-fold cross-validation technique was used on the third day to evaluate the SVM classification accuracy. Therefore, the SVM was trained using four different conditions: (i) the SVM was trained only with Day 3 data (i.e., cross-validation); (ii) with only Day 1 data; (iii) with only Day 2 data; (iv) with both Day 1 and Day 2 data. The authors also utilized other ML techniques to assess classification using the previous four conditions: k-nearest neighbours, centroid displacement-based, linear discriminant analysis, and random forest. Their results suggested that there were no significant differences between the five ML techniques utilized. However, their data implied that SVM demonstrated the most consistent classification performance. Therefore, SVM was used as the classifier in their final analyses. The classification accuracy across the four conditions was 66.67% (cross-validation), 63.89% (Day 1), 66.67% (Day 2), and 72.22% (Day 1 and Day 2). The authors concluded that their craving classification method among disordered gamers had high test-retest reliability, noting that ML techniques can detect craving with data collected on a previous day with an accuracy comparable to data collected on the same day. They suggest that this could have practical implications for addiction treatment because only a small number of brief calibration sessions would be needed.

Discussion

The present systematic review provides an overview of studies which have utilized ML techniques – and a brief overview of the ML techniques themselves – through the lens of gaming disorder (GD). The ML techniques utilized appear to demonstrate that ML analyses can be a valuable tool when used with psychometric, neurophysiological, and physiological data. The psychometric studies utilized a wide variety of different techniques to establish the optimal ML algorithm, while the neurophysiology and physiology studies utilized SVMs within varied styles of models or analyses. Each of the papers utilized supervised ML methods for their main analysis. While some previous addiction studies have utilized unsupervised ML methods (Mak et al., 2019), no studies utilizing unsupervised methods relating to GD were found in the present search. All studies that were included were conducted and published in recent years, indicating that the development of ML techniques has provided researchers with new opportunities to adopt novel analytical approaches. Indeed, the present paper provides evidence of ML being utilized to screen and predict GD along with the development of potential treatment frameworks (e.g., through craving; Kim et al., 2018).

Psychometric Studies

There were several different ML techniques considered in each of the psychometric studies. Each study explored multiple models in order to apply the model which contained acceptable predictive power. The random forests and decision techniques appeared to have the greater classification compared to naïve Bayes, and logistic regression analysis results appeared to vary. The LASSO technique performed favourably when compared to other ML techniques. Moreover, LASSO also demonstrated higher accuracy when compared to traditional linear regression models (Ioannidis et al., 2018), highlighting the potential of ML analyses to be used in a GD context.

The psychometric studies also provided diverse samples from Southern Asia, North America, South Africa, and South Korea. Two papers utilized logistic classification and regression based on various predictors (Aggarwal et al., 2020; Ioannidis et al., 2016). Aggarwal et al. (2020) explored a novel approach by including online game statistics within their methods. Using this in conjunction with demographic variables yielded a high prediction rate of disordered gaming. Rho et al. (2016) also investigated offline gaming-related factors (e.g., gaming costs, offline community engagement) and found they contributed distinctively to three overarching gamer types, with each of these types of gamers exhibiting specific offline behaviours related to gaming. Scholars have suggested that online contextual factors (e.g., gamer statistics) should be considered along with offline factors (e.g., demographic measures) in order to obtain a more holistic view of gaming behaviours (Burleigh et al., 2018). Indeed, each of the studies reviewed demonstrated that various other psychometric measures (e.g., impulsivity) also contributed to the classification of GD when using ML methods (Ioannidis et al., 2016), mirroring more traditional analysis methods in the field (Nuyens et al., 2016). Therefore, the four studies reviewed reinforce the idea that online and offline gaming-related factors can be useful metrics to include in both traditional analyses and ML analyses.

Neurophysiological Studies

The four neurophysiological studies were exclusively conducted among Chinese populations, and all published in 2020. The use of ML has also supported the basis for GD to be recognised as a disorder due to its specific neurophysiological features when compared to RGUs (Dong, Wang, Dong, et al., 2020). This therefore provides support for GD as an independent disorder, instead of being secondary to other psychopathologies (van Rooij et al., 2018). However, in relation to one study which investigated the diagnostic threshold of GD, the authors found evidence in support of a neurophysiological basis of GD based on a threshold of six or more DSM-5 criteria, rather than recommended five or more DSM-5 criteria (Dong et al., 2020). The authors concluded that the current diagnostic criteria in relation to the DSM-5 may not be stringent enough (Dong, Wang, Dong, et al., 2020).

The collective results indicated that ReHo displayed stronger predictive power when compared to FC (Dong, Wang, Dong, et al., 2020) and highlighted several brain regions that were more associated with GD compared to those of RGUs. The middle frontal gyrus (Dong et al., 2020; Wang, Dong, et al., 2020; Wang, Potenza et al., 2020) and the parahippocampal gyrus (Dong et al., 2020; Wang, Dong, et al., 2020) were found to be commonly identified across studies and contributed highly to the classification of GD. The middle frontal gyrus plays an important role in cognitive control, which includes error processing and decision-making in relation to reward through memory (Walton & Mars, 2007). This suggests that relationships between impaired control and long-time videogame engagement may persist even if an individual tries to stop playing (Wang, Dong, et al., 2020). This may be akin to 'addiction memory' wherein drug-abstinent individuals can keenly recall the experience of using drugs (Dunbar & Taylor, 2016) – a process which has been implicated in drug addiction (Hyman et al., 2006). The parahippocampal gyrus may also be associated in the formation of addiction memory because it contributes to memory recall (Eichenbaum et al., 2007), and has also been found to play an important role in the formation of addiction memory of substance use in the default mode network (Šlamberová et al., 2014). The FC results also suggest that the default mode network is a significant predictor of GD (when compared to RGU; Dong et al., 2020; Song et al., 2020). Therefore, the similarities across these studies provide preliminary support for the detection of neurophysiological underpinnings of GD utilizing ML methods and corroborate other statistical methods and findings in the field (Brand et al., 2019; Dong, Wang, Zheng, et al., 2020).

Physiological Studies

The two physiological studies were conducted in South Korea, and both investigated craving in GD – the 2018 study was the initial study (Kim et al., 2018) and the 2019 study was a follow-up (Kim et al., 2019). The results indicated that craving can be predicted among disordered gamers using physiological measures in conjunction with ML techniques. However, in order to get an optimal SVM mode, the authors noted that a long training session was needed (Kim et al., 2018). In order to overcome this limitation, a second study explored the practicality of using ML craving detection over multiple days with shorter sessions (Kim et al., 2019). The results suggested that craving detection among participants on the third day (using the previous two days as training data) predicted craving comparable to that achieved using data required on the first day in the previous experiment (Kim et al., 2018). The results suggest that a craving detection system with high accuracy may be able to be developed to assist in the treatment of GD (Kim et al., 2018, 2019). Indeed, a number of prior addiction studies have investigated physiological data produced by craving-induced stimuli or the difference in physiological responses of control and addiction groups (Lu et al., 2010; Mogg et al., 2003). A craving detection system would aid treatment frameworks that utilize computer-assisted treatment strategies such as cue exposure therapy because this system would complement the goal of reducing or managing craving with accurate feedback (Kim et al., 2019). However, the authors note that this would require further testing and the development of generic classifier models (Kim et al., 2019).

Limitations

There are several limitations concerning the studies assessed within the present review. First, it appears that ML application within the scope of assessing and predicting GD is not yet widespread, therefore the small number of studies may not fully capture the potential of ML in the wider field. Secondly, there was little variation in sample types within the neurophysiological studies, which indicates that results cannot be generalized to the wider cultural contexts. Furthermore, all but the physiological studies were cross-sectional in nature, and therefore no casual relationships can be drawn. It should also be noted that in regard to the psychometric studies, only two (Aggarwal et al., 2020; Rho et al., 2016) utilized official diagnostic criteria (i.e., DSM-5) while the latter two (Ioannidis et al., 2016, 2018) used broader definitions. This may result in the findings not being generalizable to the because they employed a broad framework that did not account for nuanced investigation of GD specifically.

The present review itself is also subject to some limitations. Firstly, the methodology utilized was descriptive in nature and not quantitatively synthesized. Therefore, no statistical conclusions can be drawn from the results. Secondly, due to the inclusion criteria, only peer-reviewed papers published in English from four databases were used. Consequently, important findings could have been overlooked because they may have been available in other languages or databases. It should be noted that gray literature was excluded from the present review, which is inconsistent with the recommended systematic methodology put forth by Siddaway et al. (2019). According to their approach, unpublished works should be included in systematic reviews and meta-analyses in order to minimize the impact of publication bias. Therefore, the present review cannot be regarded as representative of both peer-reviewed and grey literature; and while there were efforts to reduce biases through the synthesis of literature, publication bias may be present. Finally, despite including broad research terms in several databases, it is possible a number of studies were missed due to a lack of fit with the inclusion criteria.

Future Directions

It is plausible that future ML methodologies will help play an important role in the identification of GD, using both psychometric and neurophysiological data. Screening tests with higher sensitivity and specificity will mean earlier clinical diagnosis and treatments (Usher-Smith et al., 2016). Moreover, in conjunction with neurophysiological data, the potential for stage-specific diagnostic tests which consider biomarkers could also be implemented (Usher-Smith et al., 2016). In addition to *f*MRI data, more affordable and accessible neurophysiological technologies such as electroencephalography (EEG) should be considered (Burleigh et al., 2020). In addition, a combination of central (e.g., EEG) and peripheral (e.g., heart rate, blood measures) data may increase classification accuracy and should be further explored in future research (Kim et al., 2019). Within the scope of GD, applications of ML should consider the co-occurring aspect of behavioural and substance addiction because this may offer new and novel insights to an emerging research area (Burleigh, Griffiths, et al., 2019). However, it should be noted that one of the shortcomings of ML is that it can be difficult to interpret (Ley et al., 2022); thus, ML should be used alongside, and in conjunction with, traditional statistical methods (where it is most appropriate). Moreover, the feasibility of other ML methods should also be investigated and trialled in the field (e.g., spiking neural networks). Finally, future research should consider multi-cultural samples when considering neurophysiological data. Such studies are integral to gain a better understanding of the neurophysiological profile of GD across cultures.

Conclusion

The present review suggests that ML techniques are gaining traction within the GD literature. A wide variety of ML techniques have been utilized in psychometric studies and reported high accuracy in differentiating disordered gamers from recreational gamers. The results also demonstrated support for the use of both offline and online gaming factors in ML models. Studies that investigated neurophysiological and physiological data utilized similar ML techniques, and all reported high accuracy. The physiological studies demonstrated preliminary evidence for craving detection systems which could be used in the context of GD treatments. Future research should consider utilising ML to investigate other areas within the GD field, such as the detrimental aspects of co-occurrence in disordered behaviour and substance use. However, this should not come at the expense of traditional statistical methods, as these methods still have a place in identifying relationships between variables and can provide useful comparison results (Ley et al., 2022). Indeed, further investigation of potential applications of ML and related techniques in the detection and prediction of GD are needed.

Introduction Summary

Throughout the introductory chapters it has been highlighted that a number of studies which have explored the co-occurrence of GD with other disordered behaviours and substance use. It has also demonstrated that there are calls to consider multi-modal treatments. However, in order to better understand the role of GD in co-occurrence an improved conceptualisation of the neurophysiological expression, ways to identify GD should be considered. Due to its cost-effective and non-invasive application, EEG methodologies appear to be an appropriate way to highlight an individual's neurophysiological state uniquely and objectively in relation to GD. Moreover, ML methods offer a unique opportunity to interpret and classify GD with high accuracy, which may aid in the identification of GD as a co-occurring or primary disorder; thus, aiding in treatments as GD can be identified. Therefore, the present doctoral research project aims to address these issues, by providing insight into the following questions and aims in the respective empirical chapters:

1. Can novel artificial intelligence methods identify problematic gaming? The aim is to assess the viability of using EEG methodologies in conjunction with artificial intelligence as a means to explore the neurophysiological underpinnings and conceptualisation of GD (Chapter 4).
2. Are gamers more likely to experience co-occurrence? The aim is to understand which factors may contribute to gamers developing co-occurring addictive behaviours and if gaming contributed as a risk factor (Chapter 5).
3. Is the risk of co-occurrence stable across multiple locations? The aim is to assess a variety of identified risk factors and explore if they differ in three different geographical locations (Chapter 6).

The first three chapters of the present doctoral thesis systematically reviewed the relevant literature on GD, with a focus on co-occurrence, EEG methodologies, and the use of ML algorithms within EEG resting state data. These chapters have contextualised the current understanding of the neurophysiological conception and identification of GD, as well as reviewed risks associated with co-occurrence. Consequently, the following three empirical chapters will build from their respective review chapters, which will then be followed up with a discussion chapter, which will explore the findings in a broader setting, contextualising, and synthesising them in light of the current scientific literature (Chapter 7).

Part II: Empirical Studies

Chapter 4

EEG-Based Detection and Classification of Gaming Disorder using a Brain-Inspired Spiking Neural Network

Introduction

There has been a wide range of negative consequences associated with gaming in recent years (Burleigh, Griffiths, et al., 2019). Consequently, the American Psychiatric Association (APA) and the World Health Organization (WHO) have added Internet Gaming Disorder (IGD) and Gaming Disorder (GD) into the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013) and International Classification of Diseases (ICD- 11; World Health Organization, 2019), respectively. To maintain consistency, the term ‘gaming disorder’ (GD) in the present paper refers to the clinically defined measures of IGD/GD as defined by DSM-5/ICD-11. There have been associations made between disordered gaming (and/or problematic gaming) and psychiatric disorders, including depression (Burleigh et al., 2018) and anxiety (Adams et al., 2019), and behavioural disorders, such as substance use disorders (e.g., Alcohol Use Disorder [AUD]; Na, Lee, Choi, & Kim, 2017), and even stress (Andreetta et al., 2020).

Due to the multifaceted nature of GD, several different techniques have been used to identify and assess problems, predict outcomes, and inform treatment (Kuss & Billieux, 2017). Some methods include psychometric self-report (King et al., 2017), clinical assessment and intervention (Yau et al., 2012) and brain imaging methods (e.g., EEG; Burleigh et al., 2020; functional magnetic resonance imaging, *f*MRI; Kuss et al., 2018). Indeed, the topic of assessment and prediction has long been explored by data analysts, experimental scientists, and psychologists. However, there is debate surrounding the diagnostic criteria of GD and the inclusion of dimensions such as tolerance and withdrawal, resulting in wider debates on GD presentation and features (Deleuze et al., 2017; Griffiths et al., 2016; Kardefelt-Winther et al., 2017; Petry et al., 2016). In addition, potential predictive factors (Wartberg et al., 2019) and negative effects (G. Dong, Liu, et al., 2019) have also been debated by a number of scholars, and whether GD could potentially be considered a disordered behaviour, and thus remains somewhat controversial (Potenza, 2018; van Rooij et al., 2018). Thus, further research is needed into GD, with a focus on defining features and how it may be different from recreational videogame use (RGU). One such difference may be found in specific neural underpinnings.

The US National Institute of Mental Health (NIMH) advocates using Research Domain Criteria (RDoC) and a multidimensional approach that includes observable behaviour and neurophysiological measurements to understand complex human behaviours and the mental disorder continuum (Clark et al., 2017). Therefore, GD research should consider the underpinnings of neurophysiological mechanisms. Several papers have considered the use of neurophysiological data (i.e., EEG data) in the investigation of GD (see Burleigh et al. 2020 for review). There are several advantages to using EEG over other neuroimaging techniques; for example, EEG offers a high temporal resolution, it does not require invasive scanning, it is more mobile than other neuroimaging machine (e.g., *f*MRI), it is also more accessible, and has a lower financial cost to utilise (Burleigh et al., 2020). In addition to this, quantitatively measured EEG (QEEG) has been used to investigate various disorders, with spectral and coherence analyses being employed to investigate addiction (Houston & Ceballos, 2013). Indeed, investigating the underpinning neurobiological mechanisms using EEG data would benefit the conceptual development of GD, and carry practical implications for understanding aetiology, establishing diagnostic criteria, improving intervention, and to accurately differentiate problematic or disordered gaming from recreational gaming. While there have been several studies that have explored this issue using various statistical techniques (e.g., coherence analysis) and EEG data (Burleigh et al., 2020) there has been a dearth of literature which has considered the use of AI related methodologies in conjunction with EEG.

Artificial Intelligence, Machine Learning, and Spiking Neural Networks

The use of artificial intelligence (AI) has increased across multiple disciplines (Orrù et al., 2020), bringing new insights and debate into the way researchers utilise statistics due to its capacity to model data for various applications (Friedrich et al., 2021). The term 'artificial intelligence' is used to describe the act of a machine emulating the mind-related cognitive functions, such as learning and problem solving (Elliott, 2021). Since its inception, the expansion of AI-related research has extended into the automation of research techniques ranging from hypothesis generation to experimentation (Lin et al., 2020; May, 2021). AI-related methodologies have demonstrated a strong aptitude for extracting meaningful patterns from complex data sets for the purpose of regression, prediction, and classification-related tasks (Lin et al., 2020). In doing so, AI is able to use the data to aid in the optimisation of procedures and parameters and offer unique insights into decision-making and support (Lin et al., 2020). Traditional statistics is often utilized in data-reprocessing, interpretation, visualisation, and prediction, whereas AI implements models that are used to forecast future events (Orrù et al., 2020). Therefore, in order to move beyond conventional data analysis and interact with complex clinical data the present review seeks to explore the use of AI within the psychological field.

Originating in the computer science field, ML became a popularized AI-related methodology and has become increasingly used across multiple disciplines (Orrù et al., 2020). In order to forecast future events, ML methodologies require various data inputs (based on historical data; Hastie et al., 2009), and typically fall into four categories: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning (Vieira et al., 2020). Supervised learning allows for dependent or outcome variables to be predicted by independent or predictor variables (i.e., features) through classification using ML techniques (Hastie et al., 2009). Unsupervised learning works with unlabelled datasets. When given data, the algorithm seeks to identify trends and clusters of distinctive characteristics, and will then seek to place new data within these trends or clusters (Vieira et al., 2020). Semi-supervised learning is an amalgamation of the previous two techniques and uses a dataset in which only a select number of datapoints are labelled (Vieira et al., 2020). Lastly, reinforcement learning uses goal-orientated algorithms and places an emphasis on the interactive environment and learning through trial and error (Vieira et al., 2020). While these are the most dominant AI methodologies in use, there is another methodology gaining traction: artificial neural networks (ANN; Tan, Šarlija, & Kasabov, 2020).

An ANN is a network of neurons that, like other ML methodologies, can perform computations and solve problems. However, unlike some ML methodologies which use regression and classification algorithms (e.g., supervised learning), a neural network uses multiple layers of neurons and depending how these neurons are used will depend on which ANN generation is being used. ANN can be categorized into three distinct generations, ranging from first-generation to third generation (Tan et al., 2020). In brief, first-generation ANNs are composed of ‘perceptron’ neurons (Rosenblatt, 1958) which contain pre-defined thresholds (or threshold gates); the neurons compute a weighted sum of binary inputs and outputs, producing a 1 if the sum crosses the pre-defined threshold or a 0 if the threshold is not reached (Tan et al., 2020). Second-generation ANNs contain sigmoid neurons, which apply a nonlinear activation function to the sum of weighted neuron inputs. This allows backpropagation algorithms, which are based on error function gradient computation, to train the ANNs. Through the use of multiple neuron layers and backpropagation algorithms, a deep learning neural network can be constructed. Deep learning networks are widely used for their problem-solving abilities across multiple areas, such as visual recognition (Russakovsky et al., 2015), pedestrian detection (Ouyang & Wang, 2013), and speech recognition (Hannun et al., 2014). However, it has been argued that the linear nature of backpropagation within ANNs is not biologically plausible. Consequently, these ANNs are not an accurate representation of the biological neurons that inspired them, as they learn in a fundamentally different manner than neurons (Bengio et al., 2015; Tan et al., 2020). Therefore, spiking neural networks (SNNs) – third-generation ANNs – were created (Maass, 1997).

Similar to their biological counterpart, SNNs utilize spiking neuronal units to communicate discrete input spikes. If the combined outcome reaches a specific threshold, an output spike is achieved, otherwise the output is zero (Tan et al., 2020). In addition to this, they also utilize a temporal component in their operations. Therefore, an SNN can perform updates based on event-driven and data-driven inputs, making them suitable for real-time operation (Doborjeh et al., 2016; Tan et al., 2020). Many methods and systems have been developed and applied using SNNs, such as audio–visual information processing (Wysoski et al., 2010), brain–computer interfaces (Anderson et al., 1998), personalized prediction systems (Tu et al., 2014), and spatiotemporal brain data (STBD) modelling (Kasabov, 2014). Due to the compact representation of space and time, fast data learning, and time-based and frequency-based information representation, SNNs are considered a fitting technique for analysing neurophysiological EEG data (Doborjeh et al., 2018, 2019, 2020; Kasabov & Capecci, 2015).

EEG can capture STBD when the human brain is activated by cognitive tasks, or even when it is at rest. Consequently, EEG is capable of recording STBD with high temporal resolution, allowing it to detect changes across the brain in milliseconds (Doborjeh et al., 2016). Moreover, EEG is able to detect and capture changes associated with perception and cognitive function, such as memory and attention. For example, AI and EEG have been utilised in classifying an individual’s video game play experience and engagement (Parsons et al., 2022). In this specific study, arousal and effective states were assessed using spectral power analysis, and then ML techniques were used to classify engagement and arousal-based events (e.g., death of character or general gameplay) using neurophysiological feedback. Another study utilised ML methodologies and EEG data in the classification of expertise level while playing videogames (i.e., novice or expert; Hafeez et al., 2021). Indeed, EEG data analysis is a complex task and researchers have employed a wide range of methodologies to interpret the data, such as AI-related approaches (Burleigh et al., 2020). More specifically, ML methodologies have been used to improve classification of depressive disorders with neurophysiological data (Drysdale et al., 2017), and to improve prognosis and diagnosis in other mental health disorders, such as anxiety disorders (McGinnis et al., 2018; Tekin Erguzel et al., 2015). In recent years, there has also been preliminary use of SNN models and methodologies in conjunction with EEG data to analyse and interpret substance abuse data (Doborjeh et al., 2016; Doborjeh & Kasabov, 2016). When using SNN models (to analyse and interpret EEG-related STBD), results have demonstrated superior classification accuracy when compared with more traditional ML techniques (Doborjeh et al., 2016).

The SNN-based methodology has demonstrated a high accuracy when being used to demarcate opiate addicts, and depressed individuals from healthy controls (Doborjeh et al., 2016; Shah et al., 2019), indicating its potential to be used in the classification of behavioural disorders. Moreover, deeper modelling insight into neural circuitry, information processing, and plasticity in the brain areas is important in building an understanding between disordered gaming symptoms at the neural level and the resulting behavioural disorder of an individual. In order to provide novel insights into the potential use of neural networks and to identify specific neurological behaviour and disordered behaviour, the current research designed and applied a novel computational framework of Brain-inspired SNN to resting EEG data to investigate the differences between gamers and recreational gamers. SNN models have been considered as a suitable tool for the analysis of STBD, where both *space* and *time* components are crucial to be learnt. Here, it was hypothesised that using the SNN architecture will result in a higher classification accuracy of recreational gamers and problematic gamers when compared to comparative machine learning techniques. Figure 1 presents the protocol of study, as well as the designed computational SNN-based methodology for visualisation, classification, and prediction.

The Present Study

This research addresses the following aims:

(i) To use a brain inspired SNN architecture which utilises resting state EEG data to explore neurophysiological expression of gamers.

(ii) To assess whether the brain-inspired SNN model could successfully classify recreational gamers from problematic gamers based on EEG data.

It is hypothesised that the SNN model will result in a higher classification accuracy of recreational gamers and problematic gamers when compared with comparative machine learning techniques.

Methods

Participants

Participant data were collected in the United Kingdom. For the current study, participants from a wider cohort, for whom it was logistically practical to attend the laboratory assessments, were invited to then take part in the present study (see chapter 6). Participants were offered £20 renumeration for their time. The inclusion criteria for this sample were: (i) being aged 18 years or over; (ii) having previously taken part in a related survey study, and (iii) scoring either 9 (as this is the lowest score attainable) or over 21 (which may indicate problematic gaming; Monacis, Palo, et al., 2016) on the Internet Gaming Disorder Short Form-9 (IGDSF-9) screening tool. The sample comprised 16 participants, including eight women (M_{age}= 22.87; *SD*= 2.35 years) and eight men (M_{age} = 22.87; *SD* = 5.24 years), aged between 19 and 34 years (M_{age} = 22.87 years; *SD* = 3.93). Additional demographic statistics by group can be found in Table 1. All participants were given information prior to the study, including data use, potential risks, and benefits, along with their right to withdraw from the study until data analysis. The study was approved by the university's ethics committee.

Table 1

Game Demographics by Cohort

	Recreational Gamers	Problematic Gamers
Years playing videogames (*M* ± *SD*)	11.9 ± 6.20	15.6 ± 6.46
Hours spent playing videogames during a weekday (M ± SD)	3 ± 1.06	8 ± 2.73
Hours spent playing videogames during weekend day (M ± SD)	4 ± 1.16	10 ± 3.16

EEG Data Collection and Processing

EEG data were collected under strict monitoring with two minutes eyes open state and two minutes eyes closed state (Shah et al., 2019). Recordings were carried out using a BioSemi amplifier and 64 channels (Fp1, AF7, AF3, F1, F3, F5, F7, FT7, FC5, FC3, FC1, C1, C3, C5, T7, TP7, CP5, CP3, CP1, P1, P3, P5, P7, P9, PO7, PO3, O1, Iz, Oz, POz, Pz, CPz, Fpz, Fp2, AF8, AF4, AFz, Fz, F2, F4, F6, F8, FT8, FC6, FC4, FC2, FCz, Cz, C2, C4, C6, T8, TP8, CP6, CP4, CP2, P2, P4, P6, P8, P10, PO8, PO4, O2) with electrode placements based on a standard 10–20 international system. The data were recorded at 2048 Hz and down sampled to 512 Hz. Signal processing was performed using EEGLab (Delorme & Makeig, 2004). Eye movement and muscle artifacts were reduced or removed off-line using ICA methods.

With regard to differentiating healthy and problematic gamers, participants with scores between 9-20 (on the IGDSF-9) were considered as healthy participants and those with scores of 21 and over were considered to be problematic gamers within the present study (Monacis, Palo, et al., 2016). Thus, there were two groups (n=8 each). The recreational gamer group contained four males and four females; the group had a GD score ranging between 9 (lowest possible score) and 14. The problematic gamer group contained four males and four females; the group had a GD score ranging between 21 and 34. After data pre-processing techniques, each participant's data consisted of eight time points containing four eyes open and four eyes closed blocks.

Proposed SNN Model for Classifying and Analysing the Brain Regions Using EEG Data of Recreational Gamers and Problematic Gamers

The SNN that was based on the NeuCube architecture (Kasabov, 2014) includes several algorithms that allow for the investigation of EEG data. The model contains several main modules, which contain several processes which produce a STBD model.

i. *Data encoding:* The present study will utilise the threshold-based method of data encoding (Petro et al., 2020). This method generates discrete spikes based on the continuous real values of the EEG spatio-temporal data. In this model, when the discrete spikes increase above the spike threshold a positive spike is generated. Whereas if the discrete spikes fall below a certain threshold, then a negative spike is generated – or no spike will be generated.

ii. *Mapping:* The EEG data was mapped into a SNNr (spiking neural network reservoir) using the Talairach brain template (Talairach, 1988). Briefly, a SNNr is a collection of spatially located spiking neurons, and are placed with respect to the x, y, z co-ordinates based on the Talairach brain atlas. Furthermore, a leakyintegrate and fire model of spiking neurons was utilised in the SNNr (Abbott, 1999), in line with previous literature (Shah et al., 2019).

iii. *Unsupervised learning:* Spike-based learning was based on the spike-timing dependent plasticity (STDP) rule (Caporale & Dan, 2008), allowing the SNNr to learn spike sequences form the input data. Through this process, new connections are generated in the SNNr that signify spatio-temporal interaction between the input variables distributed in the SNNr. Briefly, the STDP rule states that strength of the synaptic weight is proportional to the degree of correlation between the spikes in the pre-synaptic and post-synaptic neuron (Caporale & Dan, 2008).

iv. *Visualisation of learned patterns:* To better understand the various connections throughout brain regions (64 EEG channels) in recreational gamers and problematic gamers, the SNN models were visualised in a 3D space.

v. *Pattern classification:* This algorithm maps the resulting SNN connectivity and temporal activity to the known class labels for classification related tasks. The output classification layer is then trained using the dynamic evolving spiking neural network (deSNN) method (Kasabov et al., 2013). The deSNN method allows for the SNNr connectivity to be analysed and observed, this step allows for improved interpretability of the data when compared to traditional data processing and learning methods (Tan et al., 2020).

Experimental Design

The finalised dataset contains 62,000 rows (temporal features) and 64 columns (spatial features) for each participant in both conditions (8 problematic gamers, 8 recreational gamers). This equates to approximately 60 seconds of data for both the EO and EC condition. For classification purposes, the data were cleaned to suit the requirements of the NeuCube architecture in line with previous papers (Shah et al., 2019). Each participant is termed as a 'sample' which consists of a spatio-temporal dataset ('.csv'). After reformulation, each sample matrix was divided into four blocks containing 7680 rows and 64 columns for both the EO and EC conditions. Consequently, a total of 128 samples (64 problematic gamers, 64 recreational gamers) with 7680 time points (rows) were generated while keeping the number of columns consistent (64) across all samples. We also compared the classification accuracy using other traditional machine learning methods, including multi-layer perceptron (MLP), multi-linear regression (MLR), and support vector machine (SVM). To apply the traditional classifier techniques, for each sample, features from all time points were concatenated into a single feature vector, which unlike the SNN model disregards the intrinsic temporal structure of the data. The classification accuracy was also compared to traditional statistical methods. More specifically, a repeated measures ANOVA was conducted to investigate whether there were any significant differences in connectivity patterns among the different hemispheres and sites in both the eyes open and eyes closed conditions, and whether there was an interaction effect between hemisphere, site, and group (i.e., type of gamer).

Classification Accuracy

NeuCube is a stochastic model, and therefore classification accuracy depends on the parameters' settings (Petro et al., 2020) as described below:

i. Spike threshold was set to 0.5 for converting the input data to sequences of spikes. The spike rate depends on this threshold value.

ii. The threshold of firing, the refractory time and the potential leak rate were set to 0.5, 6ms and 0.002 respectively, after optimization.

iii. The STPD learning rate parameter was set to 0.01, which caused changes in the connection weights (increase or decrease) of two connected neurons depending on the order of firing.

iv. For unsupervised learning, the training iteration was set to one, which is considered optimal for incremental on-line adaptive learning. (Shah et al., 2019).

v. For supervised learning, the deSNN classifier parameters ‘mod’ and ‘drift’ were set to 0.4 and 0.25, respectively. The K-NN classifier was set to k=3 for mapping the input data to the labelled outcome in the training procedure.

In regard to step ii, to optimise the model parameters, a comprehensive grid search method has been implemented in order to minimise the classification error obtained from cross-validation. This method has been used in other studies (e.g., Shah et al., 2019) to minimise classification error and is considered best-practice when using the NeuCube architecture. More specifically, the search is performed for each parameter within a specified range, starting from the minimum value and moving towards the maximum value in a fixed number of steps. In this study, three key parameters, namely STDP learning rate, neuron firing threshold, and classifier parameter mod, were selected for optimization. Each parameter is then searched within ten steps between its minimum and maximum values. Therefore, for every model generated, a thousand iterations of training (using 128 samples) and testing (using a single holdout sample) are performed using different combinations of these three parameters. The optimal parameters are then chosen based on the highest accuracy achieved in most of the iterations. The optimization process resulted in STDP learning rate = 0.01, neuron firing threshold = 0.5, and deSNN classifier parameter mod = 0.4 as the most frequently selected values across all the models.

While spike encoding, STPD, and hyper parameters can minimise classification error in the classification/verification stage, the present study contains a high number of samples from a small number of participants. Thus, additional analyses were conducted to ensure no significant data leakage occurred (as each participant has multiple samples). More specifically, steps *i* through *v* were conducted with an additional step *vi* added. Step *vi* used a cross-validation function which encompassed both the unsupervised and supervised learning stages (i.e., step *iv* and *v*). The fold number was set to 8 (in order to capture all samples provided by one participant), thus preventing data leakage. Each participant sample is listed sequentially (i.e., participant 1 contains sample 1-8, participant 2 contains sample, 9-16, etc.) the cross validation holds out 8 samples (i.e., one participant) to test against the remaining data. This ensures that no data leakage occurred, however, this produced a sub-optimal model as it contradicts the optimised model parameters. Nevertheless, this was done to ensure the veracity of the results from the optimised parameters.

A selection of comparative classification analyses was conducted alongside the NeuCube SNN analysis. More specifically, in both the EO and EC conditions, the NeuCom software was used to run a MLP neural network, and MLR and SVM ML statistical models. In regard to the MLP, the NeuCom program created a two-layer MLP network and contained 100 training cycles, with output value and function precision set at 0.001. The SVM utilised the Gaussian RBF Kernel. Each comparative analysis (i.e., MLP, SVM, MLR) applied five-fold cross-validation, after which the classification accuracy was recorded, these parameters were chosen as they were default parameter provided by the program.

In addition to this, a traditional statistical analysis was also performed to validate the SNN results. The connection weights for each EEG channel were extracted and then averaged into a single vector per participant (n = 8 per group). The averaged weights were then divided into five sites for each hemisphere with their topographical features: frontal (AF4, F6, F4, AF3, F5, F3), frontocentral (FC6, FC4, C6, C4, FC5, FC3, C5, C3), temporal (FT8, T8, TP8, FT7, T7, TP7), centroparietal (CP6, CP5, P6, P4, CP5, CP3, P5, P3), and occipitoparietal (PO8, PO4, O2, PO7, PO3, O1). A repeated measures analysis of variance (ANOVA) was performed to assess differences in functional activity between recreational and problematic gamers. Independent variables include Hemisphere (left, right), Site (frontal, frontocentral, temporal, centroparietal, and occipitoparietal), and Group (recreational gamers and problematic gamers). All violations of sphericity were corrected using Greenhouse–Geisser corrections.

Results

The results of the optimised NeuCube classification demonstrated a high success rate of classification based on the EEG data. The optimised NeuCube model was able to classify recreational gamers vs. problematic gamers with an overall accuracy of 73.44% in the EO condition and 88.28% in the EC condition. The 8-fold NeuCube model achieved similar results (EO condition 76.56% vs. EC condition 81.25%), thus suggesting the optimised NeuCube model was not significantly compromised by data leakage. The comparative analyses conducted through the NeuCom demonstrated poorer classification accuracy when compared to the NeuCube results. The results for the NeuCom analyses can be found in Table 2.

Table 2

Classification Accuracy of NeuCube and NeuCom Analyses

SNN and ML Analysis	Eyes Open Condition	Eyes Closed Condition
NeuCube SNN (Optimised) Model	73.44%	88.28%
NeuCube SNN (8-fold) Model	76.56%	81.25%
Multiple Linear Regression (MLR)	44.31%	43.02%
Support Vector Machine (SVM)	13.94%	41.45%
Multi-layer Perceptron (MLP)	47.63%	38.37%

The results suggest that the classification accuracy for second generation neural network models (i.e., MLP) and traditional ML models (i.e., SVM and MLR) is lower than for the NeuCube. The results highlight that the NeuCube SNN model is an appropriate fit for STBD; furthermore, the NeuCube models not only demonstrated a higher classification accuracy, but also revealed patterns of brain activities related to both recreational and problematic gamers. In order to explore the NeuCube findings further, and to compare the NeuCube results to more traditional statistical analysis, a repeated measures ANOVA was conducted on the averaged connection weights extracted from the NeuCube. As show in table 3 there were two separate main effects found in relation to hemisphere and site (for both eyes open and eyes closed condition), however the ANOVA had no statistically significant findings in relations to the interaction between hemisphere, site, and group (i.e., type of gamer).

Table 3

Repeated Measures ANOVA Results

Eyes opened condition	F-value	Degrees of Freedom	*p*-value	Eta^2
Hemisphere	299.16	1	<.001	0.96
Site	47.69	2.27	<.001	0.79
Hemisphere*Site*Gamer	1.48	2.52	0.24	0.11
Eyes closed condition	F-value	Degrees of Freedom	*p*-value	Eta^2
Hemisphere	233.30	1	<.001	0.95
Site	77.20	2.63	<.001	0.86
Hemisphere*Site*Gamer	1.74	2.49	0.18	0.12

Note. Greenhouse-Geisser values have been reported to correct for the violation of sphericity.

As shown, the ANOVA was able to explain approximately 11% (eyes opened) and 12% (eyes closed) of the variance found between hemisphere, site, and gamer; however, this did not reach a statistical significance-based p-value. Nevertheless, the optimised NeuCube model obtained higher classification accuracy, and the outputs allow for a nuanced interpretation and understanding of each group and the differences exhibited in their resting state neurophysiological brain activity. Therefore, the present chapter will focus on the optimised NeuCube model findings, as it performed better than the traditional statistical methods and does not appear to be compromised by data leakage (as suggested by the 8-fold NeuCube model).

Brain Activities of Recreational Gamers Versus Problematic Gamers Through Visualization of the NeuCube Models

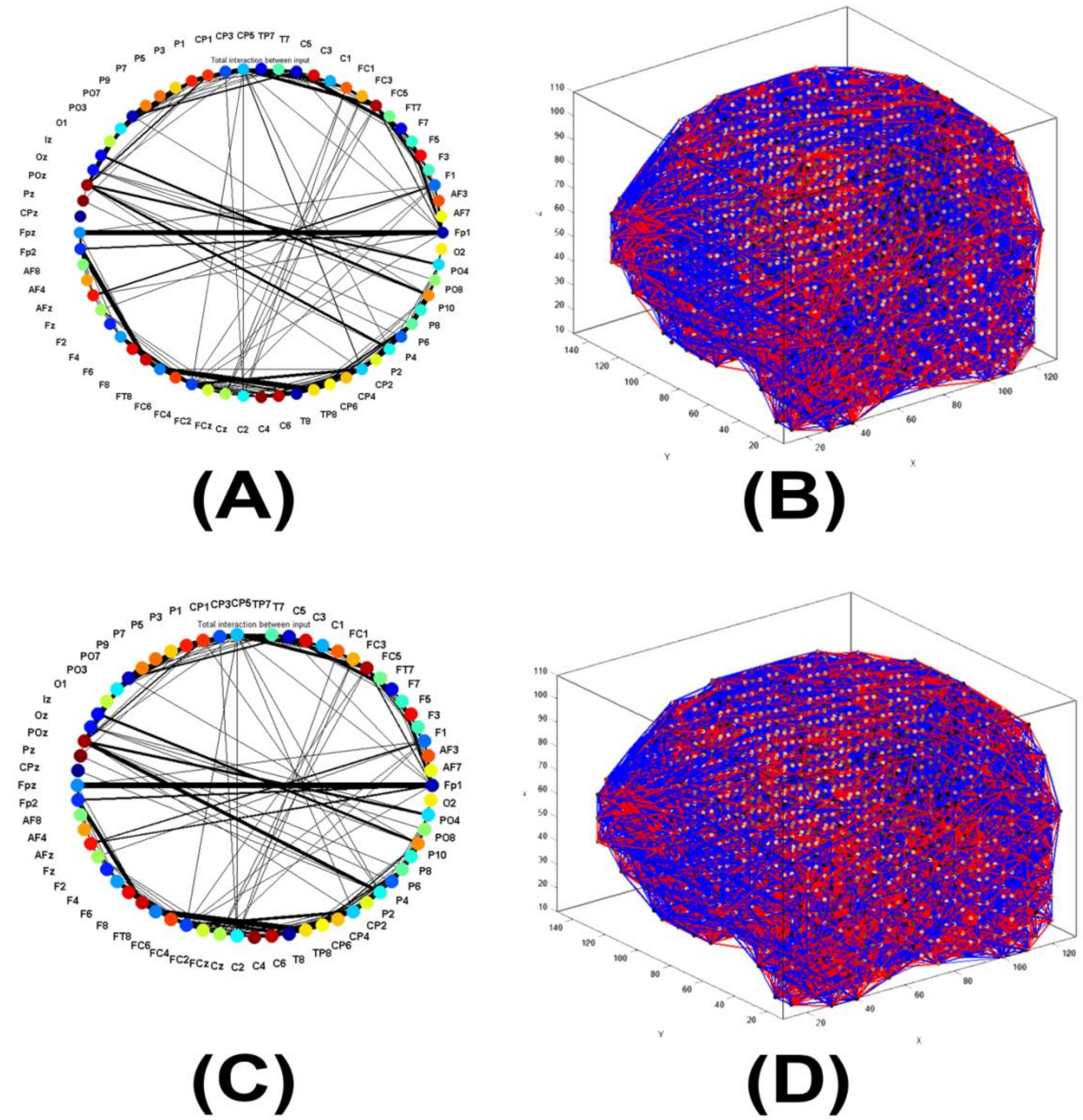
In order to explore functional connectivity across the brain, a visualisation of the feature interaction network (FIN) graphs and SNN connectivity graphs was created using the NeuCube software. These were produced for both the EO and EC conditions.

Eyes Closed Condition

In order to identify the similarities and differences between recreational and problematic gamers in the eye closed resting state condition, a FIN and SNN were created (see Figure 2) across 64 EEG channels (i.e., features).

Figure 1

NeuCube Graphic Outputs for Eyes Closed Condition



Note. Feature interaction network (A and C) and spiking neural network graph (B and D) for eyes closed condition. A and B represent problematic gamers, while C and D represent recreational gamers.

In terms of similarities between recreational gamers and problematic gamers, there are FIN throughout each of the brain regions as indicated by the lines observed across all areas in Figures 1a and 1c. Within both the recreational and problematic groups, there appeared to be strong associations across the frontal (FPz, Fp2, Fp2, F8), centroparietal (CP3, CP1, CP4, P1, P2, P6), and temporal (FT8, T8, FT7, T7) regions. Some additional associations displayed in both groups were in the occipitoparietal (POz, P1, P2, PO4, Iz, P10), occipitoparietal and temporal areas (PO7, TP7), and frontocentral (FC3, Fp1) regions. Both groups demonstrated consistent cross-hemispheric associations between CP3 and CP4, although the recreational gamers demonstrated a stronger association than problematic gamers.

There were also some differences between the groups. Problematic gamers had unique associations across frontal (Fp1, AFZ, AF8, F4), frontocentral (FC4, F2, FC6, C6, F6), and temporal (TP8, P10) regions.

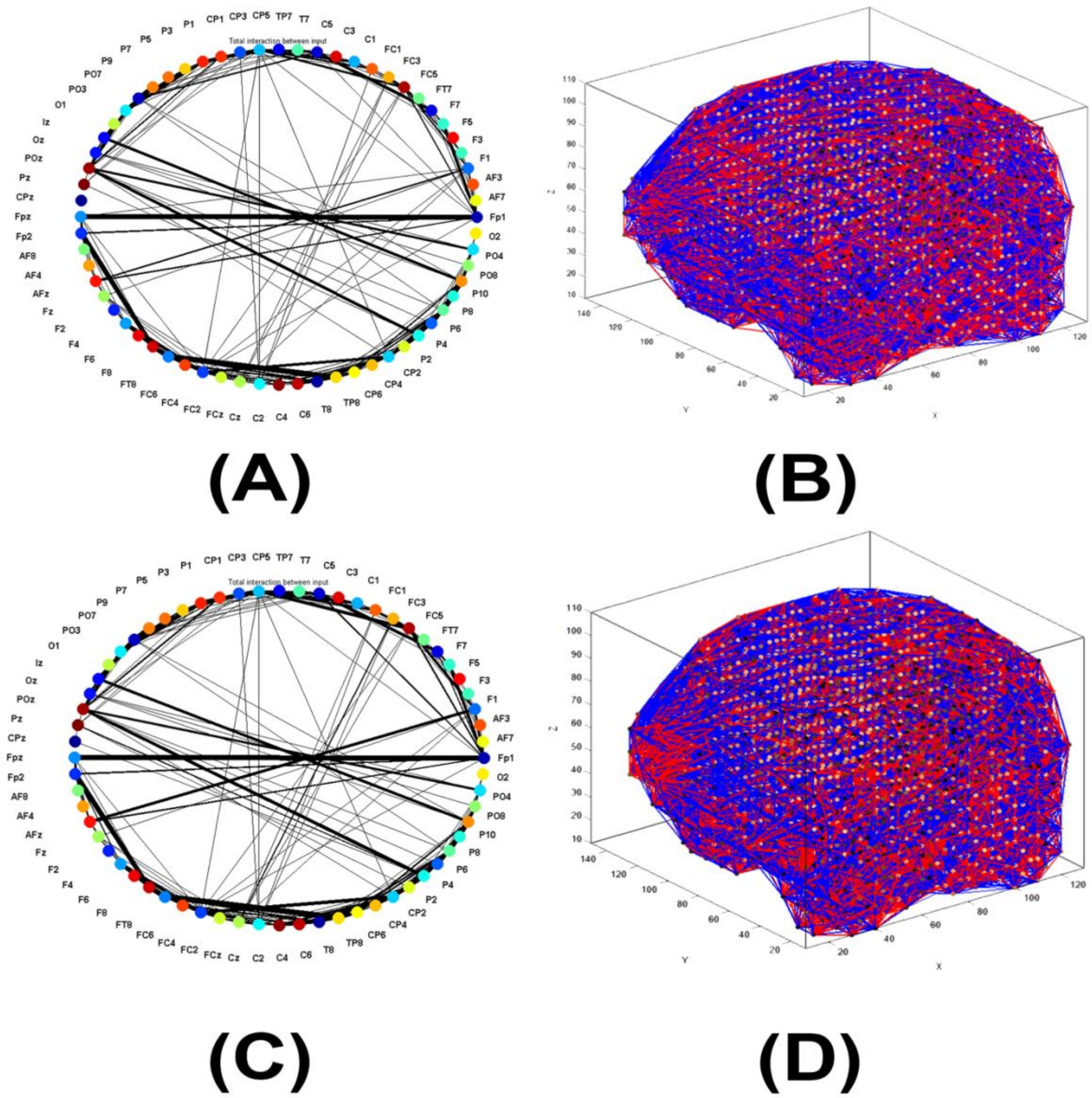
Furthermore, problematic gamers demonstrated additional associations in the parietal (P2, P1, POz, CPz; with nodes P2 and POz having a stronger connection than the recreational gamer group) and occipitoparietal (PO3, PO5, P3) areas. In regard to recreational gamers, they had stronger interactions in the frontal (Fp2, F8), frontocentral (C1, FCz, FC3, CP3, CP4), and temporal regions (FT8, T8, FT7, T7), with unique associations found in the frontocentral (FC4, F4, AF4) and centroparietal and temporal (CP4, CP6, FT8) regions. By analysing the SNN connectivity network (Figures 1b and 1d), it can be seen that problematic gamers had more negative connections (red colour) in the frontal frontocentral regions of the brain, which indicate inhibitory activity, whereas the recreational gamers exhibited more positive (excitatory) connections throughout this region (blue lines). In addition, within the problematic gamer group, there was a saturation of negative connections throughout the parietal and occipital regions of the scalp, whereas the recreational gamers exhibited a higher saturation of positive connections across the scalp in each region.

Eyes Open Condition

In order to identify the similarities and differences between recreational and problematic gamers in the eye opened resting state condition, a FIN and SNN were created (see Figure 3) across 64 EEG channels (i.e., features).

Figure 2

NeuCube Graphic Outputs for Eyes Open Condition



Note. Feature interaction network (A and C) and spiking neural network graph (B and D) for eyes opened condition. A and B represent problematic gamers, while C and D represent recreational gamers.

In terms of similarities between the two groups, there were several strong feature input interactions throughout each region of the brain as indicated by the thick black lines found in Figures 2a and 2c. Within each group, there were strong connections across the frontal (Fp1, FPz, F7, AFz, F1, Fp2, F8), frontocentral/centroparietal (CP3, C1, C3, FC3, CP4, FC4), and the parietal/parietooccipital areas (P3, P1, POz, P2, PO4, P10). In addition to this, each group also demonstrated a high amount of activity interaction in the right hemisphere across the frontocentral, temporal, parietal and occipitoparietal regions (moving left to right from F6 to PO4 in Figures 2a and 2c).

In regard to differences between recreational and problematic gamers in the eyes open condition, there were two unique associations in problematic gamers: long range communication can be seen between T7 and PO7, and consistent communication between Fp1 and F1 – all of which are located in the left hemisphere. On the other hand, recreational gamers had stronger connections throughout the brain, specifically in the left hemisphere. The results suggest they experienced a stronger interaction in the frontocentral (CP4, C2, FC4, CP3, FC3, T7, FC1) and frontal (Fp1, AFZ) regions than problematic gamers. The unique differences in recreational gamers can be seen in the frontal (Fp1, FT7), frontocentral (FCz, FC1, C1), temporal / parietal / occipitoparietal (P5, TP7, T7, P9, CP3, PO7, P1, PO3, P2, Pz, CPz, CP2) regions. Therefore, recreational gamers exhibited higher activity across the left hemisphere than the problematic gamers. By analysing the SNN connectivity network (Figures 2b and 2d), it can be seen that recreational gamers had more negative (inhibitory) activity in the frontal region of the brain, but more positive connections in the frontocentral area of the brain. Problematic gamers exhibited more positive connections throughout frontal regions and more negative connections in the frontocentral region. In addition, there was a combination of positive and negative connections across both the parietal and occipitoparietal regions.

Discussion

In the present study, it was hypothesised that the NeuCube SNN framework would be able to identify recreational gamers and problematic gamers based on spatial-temporal brain EEG data in two resting state conditions. The NeuCube SNN framework was able to successfully classify recreational and problematic gamers with a high degree of accuracy. Comparative analyses were applied using other machine learning techniques in order to demonstrate the advantage of using the SNN approach to investigating STBD modelling. The Neucube SNN framework attained a higher accuracy percentage when demarcating recreational gamers from problematic gamers compared to the comparative ML analyses. Therefore, the hypothesis was supported. The aim of the present paper was to also expand on the current knowledge of the neurophysiological expression of gamers and to examine the difference between recreational gamers from problematic gamers. The results suggested that there were a number of differences found across each of the groups in both conditions and provided informative patterns of neurophysiological brain activity.

Eyes Closed Condition

Each of the groups in the eyes closed condition demonstrated strong association across electrode sites in the central parietal region crossing both hemispheres. Recreational gamers demonstrated a stronger cross-hemispheric association in the central parietal region, while problematic gamers showed stronger cross-hemispheric associations further back on the scalp in the parietal/parietal-occipital region. Furthermore, the results indicated that the activity across the parietal region differed with problematic gamers exhibiting a higher number of inhibited connections, while the recreational gamers exhibited more excitatory connections. The parietal region of the brain is known to be part of the attention network within the brain (Ptak, 2012), and GD has been implicated in influencing brain activity within the attention network (Bavelier et al., 2012; Dye et al., 2009). Indeed, in a recent paper on parietal dysregulations in early stages of GD, researchers suggested that gamers experienced changes in the parietal (i.e., posterior parietal) region of the brain, which is related to daily engagement with gaming (Yu et al., 2021). Their results suggest that neural cue reactivity was observed within daily gamers, which resulted in increased reactivity towards gaming related cues. Furthermore, these regions corroborate previous cue-related meta-analytic studies which suggest that the parietal region is associated with the default mode network and visual networks of the brain in relation to GD (Zheng et al., 2019). This also aligns with the findings in substance abuse research, which suggests that the default mode network and visual network may reflect a stronger engagement of self-referential or attentional/salience processes (Zhou et al., 2019; Zilverstand et al., 2017). The findings here add to the body of literature which suggests that GD can influence brain-related networks in similar ways to other problematic substance use. Therefore, in the context of the present study, these differences may suggest that problematic gamers who engage with gaming daily exhibit unique changes in the neural resting states when compared to recreational gamers, and these changes may be reflective of stronger engagement of the attentional/salience processes associated with problematic behaviour.

Each of the two groups also demonstrated strong associations extending from parietal regions of the scalp to the frontocentral and frontal region of the brain. However, while both groups demonstrated activity across these regions, the problematic gamer group exhibited more inhibitory connections. The frontal region (i.e., prefrontal cortex) has been associated with response inhibition, working memory, decision-making, and emotion regulation, and GD has been associated with reduced function in the prefrontal cortex (Kuss et al., 2018; Lee et al., 2022). Brain imaging studies have found decreased cortical thickness in these regions in disordered gamers, which is correlated with higher GD scores and indicates poor inhibition of game-seeking behaviours (Wang et al., 2018). Moreover, more broadly, prefrontal dysfunction in response inhibition is frequently associated with addiction (Goldstein & Volkow, 2011), which further supports the notion that disordered gaming behaviours influence the brain in similar ways to substance-related addictions. Therefore, the inhibited activity through the frontal regions of the brain may be indicative of poor response inhibition within the problematic gamers within the sample.

Eyes Open Condition

In the eyes open condition, both groups exhibited strong associations across the frontal region of the brain, with localised communications through the central, centroparietal, and occipitoparietal regions. Problematic gamers exhibited only a small number of unique connections. There were short-range associations in the frontal region of the brain and long-distance associations between the occipitoparietal and temporal regions. Recreational gamers on the other hand, exhibited more unique associations than the problematic gamers, with many connections in each region of the brain in the left hemisphere, with some smaller local connections in the frontal and centroparietal regions of the right hemisphere. Indeed, there were differences between the communications exhibited in each group, with the recreational gamers exhibiting a marked difference over the problematic gamers. Gaming disorder has been associated with physical changes within the brain, specifically in the right frontal and frontocentral region (Wang et al., 2017). The lack significant communication between electrode sites in this area in the problematic gaming group may be reflective of these changes. This is important to note, as these brain regions are related to reward and cognitive control processes. Furthermore, structural and functional abnormalities in these areas have been related to both substance abuse and gambling disorder (Wang et al., 2019).

By examining SNN connectivity, it can be seen that the problematic gamers exhibited more inhibitory connections across the frontal and frontocentral region of the brain, lending support to previous literature that suggested problematic/disordered gamers may experience poor response inhibition (Wang et al., 2018). The recreational gamer group on the other hand, demonstrated more excitatory connections in the frontal and frontocentral regions, but exhibited localised inhibitory activity in the frontal region of the right hemisphere. Previous neurophysiology research suggests that spontaneous EO activity is significantly greater in EO conditions across the attentional areas, such as the parietal and occipital regions (Wei et al., 2018). The recreational gamers demonstrated a higher number of unique associations across the scalp when compared to the problematic gamers, which may be indicative of more spontaneous activity. Therefore, it could then be posited that a lack of unique spontaneous activity could indicate some level of neurophysiological dysfunction, supporting the notion that problematic gamers may have unique neurophysiological states when compared to recreational gamers, which may indicate a potential neurophysiological marker of GD (Burleigh et al., 2020).

The NeuCube

The overall aims of the present paper were to utilize the NeuCube within the GD field to investigate if an SNN architecture could be used to classify problematic gaming behaviours based in EEG data. The results suggest that the NeuCube appears to be an effective tool when demarcating problematic gamers from recreational gamers. In addition, a number of differences in the resting state data of problematic and recreational gamers were found. These findings may be potentially used to identify specific neurophysiological states of different types of gamers, which will aid in the classification and understanding of how disordered gaming may affect the neurophysiology of the brain. Furthermore, these findings could be used to expand and aid in the early prediction and classification of problematic gaming, aiding in early interventions. It is also important to note that the findings of the NeuCube were congruent with the currently known neurophysiological phenomena within disordered and problematic gaming. For example, the NeuCube identified increased activity across areas such as the parietal region, which is in line with meta-analytic studies in the GD field (Zheng et al., 2019). Moreover, the NeuCube also demonstrated congruent findings when considering the SNN graph; literature suggests that problematic gamers exhibit increased inhibitory connections in the brain (Wei et al., 2018), and the NeuCube data also suggest that these inhibitory connections are present. Therefore, findings from the NeuCube appear parallel existing findings and can therefore be interpreted with confidence. Thus, the present findings suggest that the NeuCube may be utilised across not only psychiatric disorders like depression (Shah et al., 2019), but behavioural disorders such as gaming disorder.

Indeed, the NeuCube could be used to more accurately aid in the classification of disordered behaviours, when compared to other ML methods used (e.g., SVM, MLR, MLP). The increased accuracy over other ML techniques may be due to the inherent qualities of the deSNN. The ML techniques used in the present paper required that the STBD collected from the EEG were converted into one vector for each of the features. Due to this inherent limitation of ML, the temporal connections cannot be obtained and thus the variance found within these temporal differences are lost. Thus, the ML methods used can only analyse the data in the form of a static vector and are not exposed to the resulting spatiotemporal associations or variations. However, the Neucube utilizes 3D brain-inspired SNN models, which allow for the integration of dynamic spatiotemporal interactions between brain functions and distinct psychological states. Furthermore, unlike ML methods, SNN models can process temporal information along spatial information while streaming the EEG data. Therefore, each of the samples includes the amplitudes powers of all EEG channels within an entire time interval – unlike traditional ML techniques which require every data sample be represented as a single vector. Consequently, the integrated spatial and temporal information within the single vector is then lost. Therefore, the brain-inspired SNN architecture can be used for the detailed analysis of various STBD (e.g., EEG), and has the advantage of maintaining both temporal and spatial components of the collected data which is regulated by a SNNr (i.e., the

Talairach brain atlas). The SNN also uses a biologically plausible learning rule to detect spatiotemporal patterns from data, and consequently is able to better explain the spatiotemporal associations in the STBD. This provides a more accurate classification of recreational and problematic gaming.

Limitations, Strengths, and Future Directions

There are number of limitations that should be considered within the present study. First, it should be noted that there was no control group (i.e., participants that did not play videogames at all). However, in a recent study using microstate EEG, the researchers found that there were no significant differences in the microstate parameters between recreational gamers and healthy controls (Wang et al., 2021). Nevertheless, future research should address this gap by implementing a control group to investigate this difference using SNN.

Second, further analysis to explore the connection weights extracted from the NeuCube via traditional statistical methods (i.e., ANOVA) did not yield a statistically significant result, which may be due to a number of factors. For example, in order to conduct the ANOVA, each electrode had to be averaged into a single vector (i.e., one data point). This vector was then averaged again to create site and hemisphere variables. As previously mentioned, when averaging the SNN data points into a single vector, the integrated spatial and temporal information within the data is lost. Therefore, this may have contributed to the non-significant results of the ML methods and the traditional statistic models. Moreover, in order to conduct ANOVA analyses, a specific number of participants are required to sufficiently power the analysis. A power analysis of the current sample size indicated that at least two more participants were required in each condition in order to have sufficient sensitivity. As previously mentioned, due to various factors such as the global COVID-19 pandemic, it was not possible to secure additional participants. Consequently, future research should consider an adequate sample size if conducting additional traditional analysis as this will give further insight into various connectivity regions.

Third, while the NeuCube appears to be effective in classifying recreational gamers and problematic gamers, it is possible that the amount of time spent gaming may also contribute to the classification. Research suggests that individuals who spend more time gaming may have different patterns of brain activity compared to those who spend less time gaming (see Chapter 2). In that line, the NeuCube may be classifying gamers based on the neurophysiological change influenced by time spent gaming, rather than disordered gaming specifically. Future research should explore this issue by controlling the amount of time spent gaming when examining differences in brain activity between problematic and recreational gamers. More specifically, to gain a better understanding of disordered gaming, while controlling for the influence of time spent gaming, future research could investigate both high engagement gamers and problematic gamers who spend similar amounts of time gaming. Such an approach would enable researchers to differentiate the neurophysiological states of disordered gamers specifically and to investigate whether time spent gaming plays a significant role in the underlying brain activity of problematic gaming.

Forth, the present study used a convenience sample, and these results may not be extrapolated to all gamers. Indeed, using a clinical population would provide rich data which may make any neurophysiological dysfunction more noticeable, as it has been found that higher severity disorders increase the accuracy of ML methods which utilise STBD (Park et al., 2021). Therefore, future research should consider healthy, problematic, and disordered gamers. Furthermore, it remains to be seen whether the NeuCube can classify a new participant as recreational or problematic. Thus, future research should recruit higher sample numbers which can be split and allow for new unseen participants to be classified by the SNN.

Fifth, there still remain technical challenges within the SNN field. For example, there is currently no robust information theory supporting the design and implementation of SNN, the choice of network structure (e.g., the placement of input neurons), and additional hyperparameter for each application (e.g., classifying mood disorders, or behaviour disorders) is based on heuristic measures and expert opinion (Tan et al., 2020). This makes it difficult to generalise and optimise the operation in a number of different settings (e.g., clinical setting). Consequently, future research should be conducted into the use and parameter optimisation of SNN, making them more accessible to the scientific community.

However, the use of the NeuCube SNN architecture is also one of the present study's strengths. The present study utilized STBD, and the NeuCube's 3D SNN structure provides new opportunities to explore and understand complex clinical data sets that use these data. The present study was also the first of its kind (to the authors' knowledge) that utilised the NeuCube within the behavioural addiction field, providing novel AI-related methodology. Moreover, the use of the NeuCube within this context paves the way for SNN to be used in the classification and prediction of other disordered behaviours, such as gambling disorder. Lastly, the results found through the present study strengthen the idea that behavioural addictions appear to have a specific neurophysiological basis similar to other substance use addictions (Park et al., 2021).

Conclusion

The present study utilized the novel NeuCube SNN architecture within the GD field. The findings suggest that the NeuCube accurately classified recreational gamers from problematic gamers within the current sample with a high success rate. In addition to this, the FIN and connectivity maps showed congruent data with the current understanding of the neurophysiological effects of gaming, lending validity to the use of the NeuCube within the behavioural sciences. Moreover, the results also suggest that recreational gamers and problematic gamers appear to have different resting state brain activity. Understanding these differences could aid in the early detection and classification of GD. Taken together, the NeuCube appears to be a viable tool to use in future studies which implement STBD in the behavioural addiction field. Future research should expand on the current study by implementing a control cohort which includes no gamers, and a clinical cohort which includes individuals experiencing GD. In addition to this, future research should also implement the NeuCube SNN architecture to investigate other behavioural addictions. Following the identification of GD using neurophysiological data, the following chapter will explore the association of co-occurrence in both a control cohort and a clinical cohort of gamers.

Chapter 5

Coping and Co-occurrence within Gaming Disorder and Substance Use among Recovering Substance Users

Introduction

Research into substance use disorders (SUDs) has demonstrated a wide range of negative effects on neurocognitive functions and psychological wellbeing (Hughes et al., 2014). Similarly, specific behavioural disorders (e.g., problematic online gaming) are now understood as mental health disorders due to evidence associating excessive use with adverse changes in brain function and psychological wellbeing (Kuss et al., 2018). Consequently, Internet Gaming Disorder (IGD) was included in the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5) as a tentative behavioural addiction warranting further investigation (American Psychiatric Association [APA], 2013). Furthermore, the World Health Organization (WHO) has now officially recognized *Gaming Disorder* (GD) in the latest eleventh revision of the *International Classification of Diseases* (ICD-11; 2019).

Prior to the inclusion of GD/IGD in the DSM-5 and ICD-11, several other terms were used to describe problematic video gaming including (but not limited to) videogame addiction, pathological video gaming, gaming use disorder, and gaming use dependency (Estévez et al., 2017). Furthermore, some scholars have included problematic online gaming within the umbrella terms of internet addiction, problematic internet use, and pathological internet use (e.g., Brand, Laier, & Young, 2014). In order to maintain consistency throughout the present paper, the term 'problematic gaming' will be used to describe a range of similar and/or overlapping addictive, compulsive, and/or subclinical behaviours related to gaming. When referring to clinically defined cases, the term 'GD' will be used, in line with the ICD-11. Furthermore, in relation to other potentially addictive behaviours or substance use, the term 'problematic' will be used to describe sub-clinical conditions that do not fully meet all the criteria in the DSM-5 or ICD-11 (e.g., 'problematic gambling'), while the term 'disordered' will be used to describe clinical conditions that meet the requisite criteria in the ICD-11 (e.g., gambling disorder).

Gaming Disorder and Behavioural Disorders

Several studies have reported an association between GD and mental health disorders, such as anxiety (Adams et al., 2019), depression (King et al., 2013), and personality disorders (Schimmenti et al., 2017). Similarly, the literature suggests that disordered gaming can co-occur with other problematic and disordered behaviours (Burleigh, Griffiths, et al., 2019). It is worth noting that not all problematic behaviours are recognized as disorders. Instead, they may be considered as 'potential' behavioural addictions, such as shopping addiction (often referred to as 'compulsive buying'), social networking site addiction, and work addiction (Burleigh, Griffiths, et al., 2019). These behaviours (including GD) share a conceptual basis with substance use disorders. However, the use of 'addiction' terminology to describe these behaviours is heavily debated in the literature. For example, some scholars believe that there has not been a sufficient scientific basis established for the GD diagnosis (van Rooij et al., 2018). It has been suggested that the excessive 'disorder-like' activities which relate to these disorders may instead be a reflection of investment rather than clinically disordered behaviour (Aarseth et al., 2017; Colder Carras & Kardefelt-Winther, 2018). For example, one specific symptom of disordered behaviour is salience (i.e., being consistently preoccupied with the disordered behaviour), which may not be accurately reflected in the context of gaming. This is due to the time investment discussing and optimizing the game experience. Consequently, there are claims that the diagnosis has poor specificity which could lead to inaccurate diagnosis of approximately one-third of gamers (Colder Carras & Kardefelt-Winther, 2018). Nevertheless, evidence consistently indicates that disordered or problematic gaming is associated with an increased risk of psychopathology (e.g., depression, anxiety; Kuss & Griffiths, 2012), disordered behaviour, and disordered substance use (Burleigh, Griffiths, et al., 2019). Consequently, it has been posited that these increased risks may instead be a result of, or partly attributed to, maladaptive coping strategies (Schneider et al., 2018) or other psychopathological conditions.

Coping

Coping refers to the cognitive and behavioural responses that process and manage stressful events and emotions (McMahon et al., 2013). Several studies have considered the relationship between coping and gaming (Burleigh, Griffiths, et al., 2019). The Brief COPE (Carver, 1997) has been used, which is based on Lazarus and Folkman's (1984) transactional model of stress and Carver and Scheier's (1981) behavioural self-regulation model. The domains assessed used are emotion-focused coping and problem-focused coping. Problem-focused coping involves efforts to modify the stressful event and includes strategies, such as producing options to solve the problem, evaluating the pros and cons of the options, and implementing steps to solve the problem. Emotion-focused coping is typically defined as the attempt to manage emotional distress that is associated with a stressful event (Lazarus & Folkman, 1984). There are a broad range of strategies which fall under this domain, such as the use of humour, positive reframing of the distressing situation, acceptance, seeking social support, and/or the use of religion. However, emotion-focused coping has also included strategies such as denial, venting and/or fixating on negative emotions (Carver, 1997). Therefore, it is not surprising that the effectiveness of emotion-focused coping can vary depending on which strategy is employed (Carver, Scheier, & Weintraub, 1989).

As a result of these (somewhat) opposed groupings, it appears that engaging in emotion-focused coping can be considered maladaptive. While Carver et al. (Carver, 1997; Carver et al., 1989) did not utilise specific domains of coping, the domains of emotion focused and problem focused have been used in conjunction with their measures in previous research (Kuss et al., 2017; Schneider et al., 2018). Therefore, the present study adopts the definitions of previous papers which define emotional coping as a specific subset of emotion-focused strategies which actively engage with distress (e.g., humour) as opposed to avoiding the stressful event in a passive and static way (e.g., denial; Carver, 1997; Baker & Berenbaum, 2007; Kuss et al., 2017; Schneider et al., 2018). In line with previous literature, the present study also uses a third domain of coping, which focuses on dysfunctional coping (Kuss et al., 2017). Within the scope of the present paper, dysfunctional coping is defined as disengaging with a stressful event in an avoidant manner through avoidant coping strategies such as denial, substance use, and self-distraction (Brand et al., 2014; Kuss et al., 2017).

Some evidence suggests that individuals may play videogames excessively to cope with everyday stressors and to regulate their emotions (Hemenover & Bowman, 2018). While using videogames to de-stress and 'escape' is not maladaptive itself, for some gamers, excessive game play has predicted maladaptive escapism or self-distraction (e.g., turning to work or other activities to take their mind off things) as a coping strategy (Kuss, Louws, & Wiers, 2012), which can result in poorer mental health outcomes and is linked with excessive gameplay, creating a cycle of reciprocity (Burleigh, Griffiths, et al., 2019). Moreover, this type of avoidant coping has been reported in both the gaming literature and the substance use literature (Burleigh, Griffiths, et al., 2019; Heggeness et al., 2020). These dysfunctional strategies are often overly relied upon among adolescents (Kuss et al., 2017) and could carry through into emerging adulthood and adulthood (Burleigh et al., 2018), resulting in poor emotional regulation (Ream et al., 2013).

Substance Use and Gamers

Parallels exist between the way gamers and substance users regulate their emotions (Ream et al., 2013). It has been suggested that this could be due to the aforementioned similarities in the common coping strategies employed by each group, such as behavioural disengagement (i.e., self-distraction; Burleigh et al., 2019). This association may be explained through the self-medication hypothesis; i.e., within addiction-related disorders, substances (or specific behaviours) can be used to overcome distressing affective states and unpleasant symptoms (Khantzian, 1985). This behaviour is indicative of a dysfunctional coping strategy, which has been suggested to play a role in the development of co-occurring behaviours within disordered gaming (Burleigh, Griffiths, et al., 2019) and substance use (van Rooij et al., 2014). While some literature has suggested that dysfunctional coping strategies play a role in disordered gaming and substance use, there is a dearth of literature that considerers clinical substance users who may also engage in problematic gaming behaviours (Burleigh, Griffiths, et al., 2019; van Rooij et al., 2014). This is problematic because the literature consistently provides evidence on the similarities between problematic/disordered behaviours, substance use disorders, and the coping strategies they employ along with the potential of their co-occurrence (Gallimberti et al., 2016; Nicola et al., 2015; Sussman et al., 2015; Tsai et al., 2016). Moreover, the evidence suggests that when individuals are faced with distressing situations and engage in the use of dysfunctional strategies, symptoms of disordered behaviour or substance use increase – more so than the engagement in either one on their own (Heggeness et al., 2020; Kuss et al., 2017). Gaming disorder, similar to other addictions, including other behavioural addictions (e.g., gambling disorder), can co-occur with other problems (Walther et al., 2012). Therefore, disordered gaming may also interact and/or co-occur with other conditions such as disordered substance use.

Replacement, Co-occurrence, and the Cycle of Reciprocity

Within the present study, co-occurrence refers to when two or more potentially addictive behaviours (behavioural and/or substance) are engaged in concurrently. It has been suggested that co-occurrence of problematic or disordered behaviour and substance use can be attributable to shared psychological mechanisms underlying these behaviours (e.g., the aforementioned coping mechanisms; Kuss et al., 2017; Schneider et al., 2018) in the development and maintenance of co-occurrence between and within problematic behaviours and substance use (Burleigh, Griffiths, et al., 2019).

Different theories have been put forward regarding how various potentially addictive behaviours, such as gaming and substance use, may co-occur with one another. For example, replacement theory suggests that substances or behaviours have the potential to replace each other (Sussman & Black, 2008). This theory aligns with the behavioural self-regulation model of coping (Carver & Scheier, 1981) and the self-medication hypothesis (Khantzian, 1985). Behavioural self-control theory suggests that an individual engages in a feedback loop of self-regulation (i.e., a coping strategy) when trying to reach a goal. In doing so, an individual monitors their progress and adjusts their behaviour accordingly to improve their efforts. If individuals begin to use substances or engage in behaviours to alleviate the affected mood state, this may result in the development of a dysfunctional coping strategy. As a result, when they are confronted with the stressful event, they may return to the substance or behaviour that alleviated the last mood state effectively (i.e., self-medication; Khantzian, 1985). However, when ending the disordered behaviour in question (either voluntarily or involuntarily), an individual may become vulnerable to other potentially disordered behaviours to explore other avenues of satisfying their needs (Sussman & Black, 2008). Therefore, replacement theory posits that disordered behaviours (i.e., behavioural or substance-related) serve a specific function (e.g., escape, coping, relaxation), and individuals who cease these behaviours will seek to replace them (Khantzian, 1985). Indeed, empirical literature has demonstrated a wide variety of behaviours or substances which some individuals can become dependent on (e.g., alcohol), or repeat excessively (e.g., gaming) when abstaining from disordered substance use (i.e., reciprocity; Sussman & Black, 2008).

It has been suggested that the abstaining individual may then seek to substitute these behaviours with an activity they perceive as being less detrimental than the original disordered behaviour. To the abstaining individual, the replacement behaviour may appear adaptive and reasonable. However, it may be disadvantageous depending on which behaviour is chosen (Sussman & Black, 2008), indicating there is an at-risk group of individuals who are abstaining from problematic or disordered behaviours/substance use. Indeed, it has been shown that substance users, when abstaining from the primary substance, may develop other behaviours that fill that dysfunctional process. For example, substance users may replace illicit substances with smoking or sexual behaviour, behaviours that they may feel are less detrimental than illicit substances (Sussman, 2005). It has also been highlighted that individuals with disordered substance use believe that internet use is a safe substitute to utilize in their repertoire of existing coping strategies (Sussman & Black, 2008). Likewise, the literature suggests that other problematic behaviours can also be utilized in similar way (Kuss et al., 2017). However, there are few studies which explore the role of gaming in the context of abstinent substance users (Burleigh, Griffiths, et al., 2019). This is especially important given that gaming has been found to be significantly correlated with a number of addictive behaviours and substances (Sussman et al., 2015; Tsai et al., 2016).

In a recent epidemiological study on the co-occurrence of substance use and other potentially addictive behaviours, it was found that there were large overlaps between the co-occurrence of disordered substance use and/or behaviours (Kotyuk et al., 2020). More specifically, Kotyuk et al. (2020) found that alcohol and smoking were associated with problematic gaming among a large sample of emerging adults. Additionally, in a recent systematic review, Burleigh et al. (2020) also found similar overlaps of substance use and behaviours among adolescents, emerging adults, and adults. Indeed, the evidence supports the potential for disordered behaviours to increase the propensity of other related problematic behaviours. Accordingly, the overlap of two or more problematic behaviours may then create a cycle of reciprocity (Gossop, 2001; Haylett et al., 2004; Martin et al., 2014), wherein mutual exacerbation occurs. Furthermore, individuals who experience multiple problematic and/or disordered behaviours have been shown to be at higher risk of poorer mental health (e.g., depression) and physical health (Burleigh et al., 2018; Martin et al., 2014; Urbanoski et al., 2007).

Therefore, considering the co-occurrence of problematic behaviours and substance use is relevant for a number of reasons. Firstly, it is rare that clinical symptomology emerges on its own, as it can be a consequence of a collection of risk factors (Najt et al., 2011). Secondly, being aware of how co-occurring problematic and disordered behaviours react and enforce facets of a primary problematic or disordered behaviour has an important clinical significance (Burleigh, Griffiths, et al., 2019). For example, disordered gaming may mask problematic substance use within an individual, therefore hindering diagnostic assessment. Alternatively, disordered gaming may increase problematic substance use, causing symptoms of both to alternate, which can effect treatment efficacy (Freimuth et al., 2008). Therefore, co-occurrence has the potential to influence the onset, course, and outcomes of treatment interventions (Burleigh, Griffiths, et al., 2019). Thirdly, understanding these associations will aid future assessment and treatment paradigms through the consideration of both the presenting primary disordered (or problematic) behaviour (or substance use), and any potential co-occurring behaviours or substance use, which may enforce a cycle of reciprocity (Carrà et al., 2015; Roncero et al., 2017). Finally, being aware of these co-occurrences will also help inform prevention strategies (Hall et al., 2009).

The Present Study

While the understanding of the nuanced issues of diagnosis and case formulation requires evaluation and testing, there is currently a dearth of literature which has investigated the coping styles and the co-occurrence of problematic/disordered gaming with other potentially addictive substance use and behaviours within clinical populations in treatment. The literature suggests that individuals in clinical populations who experience a co-occurring behavioural, or substance use disorder (or problematic use) tend to have poorer functioning and treatment outcomes in comparison to non-clinical populations. This mirrors findings within disordered gaming because disordered gamers also experience poorer functioning and treatment outcomes (Kuss et al., 2014; Winkler et al., 2013; Yakovenko & Hodgins, 2018). Despite the acknowledged association between gaming and other addictive behaviours, it is unclear how the strength of this association is affected by an individual’s severity of addiction and coping style. According to developmental perspectives, addiction should be viewed along a continuum, ranging from functional (i.e., no problematic use) to excessive problematic use. Therefore, understanding the dynamic changes in co-occurring addictive behaviours from adaptive to pathological use has important implications for clinical assessment and treatment planning, including being able to evaluate which treatment would be appropriate based on the individual’s behaviour patterns and where they fall on the continuum.

In the present study, co-occurring problematic behaviour and substance use in clinical (i.e., substance users in treatment) and a non/sub-clinical (i.e., general population) sample of gamers and non-gamers were compared and contrasted, and the associations of coping strategies on gaming and its co-occurrence with substance use and other problematic behaviours was explored. Accordingly, the following hypothesises were formulated:

H_1: Gamers will exhibit more severe co-occurring problematic behaviours among both clinical and non-clinical samples when compared to non-gamers, with co-occurring substance use negatively influencing disordered gaming scores among the clinical sample.

H_2: The severity of gaming among both clinical and non-clinical groups will be positively associated with dysfunctional coping styles, but negatively associated with problem-focused coping styles.

Methods

Participants and Procedure

Clinical data were collected from October 2019 to January 2020 at a rehabilitation centre in New Zealand from patients who were undertaking treatment for their disordered substance use. The inclusions criteria were: (i) being aged 18 years and over; and (ii) having previously or currently experienced disordered substance use. Each participant was given a $20 NZ voucher for participating. The clinical sample comprised 64 participants, including 49 men (M_{age} = 35.73 years; *SD* = 10.95) and 15 women (M_{age} = 37.14 years; *SD* = 10.48), aged between 22 and 88 years (M_{age} = 36.06 years; *SD* = 10.77). Participants that listed that they played videogames were classified as gamers. Additional sociodemographic information can be seen in Table 1.

Table 1

Demographics and Videogame Use Information (Clinical)

Sociodemographic variables		Total (*N*=64)
Gender	Male	49 (76.5%)
	Female	15 (23.4%)
Marital Status	Same-sex civil partnership / married / Separated, but still legally in a same-sex civil partnership / married	6 (9.3%)
	Civil partnership has been dissolved / divorced	9 (14%)
	Never registered a same-sex civil partnership / married	32 (50%)
	Prefer not to say	17 (26.5%)
Qualification	Postgraduate degree (e.g., MA, PhD) / Degree (e.g., BA, BSc)	8 (12.4%)
	Professional qualification (e.g., teaching, nursing, accountancy) / Other vocational / work related qualifications	4 (6.4%)
	Foundation degree / Progression diploma / Advanced diploma / Certificate or equivalent	4 (6.4%)
	A levels / AS levels / VCEs / Higher diploma or equivalent / GCSEs / CSEs / O levels or equivalent	24 (37.4%)
	No qualifications or education / Prefer not to say	24 (37.4%)
Videogame use*	Yes	35 (54.7%)
	No	39 (45.3%)
	Years using playing videogames ($M \pm SD$)	19.96 ± 6.76
	Hours spent playing videogames during a weekday ($M \pm SD$)	4 ± 5.37

	Hours spent playing videogames during weekend day ($M \pm SD$)	3.61 ± 3.53
Videogame platform*	Online PC games	3 (8.5%)
	Offline PC games	2 (5.7%)
	Online console games	7 (20%)
	Offline console games	8 (22.9%)
	Games for smartphones and tablets	15 (42.9%)

Note. *M* = mean *SD* = standard deviation; * denotes only applicable to those that answered "Yes" to videogame use; participants who listed that they play videogames were classified as gamers

In regard to substance use details, the average age of onset for the primary substance use was 13.31 years (*SD* = 2.76). Out of the 64 substance users surveyed, 60 were currently abstinent. Abstinence ranged between seven days to ten years (M_{days} = 257.32; *SD* = 496.10). The remaining four participants (who were new to the centre) had been abstinent less than a day. In addition, 45.3% reported an accompanying mental health disorder (e.g., depression, anxiety) and of those, 21.9% had two or more comorbid mental health disorders. Additional substance use information can be found in Table 2.

Table 2

Additional Substance Use Information

Substance	How many times in the last 30 days? (in days; *Mean±SD*)*	Lifetime use (in years; *Mean±SD*)	Route of use**					Major Problem (currently abstaining)***
			Oral	Nasal	Smoking	Non-IV injections	IV injections	
Alcohol – any use	3.4 ± 2.79 (*n=5)*	16.04 ± 10.11 (*n=58)*	92.7%	-	7.3%	-	-	46.9%
Alcohol – to intoxication	1 ± 0 (*n=2)*	16.04 ± 10.11 (*n=47)*	93%	2.3%	4.7%	-	-	N/A
Heroin	1 ± *N/A* (*n=1)*	13.10 ± 13.81 (*n=10)*	-	20%	30%	-	50%	3.1%
Methadone	-	8.16 ± 11.63 (*n=12)*	36.4%	9.1%	-	-	54.5%	6.3%
Other (opiates/analgesics)	15 ± *N/A* (*n=1)*	14.90 ± 12.43 (*n=11)*	63.6%	9.1%	9.1%	-	18.2%	7.8%
Barbiturates	15 ± *N/A* (*n=1)*	19.66 ± 12.57 (*n=9)*	87.5%	12.5%	-	-	-	-
Other (sedative/tranquilizer)	5 ± 4.24 (*n=2)*	17.11 ± 14.64 (*n=9)*	66.7%	33.3%	-	-	-	3.1%
Cocaine	-	6.26 ± 9.53 (*n=19)*	11.8%	58.8%	-	-	29.4%	1.6%

Amphetamines	3.21 ± 1.70 (*n=4)*	12.8 ± 9.10 (*n=50)*	15.2%	2.2%	58.7%	2.2%	21.7%	68.7%
Ecstasy	-	8.11 ± 8.08 (*n=36)*	58.1%	19.3%	9.7%	3.2%	9.7%	4.7%
Cannabis	7 ± 12 (*n=4)*	17.02 ± 10.79 (*n=46)*	18.2%	81.8%	-	-	-	28.1%
Hallucinogens	-	12.76 ± 12.02 (*n=21)*	82.6%	4.4%	13%	-	-	4.7%
Inhalants	4.5 ± 4.94 (*n=2)*	7.90 ± 9.46 (*n=11)*	54.5%	27.3%	18.2%	-	-	-
Nicotine	27.52 ± 5.77 (*n=17)*	18.56 ± 11.22 (*n=50)*	24.4%	75.6%	-	-	-	21.9%
More than one substance per day	9.6 ± 10.16 (*n=5)*	16.62 ± 11.65 (*n=24)*	28.6%	47.6%	-	-	23.8%	N/A

Note. *Of those not abstaining and of those who have used the indicated substance; ** Of those who have used indicated substance in their lifetime; *** Participants can be abstaining from more than one substance (*n*=64).

Data from the control sample were collected from Auckland, New Zealand (between September 2019 to March 2020) which is located in a similar geographical region to the rehabilitation centre. Flyers and electronic advertisements (e.g., SONA platform) were used around a university campus. Students were offered the chance to win a $50 NZ shopping voucher. The inclusion criteria for this sample were: (i) being aged 18 years and over; and (ii) currently residing in New Zealand. The control group sample comprised 138 participants, including 72 males (M_{age}= 26.86 years; *SD* = 9.83) and 59 females (M_{age} = 27.49 years; *SD* = 9.07 years), aged between 18 and 65 years (M_{age} = 26.54 years; *SD* = 9.47). Additional sociodemographic information can be seen in Table 3. All participants were given information prior to the study, including data use, potential risks, and benefits, along with their right to withdraw from the study at any time. The study was approved by the research team's two university ethics committees.

Table 3

Demographics and Videogame Use Information (Control)

Sociodemographic variables		Total (*N*=138)
Gender	Male	72 (54.5%)
	Female	59 (44.7%)
	Other	1 (0.8%)
Marital Status	Same-sex civil partnership / married / Separated, but still legally in a same-sex civil partnership / married	29 (22%)
	Civil partnership has been dissolved / divorced	5 (3.8%)
	Widowed	1 (0.7%)
	Never registered a same-sex civil partnership / married	88 (66.7%)
	Prefer not to say	9 (6.8%)
Qualification	Postgraduate degree (e.g., MA, PhD) / Degree (e.g., BA, BSc)	55 (41.7%)
	Professional qualification (e.g., teaching, nursing, accountancy) / Other vocational / work related qualifications	5 (3.8%)
	Foundation degree / Progression diploma / Advanced diploma / Certificate or equivalent	8 (6.1%)
	A levels / AS levels / VCEs / Higher diploma or equivalent / GCSEs / CSEs / O levels or equivalent	54 (40.9%)
	No qualifications or education / Prefer not to say	10 (7.5 %)

Videogame use*	Yes	108 (81.8%)
	No	24 (18.2%)
	Years using playing videogames (*M* ± *SD*)	13.10 ± 7.51
	Hours spent playing videogames during a weekday (*M* ± *SD*)	4.24 ± 7.23
	Hours spent playing videogames during weekend day (*M* ± *SD*)	3.92 ± 3.73
Videogame platform*	Online PC games	18 (16.7%)
	Offline PC games	8 (7.4%)
	Online console games	26 (24.1%)
	Offline console games	21 (19.4%)
	Games for smartphones and tablets	35 (32.4%)

Note. *M* = mean *SD* = standard deviation; * denotes only applicable to those that answered "Yes" to videogame use.

Measures

Internet Gaming Disorder Scale – Short Form 9 (IGDS9-SF).

The nine-item IGDS9-SF (Pontes & Griffiths, 2015) was used to assess the severity of GD symptoms by examining an individual's offline and online behaviours. Items of the IGDS9-SF include: "Do you systematically fail when trying to control or cease your gaming activity?" and "Have you jeopardized or lost an important relationship, job or career opportunity because of your gaming activity?". Participants respond to each item on a five-point scale from 1 (*Never*) to 5 (*Very often*). The final GD score is calculated by summing up the individual's answers and ranges from 9 to 45, with higher scores indicating higher severity of gaming disorder behaviours. The scale has been shown to be a reliable measure with a Cronbach's α of .88 (Pontes & Griffiths, 2015). In the present study, the general and clinical cohorts' scale scores showed good reliability with a Cronbach's α of .89 and .94, respectively.

Problem Gambling Severity Index (PGSI)

The nine-item PGSI (Ferris & Wynne, 2001) was used to assess gambling behaviours over the past 12 months (e.g., *"Have you gone back on another day to try to win back the money you lost?"*). Participants respond to items on a four-point scale ranging from 0 (*Never*) to 3 (*Always*). The total score is obtained by summing up each of the answers given and can range from 0 to 27, with higher scores indicating higher gambling severity. The final score is then related to one of four domains: non-problem gambler=0; Low-risk gambler=1–2; Moderate-risk gambler=3–7; Problem gambler=8 or above. This has been shown to be a reliable scale with a Cronbach's α of .76 (Ferris & Wynne, 2001). In the present study, scale scores by the general cohort had a Cronbach's α of .96 and the clinical cohort had a Cronbach's α of .95.

Internet Disorder Scale 9–Short Form (IDS9-SF)

The nine-item IDS9-SF (Pontes & Griffiths, 2017) was used to assess problematic internet use behaviours over the past 12 months (e.g., *"Do you feel more irritability, anxiety and/or sadness when you try to either reduce or stop using the internet?"*). Responses are scored on a five-point scale ranging from1 (*Never*) to 5 (*Very often*). The final score is calculated by adding each item score which gives a total score ranging from 9 to 45. Higher scores indicate a higher severity of disordered internet use. The IDS9-SF has been shown to be a reliable scale with a Cronbach's α of .96 (Pontes & Griffiths, 2017). In the present study, the general and clinical cohorts' scale scores showed good reliability with a Cronbach's α of .92 and .95, respectively.

The Bergen Social Media Addiction Scale (BSMAS)

The BSMAS (Andreassen et al., 2016) is an adapted version of the Bergen Facebook Addiction Scale (BFAS; Andreassen, Torsheim, Brunborg, & Pallesen, 2012) and includes six items assessing addictive social media use (e.g., *Facebook, Instagram, Twitter*) in the past 12 months. Each item reflects a core addiction element (e.g., withdrawal: *"How often have you become restless or troubled if you have been prohibited from using social media?"*), is scored on a five-point scale ranging from 1 (*Very rarely*) to 5 (*Very often*) and can have a total score between 6 and 30. A higher score indicates a greater risk of being addicted to social media use. The BSMAS has very good reliability (Cronbach's α = .88; Andreassen et al., 2016). In the present study, the general and clinical cohorts' scale scores showed excellent reliability with a Cronbach's α of .90 and .93, respectively.

Bergen-Yale Sex Addiction Scale (BYSAS)

The six-item BYSAS (Andreassen et al., 2018) was used to assess participants' problematic sexual activity over the last 12 months (e.g., *"How often … have you spent thinking about sex or masturbation?"*). Each response is scored on a five-point scale, with scores ranging from 0 (*Very rarely*) to 4 (*Very often*). To obtain the total score, the scores on each item are summed. The total score can range from 0 to 24, with a higher total score indicating a greater risk of addictive sexual behaviour. The BYSAS has been found to be a reliable scale with a Cronbach's α of .82 (Andreassen et al., 2018). In the present study, the general and clinical cohorts' scale scores showed excellent reliability with a Cronbach's α of .90 and .92, respectively.

Bergen Shopping Addiction Scale (BSAS)

The seven-item BSAS was used to assess for problematic shopping behaviour (Andreassen et al., 2015). Participants respond to each item (e.g., *"I think about shopping or buying things all the time"*) on a five-point Likert scale from 0 (*completely disagree*) to 4 (*completely agree*). The final score is calculated by summing up the individuals' answers and ranges from 0 to 28, with higher scores indicating greater risk of shopping addiction. The BSAS has been found to be a reliable scale with a Cronbach's α of .87 (Andreassen et al., 2015). In the present study, the scale showed excellent reliability (Cronbach's α = .90).

Cigarette Dependency Scale-5 (CDS)

The five-item CDS-5 (Etter et al., 2003) was used to assess the degree to which participants were dependent on cigarettes. Each item is scored on a five-point scale and assesses their cigarette use (e.g., *"Please rate your addiction to cigarettes on a scale of 0 to 100?"*) and habits (e.g., *"Usually, how soon after waking up do you some your first cigarette?"*). Questions 1 to 3 are open questions (e.g., "On average, how many cigarettes do you smoke per day?") where a participant can write their response. The response is then converted into a five-point scale (e.g., “8 cigarettes per day” equates to a score of 2 [6-10 cigarettes per day]). Questions 4 and 5 require typical responses with scores ranging from 1 (*Totally Disagree*) to 5 (*Fully Agee*). Questions 3 and 4 are both reverse coded, where the lower point is scored as 5 and the higher point is scored as 1 (e.g., “For you, quitting smoking would be “Impossible” [5] to “Very Easy” [1]). The CDS-5 has been found to be a reliable scale with a Cronbach’s α of .83 (Etter et al., 2003). In the present study, the general and clinical cohorts’ scale scores showed good reliability with a Cronbach’s α of .75 and .76, respectively.

Alcohol Use Disorder Identification Test (AUDIT)

The ten-item AUDIT (Saunders et al., 1993) was used to assess alcohol consumption, drinking behaviours, and alcohol-related problems (e.g., *“How often do you have six or more drinks on the one occasion?”*). Items 1 through 8 are rated on a five-point scale, which are scored from 0 (*Never*) to 4 (*Daily or almost daily*), whereas items 9 and 10 are rated on a three-point scale and are scored as 0 (*No*), 2 (*Yes, but not in the past*), and 4 (*Yes, during the past year*). The total score comprises the summing of each of the selected item scores. The total score can range from 0 to 40. A score of 8 or more indicates hazardous drinking. A score of 13 or more in women, and 15 or more in men, may indicate alcohol dependence. The AUDIT has demonstrated good reliability. For example, in a systematic review by Meneses-Gaya et al. (2009) across ten studies the average Cronbach’s alpha was .80. The general and clinical cohorts showed good reliability with a Cronbach’s α of .85 and .95, respectively.

Drug Abuse Screen Test-10 (DAST)

The ten-item DAST-10 (Skinner, 1982) was used to assess drug use behaviours in the past 12 months (e.g., *“Do you feel bad or guilty about your drug use?”*). Each item is rated on a dichotomized scale (yes/no answers). Each “Yes” answer is scored with 1, while each “No” answer is score with 0 – except for question 3 for which a “No” is scored with 1 while “Yes” is scored with 0. The total score ranges from 0 to 10: 0=no problems; 1-2=low problems; 3-5=moderate problems; 6-8=substantial problems; 9-10=severe problems. In a systematic review on the psychometric properties of the DAS, Yudko, Lozhkina, and Fotus (2007) found it to be a reliable measure with multiple studies citing a Cronbach’s α of over .90. In the present study, the general and clinical cohorts’ scale scores showed adequate reliability with a Cronbach’s α of .72 and .82, respectively.

Brief Coping Orientation to Problems Experienced (Brief-COPE)

In order to assess coping behaviours individuals employed when experiencing stressful situations, the 30-item Brief-COPE was used (Carver et al., 1989*)*. Participants are asked to think about a recent stressful event in their life and how they coped within that situation. The Brief-COPE is rated on a four-point scale: 1 (*I haven’t been doing this at all*), 2 (*I’ve been doing his a little*), 3 (*I’ve been doing this a medium amount*), and 4 (*I’ve been doing this a lot*). The Brief-COPE has a total of 15 two-item subscales (e.g., self-distraction, substance use, humour). The subscale scores are then added together to give a score ranging from 2-8. A higher score on the subscale represents a higher utilisation of the related coping behaviour. These smaller subscales form a super-ordinate domain coping style. These are: emotion- focused coping (EFCope; scoring from 10 to 40), dysfunctional coping (DCope; scoring from 12 to 48), and problem-focused coping (PFCope; scoring from 6-24).

EFCope includes the subscales: Acceptance (e.g., learning to live with it), emotional support (e.g., comfort and understanding), humour (e.g., making jokes about it), positive reframing (e.g., look for something good in it), and religion (e.g., finding comfort in religious or spiritual beliefs). The scores of each subscale are summed and produce a total domain score from 10-40. The general and clinical cohorts showed good reliability with a Cronbach's α of .83 and .91, respectively. DCope includes the subscales: Behavioural disengagement (e.g., giving up trying to deal with it), denial (e.g., saying to myself "this isn't real"), self-distraction (e.g., turning to work or other activities to take my mind off things), self-blame (e.g., blaming myself for things that happened), substance use (e.g., using alcohol or other drugs to help me get through it), and venting (e.g., expressing negative feelings). The scores of each subscale are summed and produce a total domain score from 12-48. The general and clinical cohorts showed good reliability with a Cronbach's α of .82 and .81, respectively. PFCope includes the subscales: Active coping (e.g., concentrating my efforts on doing something about the situation I am in), instrumental support (e.g., getting help and advice from other individuals), and planning (e.g., thinking hard about what steps to take). The scores of each subscale are summed and produce a total domain score from 6-24. The general and clinical cohorts showed good reliability with a Cronbach's α of .80 and .88, respectively.

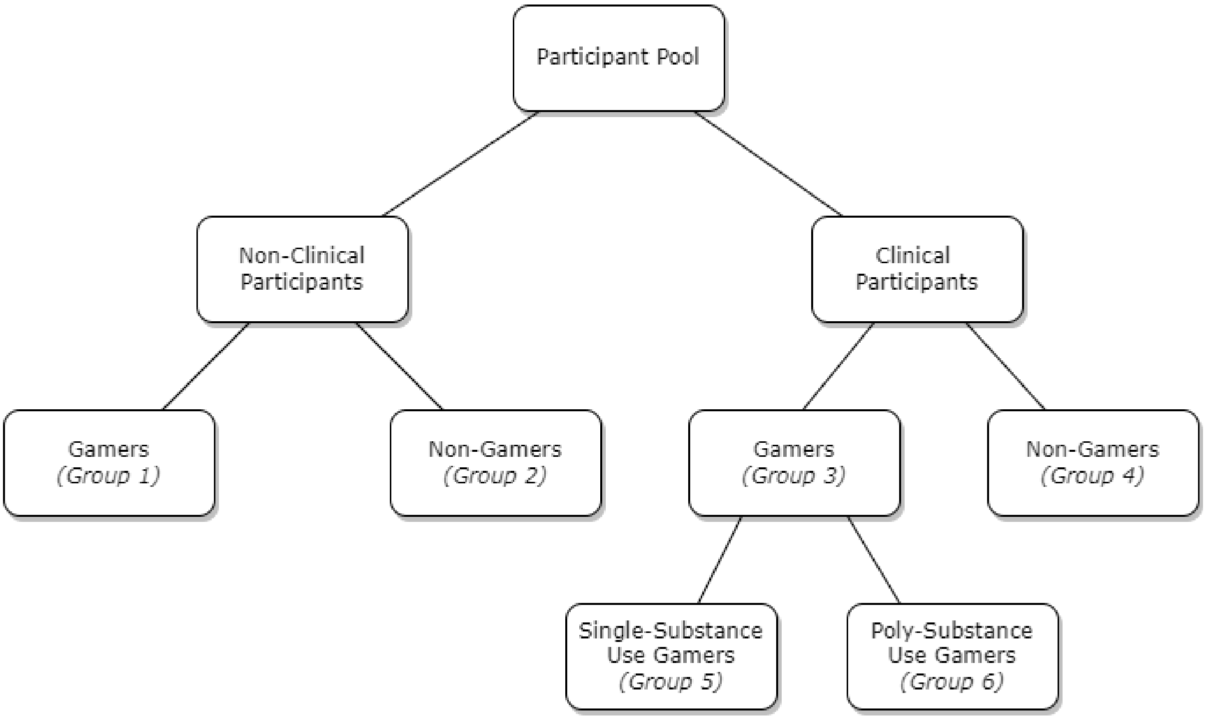
As seen above, each of the domain subscales vary in subscales used and total. In order to control for this, each domain coping style was then transformed into a z-score scale of -2 to 2 so analyses could be carried out when comparing each domain.

Data Analyses

Data were analysed using Rstudio for Windows (v3.5.1). Participants were categorised into six groups for analysis (as seen in Figure 1): (1) gamers, (2) non-gamers, (3) clinical gamers, (4) clinical non-gamers, (5) single-substance use gamers, and (6) poly-substance use gamers. In order to investigate H_1, Spearman's rho bivariate correlations (with Hochberg correction) were conducted to examine relationships between internet gaming characteristics, substance use variables (DAST and AUDIT scores were combined into a single substance use z-score). Chi-square analyses were then used to test for differences between single and poly-use gamers. In order to investigate H_2, coping domain variables were calculated and standardised (z-score), and a multiple linear regression analysis was conducted to investigate the relationship of problem-focused, emotion-focused, and dysfunction coping on GD scores in both clinical and non-clinical gamers.

Figure 1

Participant Groupings



Note. Participant groups: (1) gamers, (2) non-gamers, (3) clinical gamers, (4) clinical non-gamers, (5) single-substance use gamers, and (6) poly-substance use gamers.

Following this, an exploratory comparison of clinical and non-clinical gamers was conducted to further investigate H_1. The z-scores were calculated for the related variables (DCope, BYSAS, and IDS9) which were significantly correlated with the IGD9-SF. Non-clinical gamers were data-matched on age, qualification, and gender of the clinical gamers using the Matchit package in Rstudio (Ho et al., 2007). During this process, any non-clinical gamer who scored 3 or higher on the DAST and/or 13 or higher on the AUDIT were removed from the potential pool, as they may be potential substance abusers. A series of *t*-tests were conducted to ensure that each gaming group did not significantly differ in age, qualification, or gender. Following this, the significant variables found in clinical and non-clinical gamers in H_1 were then entered into a MANOVA to investigate the variance between the z-scores of clinical and non-clinical gamers, with appropriate follow-up post-hoc tests.

Results

Correlations Between Problematic Behaviours and Substance Use Among Gamers and Non-gamers

The results from the correlations between gamers' scores and non-gamers' scores on the respective scales are shown in Table 4. Correlation analyses showed that the gamers' GD scores were significantly correlated with BYSAS and IDS9 scores with moderate effect sizes. The non-gamers showed a significant correlation between BYSAS scores and IDS9 scores with a moderate effect size (Akoglu, 2018). Furthermore, gamers demonstrated more significant correlations overall than non-gamers. When considering clinical gamers and clinical non-gamers, it was found that the clinical gamers' GD scores correlated significantly with IDS9 scores with a strong effect size (Akoglu, 2018). The clinical non-gamers showed significant correlations among BYSAS and BSMAS scores, and BSMAS and IDS9 scores with moderate effect sizes (Akoglu, 2018), the latter of which mirrored the clinical gamers. A full list of correlations between all the variables can be seen in Table 5.

Table 4

Spearman's Rho Correlations of Non-gamers and Gamers in the General Cohort

	DA-Z	BYSAS	CDS	BSMAS	BSAS	IDS9	PGSI
DA-Z		0.12	-	0.26	-0.04	0.01	-0.14
BYSAS	0.41**		-	0.27	0.30	0.61*	-0.40
CDS	0.52	0.18		-	-	-	-
BSMAS	0.03	0.19	-0.40		0.44	0.38	0.10
BSAS	0.16	0.26	0.07	0.47**		0.29	0.29
IDS9-SF	0.10	0.46**	0.08	0.53**	0.41**		-0.45
PGSI	0.30*	0.13	-	0.17	0.26	0.14	
IGD9-SF	0.04	0.39**	0.21	0.21	0.16	0.59**	0.14

Note. Non-gamers above the line and gamers below the line; non-gamers did not complete the IGDSF; CDS was n/a in the non-gaming group due to smokers' n=2; DA-Z – drug-use disorder/alcohol disorder z-score; BYSAS – Bergen-Yale Sex Addiction Scale; CDS – Cigarette Dependency Scale; BSMAS – The Bergen Social Media Addiction Scale; BSAS – Bergen Shopping Addiction Scale; IDS9-SF – Internet Gaming Scale 9 – Short Form; PGSI – Problem Gambling Severity Index; IDG9-SF – Internet Gaming Disorder Scale 9 – Short Form

* $p \leq .05$; ** $p \leq .01$;

Table 5

Spearman's Rho Correlations of Non-gamers and Gamers in the Clinical Cohort

	DA-Z	BYSAS	CDS	BSMAS	BSAS	IDS9	PGSI
DA-Z		0.13	0.17	0.25	0.03	0.16	-0.14
BYSAS	0.19		-0.16	0.20	0.69**	0.36	0.24
CDS	-0.12	0.00		-0.01	0.25	0.69	-0.09
BSMAS	0.39	0.45	-0.07		0.25	0.67**	-0.03
BSAS	-0.01	0.08	0.22	0.38		0.35	0.15
IDS9-SF	0.21	0.38**	-0.04	0.70**	0.46		-0.01
PGSI	0.57**	0.34	0.23	0.52*	0.17	0.27	
IGD9-SF	0.50	0.39**	-0.07	0.62**	0.16	0.71**	0.37

Note. Non-gamer above the line and gamers below the line; non-gamers did not complete the IGDSF; DA-Z – drug-use disorder/alcohol disorder z-score; BYSAS – Bergen-Yale Sex Addiction Scale; CDS – Cigarette Dependency Scale; BSMAS – The Bergen Social Media Addiction Scale; BSAS – Bergen Shopping Addiction Scale; IDS9-SF – Internet Gaming Scale 9 – Short Form; PGSI – Problem Gambling Severity Index; IDG9-SF – Internet Gaming Disorder Scale 9 – Short Form

* $p \leq .05$; ** $p \leq .01$

Co-occurring Substance Use and Gaming Among Clinical Gamers

A chi-square test was used to assess gaming behaviour and co-occurring drug use. The relation between these variables was significant χ^2 (1, N = 64) = 1.01, p = 0.04 (with Hochberg correction), indicating that individuals who played videogames were more likely to use multiple substances (i.e., are poly-substance users). A *t*-test was then conducted to investigate if poly-substance users scored significantly differently on the IGDS9-SF scale when compared to single substance users. There was a significant mean difference of 8.4 (single-use M = 15.6; poly-use M = 24.09) in scores between single-substance users and poly-substance users, $t(28.25) = -3.42$, $p<0.01$, indicating that participants who reported co-occurring drug use scored significantly higher on the IGDS9-SF.

The Influence of Coping Style on Gaming Among Clinical and Non-clinical Gamers

A multiple linear regression was calculated to predict GD scores based on three different coping styles: problem-focused coping (PFCope), emotion-focused coping (EFCope), and dysfunctional coping (DCope). In relation to non-clinical gamers, a significant relationship was found (F[3, 83] = 3.61, p = 0.01), with an adjusted R^2 = 0.08. The non-clinical gamers' predicted gaming disorder scores are equal to 1.038 + .005 (DCope) + .007 (EFCope) – .009 (PFCope), where each was assessed on a scale. DCope was a significant predictor of gaming disorder scores (p = 0.01). In regard to the clinical gamers, a significant relationship was found (F[3, 32] = 4.04, p = 0.01), with an adjusted R^2 0.20. The predicted GD scores were equal to .893 + .010 (DCope) + .008 (EFCope) - .008 (PFCope). DCope was a significant predictor of GD scores with a *p*-value of 0.01.

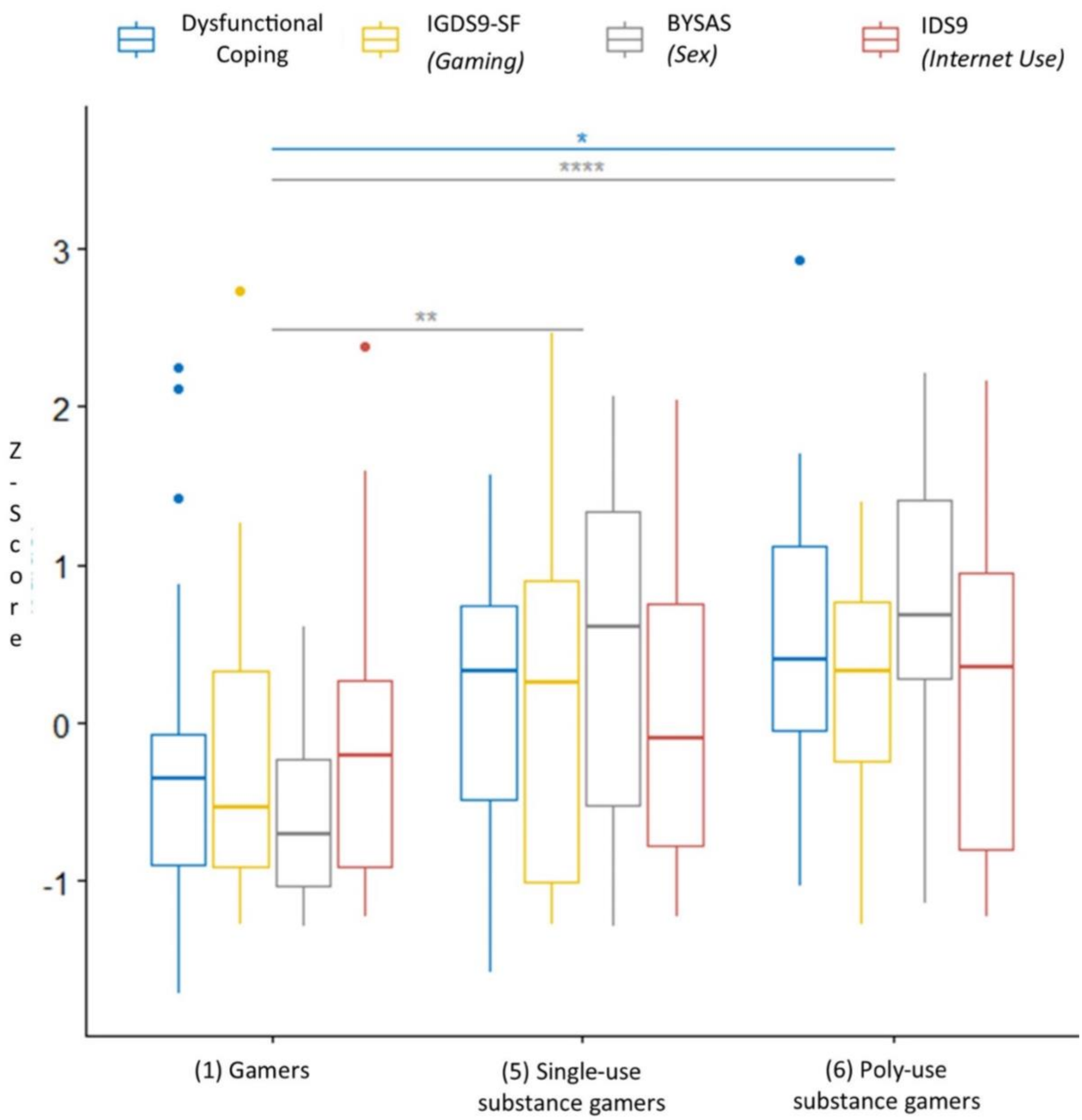
Exploratory Direct Comparisons of Clinical Gamers and Non-clinical Gamers

A one-way multivariate analysis of variance was performed to determine the effect of gamer group on dysfunctional coping, gaming disorder, sex addiction, and internet addiction scores. There were three groups investigated: (i) gamers (non-clinical), (ii) single-use gamer (clinical), and (iii) poly-use gamer (clinical). There was a statistically significant difference between the groups on the combined dependent variables of dysfunctional coping, gaming disorder, sex addiction, and internet addiction scores, $F(8, 134) = 4.23$, $p<0.001$.

Follow-up univariate Welch ANOVAs, using Hochberg correction, showed that there was a statistically significant group difference in scores in dysfunctional coping (F[2, 34.4] = 5.18, p = 0.03) and sex addiction using the BYSAS (F[2, 28.5] = 19.2, $p<0.001$). However, there were no significant differences between groups on gaming disorder scores (F[2, 35.7] = 3.11, p = 0.11) or internet disorder scores (F[2, 33.4] = 0.72, p = 0.49). Games Howell pairwise comparisons (adjusted Tukey *p*-value) were then conducted between the groups for each of the outcome variables, which can be seen in Figure 1. Significant differences were observed in dysfunctional coping between non-clinical gamers and poly-substance use gamers (p = 0.01), sex addiction scores between non-clinical gamers and single-substance use gamers (p = 0.003) and non-clinical gamers and poly-substance use gamers ($p<0.0001$). Gaming disorder scores also approached significance between non-clinical gamers and poly-substance use gamers (p = 0.057).

Figure 2

Pairwise Comparison



Note. Games Howell pairwise comparison of z-scores with Tukey correction of group 1, 5, and 6.

* p = .01; ** p = .003; **** p<.0001

Discussion

The present study compared and contrasted the co-occurring problematic behaviour and substance use in clinical and a non-/sub-clinical sample of gamers and non-gamers and explored the influence of coping strategies on gaming and its co-occurrence with substance use and other problematic behaviours.

Gaming Disorder, Problematic Behaviours, and Substance Use

In the present study, it was hypothesized that gamers would be more likely to exhibit co-occurring problematic behaviours among both clinical and non-clinical groups (H1). There were a number of correlations found within each of the groups. In regard to non-clinical gamers, it was found that GD scores were significantly positively correlated to internet addiction and sex addiction among gamers. This finding provides evidence consistent with previous observations within the field that GD is positively associated with other problematic behaviours (Burleigh, Griffiths, et al., 2019). Moreover, within gamers, it was found that drug and alcohol use were also significantly correlated with sex addiction and gambling, aligning with the substance use literature (Walther et al., 2012). This was not mirrored in the non-gamers, where there were no significant correlations with substance use. This finding suggests that gamers, when compared to non-gamers, may interact with substance use and related risky behaviours more than their non-gamer counterparts (Burleigh, Griffiths, et al., 2019).

In regard to clinical gamers, the results suggest that GD scores were significantly correlated with internet addiction, social media addiction, and sex addiction, whereas the clinical non-gamers showed significant correlations between sex addiction and shopping addiction, and between internet addiction and social media addiction. This provides evidence which aligns with the known literature on GD and substance use, in which disordered behaviours (e.g., problematic videogame use) have been linked to increased substance use (Gallimberti et al., 2016; Nicola et al., 2015). The similarities in correlations across gamers and clinical gamers appear to suggest that each group share defining characteristics in the way in which they engage with behaviours which may become problematic (e.g., sex). However, this needs to be investigated more thoroughly using a longitudinal design.

The results did not indicate any significant correlations between GD scores and substance use scores in either the non-clinical or clinical group. Previous research examining the correlations between substance use and GD has been somewhat inconsistent, as researchers have not found a consistent link between gaming and substance use (Coëffec et al., 2015). Whilst there have been a number of studies which consider videogames a risk factor for substance use, there are papers that have suggested gaming can act as a protective factor (Turel & Bechara, 2019). Recent research regarding gaming and substance use has suggested that the correlations between these two factors can vary depending on geographical location (Strizek et al., 2020). This may be a viable explanation as to why the present study did not find any significant associations between gaming and substance use specifically. To elaborate, it has been suggested that the association between gaming and substance use may be attributed to the perceived risk (i.e., the self-reported risk) of problematic gaming within the countries of which the samples were collected (i.e., Australia, New Zealand, or the United Kingdom). For example, the psychometric scales used in the present chapter (5) required participants' self-reports of problematic behaviours. However, the perceived societal acceptability of gaming is more favourable in western high-income countries (Strizek et al., 2020), and therefore participants may view their gaming habits more favourably than habits related to substance use. As such, this favourable view of gaming compared to substance use, such as alcohol, may occur due to the relatively new nature of gaming. Societal attitudes towards who can consume alcohol, in which situations and contexts, to what amount, and the consequences for transgressing these social rules can vary from country to country (Aresi et al., 2021). Due to alcohol being consumed in countries all over the world for much of history (Cavalieri et al., 2003), it, and its varying uses, have been rooted into the value framework (i.e., the values and views of citizens in a country) of the respective country (Hellman & Rolando, 2013). Therefore, the societal acceptability of alcohol may refer to a nuanced attitude, in so far as that it has clear societal expectations and consequences (both social and legal) attached to it in a variety of settings, ranging from general use to problematic use. Accordingly, gaming lacks this nuanced understanding of the expectations and consequences (both social and legal, or lack thereof) within society, with no specific and clear values or views for the larger society to frame expectations and consequences. Therefore, when participants are requested to rate their own behaviour, they may compare it to the well-known expectations and risks of substance use (e.g., alcohol use) and inadvertently underestimate the perceived risk of gaming (or other problematic behaviours; Strizek et al., 2020).

Consequently, perhaps within the present sample, the geographical location, and the associated perceived risks held in that region (e.g., New Zealand), are reflected within self-reported results, in which they may perceive gaming is less risky than substance use. It is of course possible that the results suggest that it is not the act of playing videogames that is related to substance use, but instead the similarities gamers may share with other at-risk populations (e.g., dysfunctional coping strategies; Burleigh et al., 2019; Ream et al., 2013). Indeed, it could be that co-occurring problematic behaviours or substance use, in conjunction with maladaptive coping strategies, create a negative influence within gamers (Kuss et al., 2012), which may be more pronounced in at-risk groups, such as substance users in abstinence (Heggeness et al., 2020).

The Exacerbating Effect of Co-occurrence

In order to better understand the potential effect of co-occurring substance use (i.e., poly-use) in at-risk populations, the relationship between single-substance use and poly-substance use (i.e., co-occurring use) was explored in clinical gamers and non-gamers. The results suggest that the clinical gamers within the present sample were more likely to be poly-substance users when compared to clinical non-gamers who were likely to be single-substance users. Furthermore, a post-hoc test indicated that within clinical gamers, there was a significant difference in GD scores between single-substance use gamers and poly-substance use gamers. Therefore, H_1 was supported and provides evidence in line with the current literature, which suggests that there is a potential for problematic or disordered substance use to exacerbate other existing problematic behaviours (Burleigh, Griffiths, et al., 2019; Gossop et al., 2002). The difference in scores may suggest that a cycle of reciprocity may exacerbate symptomology (as indicated by an increase in scores) between poly-substance users and abstinent single-substance users.

This is an important finding, as it highlights the complexities of clinical symptomology, and the way in which co-occurring use may manifest other potential underlying risk factors (Najt et al., 2011). Various studies have evidenced the co-occurrence of substance use and other addictive behaviours (Kotyuk et al., 2020), and the present findings add to the literature suggesting that there can be overlaps in problematic/disordered behaviours and substance use. In line with this literature, it could be that the poly-substance users are at a higher risk of developing co-occurring at-risk behaviours, therefore resulting in a cycle of reciprocity (Gossop, 2001; Haylett et al., 2004; Martin et al., 2014). In regard to gaming, there is a need for more research into the impacts of problematic gaming in abstinent substance-use populations (Burleigh, Griffiths, et al., 2019). The present paper lends further support to at-risk populations having a higher tendency to develop problematic gaming behaviours (Kotyuk et al., 2020; Sussman & Black, 2008). Moreover, individuals who experience increased poly-substance use may also substitute maladaptive substances with potentially problematic behaviour (Kuss et al., 2017).

Indeed, the findings, which show that abstinent poly-substance users score more highly than single-substance users on psychometric measures of problematic behaviours (e.g., sex addiction), lend support to replacement theory, wherein an individual who has stopped using one substance or behaviour (i.e., in abstinence), may then become more vulnerable to other problematic behaviours (Sussman & Black, 2008). This is partially due to exploration of other avenues to satisfy the behaviours' specific function (e.g., coping). Moreover, when seeking to substitute these behaviours, the individual may choose behaviours which are perceived to be less detrimental. Consequently, it is possible that the higher scores achieved across a number of problematic behaviours in this group could indicate that these behaviours are perceived to be less detrimental to the original substance use or other potential substances (Sussman & Black, 2008). This suggests that perceived risks of these behaviours are lower within the current clinical sample, aligning with the previous literature (Strizek et al., 2020) and extending it to emerging adults and adults. The literature has also suggested that individuals in abstinence can adopt behaviours that can be repeated excessively in an attempt to self-regulate their mood state, therefore adopting it into their existing coping strategies (Schneider et al., 2018; Sussman & Black, 2008).

Coping Strategies Among Gamers

The present paper explored three domains of coping to investigate the role coping played within gamers and clinical gamers. It was hypothesised that the severity of gaming among both clinical and non-clinical groups will be positively associated with dysfunctional coping styles, but negatively associated with problem-focused coping styles (H2). The results suggest that coping strategies among gamers are significantly associated with GD. More specifically, as hypothesised, dysfunctional coping strategies were significant indicators of higher GD scores for both gamers and clinical gamers; however, problem focused coping, while it had a negative association with GD scores, it did not reach significance. Interestingly, the results demonstrated that coping strategies within gamers had a smaller association with GD (8%), although within the clinical gamers they had a stronger association (20%) with GD scores. The difference in these scores supports the notion that dysfunctional coping strategies may exacerbate problematic behaviours (Heggeness et al., 2020; Kuss et al., 2017).

The present findings are also in line with the literature on the relationship between gamers and their coping strategies (Burleigh, Griffiths, et al., 2019), suggesting that there may be parallels in the way gamers and substance users regulate their emotions (Ream et al., 2013). More specifically, the results suggest that some gamers develop dysfunctional coping strategies which manifest as excessive engagement in videogame play, therefore, indicating a maladaptive form of emotion regulation which is not seen when compared to gamers who have more varied and adaptive coping strategies and therefore emotion regulation strategies (Wölfling et al., 2008). Maladaptive emotion regulation has been found to be associated with addictive behaviours, but not with substance abuse (van Rooij et al., 2014). Therefore, if abstinent substance users are gamers, and have developed dysfunctional coping strategies, they may engage in problematic gaming in order to replace (i.e., replacement theory) and/or regulate negative feelings or emotions (i.e., the self-medication hypothesis; Estévez et al., 2017; Kuss et al., 2017). The present data suggest that poly-substance users may be at a higher risk of developing a repetitive use of videogames to achieve this goal, representing a unique risk factor within gamers abstaining from substance use. Therefore, it is important to consider coping strategies, their influence on emotion regulation, and the potential development and maintenance of co-occurrence in at-risk populations of gamers.

The findings also contribute to the broader literature on coping, suggesting that the avoidant behaviours within emotion-focused coping can be considered a third distinct dysfunctional coping domain. There has been research which has utilised the problem-focused and emotion-focused domains, with avoidant behaviours being included in the emotion-focused domain (Baker & Berenbaum, 2007; Schneider et al., 2018). The dysfunctional coping domain has also been utilised in a number of studies which have considered avoidant emotion-focused coping styles as dysfunctional (e.g., denial, self-distraction; Dreier et al., 2017; Kuss et al., 2017). Therefore, the present paper provides additional support for the consideration of a dysfunctional coping domain in the literature on coping. The use of an overarching dysfunctional coping domain could help in refining the understanding of emotion-focused coping through the separation of maladaptive emotion-focused styles (e.g., denial) and adaptive emotion-focused styles (e.g., emotional support). This is important, as when considering problematic and disordered behaviours, the way in which an individual approaches a stressful situation is a significant factor when considering their coping style (Baker & Berenbaum, 2007). While the overarching domains of problem-focused and emotion-focused strategies provide approach and avoidant style behaviours, respectively, a more nuanced approach on emotion-focused strategies may be useful (Baker & Berenbaum, 2007). Therefore, differentiating between adaptive emotion-focused coping (e.g., positive reframing) and maladaptive dysfunctional coping (e.g., self-distraction) is important when drawing parallels between separate populations who may share similarities in coping strategies as different populations may develop nuanced differences in their coping strategies.

Exploring Differences Between Gamers and Abstinent Substance Use Gamers

The literature suggests that co-occurrence is linked to disordered behaviours or substance use within individuals (Burleigh, Griffiths, et al., 2019). As such, the present study explored the way in which the co-occurrence of sex addiction, internet addiction, and/or coping styles may exacerbate existing problematic behaviours and/or substance use in gamers (non-clinical), single-substance use gamers (clinical), and poly-substance use gamers (clinical). As hypothesised, gamers with substance use history exhibited more dysfunctional coping compared to non-gamers with a history of substance use. More specifically, pairwise comparisons showed that dysfunctional coping scores were significantly different between gamers and poly-substance use gamers. Furthermore, there were significant differences in sex addiction scores between gamers and both single-substance use gamers and poly-substance use gamers. Finally, it was found that GD scores approached significance between gamers and poly-substance use gamers.

As previously discussed, dysfunctional coping is part of a maladaptive process which is associated with avoidant behaviour. When controlling for various demographic factors, there was a significant difference in coping scores between gamers and poly-substance use gamers, but not between gamers and single-substance use gamers. Therefore, it appears that avoidant behaviours are an important factor involved in the development of maladaptive coping mechanisms and can lead to adverse outcomes in poly-substance use gamers. The way in which coping strategies are used in different gamer populations may explain the difference in scores (Burleigh, Griffiths, et al., 2019). More specifically, gamers may interact and engage with stressors in a more active manner, whereas clinical gamers appear to be more likely to avoid the stressor. Previous literature pertaining to the self-medication hypothesis (Khantzian, 1985) can explain why this occurs among poly-substance users and why they may be more likely to engage in dysfunctional coping strategies. Specifically, when confronted with a stressful event, substance users may return to the substance or behaviour that alleviated the negative mood state effectively (Khantzian, 1985), therefore enforcing dysfunctional coping strategies. However, further research is needed within clinical populations of individuals who play videogames.

Within the present sample, there was no significant difference in technology-related disorders, such as IA or GD across groups. However, there were some interesting findings regarding sex addiction among gamers. Single-use gamers and poly-use gamers scored significantly higher in comparison to non-clinical gamers. Sex addiction has been found to be associated with individuals with disordered substance use and substance users in abstinence (Sussman & Black, 2008). The present results align with this literature, demonstrating that sex addiction scores increased with substance use and poly-substance use when compared to those who do not engage with disordered substance use. This is a particularly interesting finding which lends support to replacement theory (Sussman & Black, 2008). More specifically, the significant difference of sex addiction scores between each of the aforementioned groups could suggest that – within this particular sample – sexual activity may replace (or supplement the replacement of) a substance among abstinent users. Moreover, the increased sex addiction scores between single-substance use gamers and poly-substance use gamers lends support to the cycle of reciprocity, wherein the overlap of problematic behaviours creates a mutual negative effect between two or more problematic behaviours (Gossop, 2001; Haylett et al., 2004; Martin et al., 2014); therefore, suggesting that the co-occurrence of multiple addictive behaviours may be a viable explanation for the increase in sex addiction and substance use scores.

The culmination of these behaviours supports the present literature which suggests that co-occurring behaviours within GD and substance abuse may be enforced through dysfunctional coping strategies (Heggeness et al., 2020). Furthermore, the present study offers novel insight into the relationship between maladaptive coping strategies and the potential for co-occurrence to aggravate disordered behaviour within a cohort of substance-abstinent gamers. What is less clear from these data is the extent to which gaming activities themselves may influence said behaviours among gamers. While it is possible that perceptions around videogame use may differ across studies due to the geographical location and wealth of the questioned sample, further multi-cultural data are required to investigate this theory.

Clinical Implications and Future Directions

The findings of the present study have implications for both clinical work as well as future research directions. The study expanded upon previous research on co-occurrence (Walther et al., 2012), coping (Schneider et al., 2018), and has utilised a clinical population sample, as recommended by previous research (Burleigh, Griffiths, et al., 2019). More specifically, the implications of co-occurring problematic behaviours on coping strategies has been highlighted, suggesting that dysfunctional coping strategies contribute to higher scores in gaming disorder, sex addiction, and internet addiction psychometric scores. This is an important finding as more research is needed to assess risk factors associated with disordered behaviour and the potential for co-occurring addictions (Burleigh, Griffiths, et al., 2019). This has practical clinical significance as it adds to the growing body of literature that suggests that underlying co-occurring disorders may require an integrated treatment approach (Carrà et al., 2015; Roncero et al., 2017). Furthermore, the findings highlight the need for more research into the specific aspects of gaming, if any, which may facilitate co-occurrence. While the present results did not suggest that gaming scores were significantly different between gamers and poly-substance use gamers (post-transformation), it suggested that other behaviours such as problematic sexual activity may instead play a replacement role in gamers. While this falls in line with the substance use literature which suggests that substance users may replace substance use with other problematic or high-risk behaviours (Sussman & Black, 2008), future research should investigate problematic behaviours with larger clinical samples, examining a variety of substance uses with a focus on specific co-occurring usage, whilst considering the onset and length of use in relation to the development of other problematic behaviours.

Importantly, the present study further expands on previous work in regards to coping strategies (Loton et al., 2016; Plante et al., 2019; Schneider et al., 2018), supporting the theory that dysfunctional coping styles related to the association between psychopathological symptomatology and videogame use. Moreover, the present research extends these findings to a sample of gamers and substance-abstinent gamers. Therefore, the findings have implications for preventative efforts in abstinent substance use gamers and non-clinical gamers. For example, psychoeducation has been shown to be a useful tool for substance users in treatment as they can often lack insight into their symptomology (Ekhtiari et al., 2017). Therefore, a psychoeducation approach could be utilized to aid substance use gamers in learning the risks of replacement behaviours and which coping styles are implicated in the process.

Understanding these connections has been shown to improve treatment outcomes, and should therefore be considered for clinic research and interventions (Ekhtiari et al., 2017). Moreover, as a preventative measure, gamers who show signs of maladaptive coping strategies should be taught alternative approaches to deal with life stressors, as these may serve to increase their resilience. Future research could consider studying the over-time development and/or maintenance of these coping strategies, identifying specific gaming-related elements (e.g., playstyle or game genre) that may act as risk or resilience factors in the development of maladaptive coping. However, there are limited relevant studies within the GD literature which consider clinical samples. Therefore, more research is needed with larger clinical samples to examine the association of gaming-related factors on coping strategies and the resulting maladaptive psychopathology.

Limitations and Strengths

While the present study contributes insightful information to a number of research areas, there are a number of limitations that should be considered when interpreting the results. The study employed self-report measures for both the general population and the clinical population. Participants may not accurately represent their behaviours related to substance use or problematic behaviours, which may lead to biased reporting. Furthermore, the collected sample may not be reflective of the wider population, meaning that these results may not be generalisable to the wider general populations or wider clinical populations. When analysing data on co-occurrence, although participants self-reported multiple substance uses throughout a given day, it is possible substances were used consecutively and not in parallel. Therefore, caution is advised when extrapolating these results beyond the current sample. In addition to this, the cross-sectional nature of the present study means that no cause-effect conclusions can be made. Finally, there are some limitations of the brief-COPE measure as it assumes specific strategies will be consistently used, rather than the use of multiple different styles to deal with different stressors.

Despite this, the present study also has a number of notable strengths. There are few studies in the field which utilise substance abstinent gamers to study the potential of co-occurrence (Burleigh, Griffiths, et al., 2019). Therefore, the present study allows unique insights into an intersection of vulnerable populations (i.e., substance users and gamers). The present study also presents a multifaced approach when comparing general gamers to clinical gamers, providing an insight into potential interactions and risks when engaging with problematic behaviours and substance use. Furthermore, the present study provides an important steppingstone for future research directions.

Conclusions

Understanding how at-risk populations interact with potentially addictive behaviours and substance use while navigating life stressors can inform preventative strategies. The study's findings suggest that gamers from different populations (i.e., general, and clinical) share similar at-risk behaviours. These problematic behaviours were more pronounced in abstinent substance use gamers, and more specifically poly-substance use gamers. The findings of the present study add to the literature which suggests that coping style and co-occurrence may have some influence on the assessment and potential treatment of substance abstinent gamers, offering support for an integrated treatment approach, wherein both substance use and the other problematic behaviours (e.g., gaming) are considered in tandem (Roncero et al., 2017). Furthermore, gamers who do not meet a clinical criterion may also benefit from the development of new adaptive, problem-focused coping strategies to supplement or replace developing dysfunctional coping strategies (Baker & Berenbaum, 2007; Loton et al., 2016). In that line, the next chapter will explore if the associated risk factors (e.g.., coping, addictive behaviour, etc.) with GD are found to differ across different geographical locations.

Chapter 6

Co-Occurrence of Gaming Disorder and Other Potentially Addictive Behaviours Between Australia, New Zealand, and the United Kingdom

Introduction

Approximately 2.9 billion individuals play videogames worldwide (WePC, 2021), and in some Western countries – such as Australia and New Zealand – over 90% of households own a videogame device, and two-thirds of the population play videogames regularly (Brand et al., 2019a, 2019b). This is not isolated to the Western countries of Australasia, but is also seen in the United Kingdom, which has the largest videogame market in Europe and the sixth-largest videogame market worldwide (Statista, 2021). Consequently, to better understand the positive and negative aspects of this rapidly growing leisure activity, research into gaming has been increasing at a rapid pace.

Understanding the way in which videogames can positively affect those who play them is important. Research has suggested that moderated videogame play can result in improved interpersonal skills, increased positive affect, and positive mental wellbeing (Jones et al., 2014; Laconi et al., 2017). Moreover, it has been shown to increase resilience and coping among adolescents (Stavropoulos et al., 2016). However, it is also important to understand the association between poor mental health and videogaming and to provide insight concerning the intrinsic and extrinsic factors that may precipitate or perpetuate gaming disorder (GD) outcomes (Laconi et al., 2017). A growing body of research associates excessive gaming with poor mental health (Anderson et al., 2017) and other negative consequences (Yau et al., 2012). Therefore, there is a need to improve screening, assessment, definition, and treatment of disordered gaming.

Gaming Disorder

Based on growing research, the American Psychiatric Association (American Psychiatric Association, 2013) included internet gaming disorder (IGD) as a behavioural addiction (warranting further investigation) in the appendix of the latest (fifth) edition of the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5). In addition, the World Health Organization (2019) has for the first time officially recognized 'gaming disorder' (GD) as a disorder with addiction-like properties in the eleventh revision of the *International Classification of Diseases* (ICD-11). The conceptualisations of each of these constructs overlap significantly. More specifically, the similarities of each indicate that (I)GD comprises a persistent engagement with videogames, to the point it cannot be willingly stopped and impairs individuals' everyday functioning. It is worth noting that the constructs of IGD and GD have undergone conceptual evolution prior to inclusion in the diagnostic manuals (DSM-5, ICD-11), with several other terms used to describe problematic and disordered gaming (e.g., pathological video gaming; Lemmens et al., 2011). Therefore, to maintain consistency, the term 'GD' here refers to the clinically defined measures of the disorder as defined by the DSM-5/ICD-11 and the term 'disordered gaming' will be used to describe a range of similar and/or overlapping addictive, compulsive, and/or problematic gaming behaviours which do not fit the clinically define GD construct.

Several studies have associated disordered gaming with mental disorders, such as anxiety (Adams et al., 2019), depression (Burleigh et al., 2018), substance abuse (e.g., alcohol use disorder [AUD]; Erevik et al., 2019; Ko et al., 2008), and personality disorders (Schimmenti et al., 2017). Findings such as these have stimulated interest into the ways that GD may influence these factors. There have been concerns that for some individuals, playing videogames may be inherently addictive, or that pre-existing vulnerabilities (e.g., anxiety and depression) increase the likelihood of GD behaviours (Kircaburun et al., 2020; Stavropoulos, Gomez, et al., 2020). There has been debate in the field as to the validity of the GD diagnosis, with scholars citing the lack of clinical populations, the heterogeneity of the gaming experience, and the risk of pathologizing ordinary gaming behaviour (Aarseth et al., 2017; Colder Carras & Kardefelt-Winther, 2018; Kuss et al., 2017; van Rooij et al., 2018). Indeed, there appears to be evidence that suggests behavioural disorders can be experienced differently by individuals over time. For example, in a longitudinal gambling disorder study, the researchers found that emotionally vulnerable and impulsive gamblers transitioned between the identified gambling subtypes, indicating that these two gambling subtypes had different experiences of problematic gambling (Dowd et al., 2020). Moreover, it is possible that disordered gaming behaviours are experienced differently across gamers. For example, within massively multiplayer roleplaying games, gamers control an avatar (i.e., virtual character) and depending on if they have high levels or low levels of interaction with their virtual avatar can influence the development of discorded gaming. In addition is has been shown that gamers with different levels of social engagement may also present different risks of disordered gaming behaviour – illustrating that the experience of disordered gaming can vary from gamer to gamer in a number of ways (Stavropoulos, Gomez, et al., 2020; Stavropoulos, Pontes, et al., 2020; Tullett-Prado et al., 2021).

Disordered behaviours, such as GD, are not created in a vacuum, and can be considered as a collection of complex processes with multiple facets that vary across different behaviours (Jacobs, 1986; Shaffer et al., 2004). This has been considered a fundamental perspective across disordered behaviours (Charzyńska et al., 2021), and within this process, personality (e.g., instability, impulsivity) has also been shown to play a part (Marmet et al., 2018; Martínez-Loredo et al., 2019). More specifically, research suggests that personality factors, such as low emotional stability, low agreeableness, and low conscientiousness are associated risk factors for disordered behaviours, including gaming disorder (Hussain & Pontes, 2019) and substance abuse (Lui & Rollock, 2020). It has also been suggested that these personality traits can vary across different disordered behaviours (Charzyńska et al., 2021). For example, gambling is positively associated with low emotional stability (i.e., neuroticism; Reid et al., 2011), while gaming is negatively associated with extraversion (Chew, 2022). However, at times the relationship between personality and disordered behaviours can be ambiguous, such as extraversion within disordered social media use, and excessive studying behaviours (Charzyńska et al., 2021). Therefore, understanding the personality nuances within disordered behaviours may help give a more holistic view of associated risk and protective factors. In addition, it has also been suggested that different coping strategies may be a result of, or partially attributed to, a diverse set of risk and protective factors among gamers (Burleigh, Griffiths, et al., 2019; Schneider et al., 2018). It is important to understand how coping may vary across different gamers and how this may also be influenced by personality factors.

Coping

Coping can be defined as the cognitive and behavioural response that occurs when an individual processes and manages stressful life events and emotions (McMahon et al., 2013). The association between gaming and coping has been considered by various scholars (Burleigh, Griffiths, et al., 2019). Among these, there have been three main domains that have been explored: problem-focused coping, emotion-focused coping, and dysfunctional coping (Brand et al., 2014; Kuss et al., 2017; Lazarus & Folkman, 1984). In brief, problem-focused coping involves an active attempt to provide and implement solutions to reduce the life stressor (e.g., planning), and emotion-focused coping involves an attempt to engage and manage the unwanted negative emotions caused by the life stressor (e.g., humour; Lazarus & Folkman, 1984). Finally, dysfunctional coping involves an attempt to avoid or disengage the unwanted negative emotions or life stressors (e.g., denial; Brand et al., 2014; Kuss et al., 2017).

A number of scholars have explored coping and its association with disordered gaming (Kuss et al., 2017; Schneider et al., 2018), with some pointing to a potential link. For instance, those with dysfunctional coping strategies tend to have an increased risk of psychopathology (e.g., depression, anxiety; Kuss & Griffiths, 2012), disordered behaviour, disordered substance use (Burleigh et al., 2019), and high neuroticism (Watson & Hubbard, 1996). In a recent study conducted among a sample of Polish students, researchers found that participants who utilise media-focused coping strategies (e.g., gaming) to regulate their everyday life stressors appeared to have a higher risk of maladaptive coping behaviours. They concluded that dysfunctional coping strategies are correlated GD symptomology (Kuss et al., 2017). This finding is supported by a study which examined over 800 secondary students, whose disordered gaming behaviour was significantly associated with denial and behavioural disengagement – two coping styles which fall under the broader dysfunctional coping strategy domain (Schneider et al., 2018). This suggests that gamers play videogames in order to destress and to escape, and therefore some scholars suggest that this may fulfill a compensatory function in supporting individuals to cope with psychosocial problems (Kardefelt-Winther, 2014).

These findings have led researchers to posit that disordered gaming may be, in part, better characterised as a manifestation of maladaptive coping strategies which have the potential to be exacerbated by other psychosocial issues (Schneider et al., 2018). For example, disordered gaming has been frequently associated with a pattern of escapism among individuals with depression (Burleigh et al., 2018). Consequently, the continued use of gaming to escape may become an over-relied upon strategy resulting in negative long-term consequences with respect to the ability to cope with subsequent situations in which the primary coping strategy is not available. This may encourage an individual to seek other maladaptive habits in order to cope (Burleigh, Griffiths, et al., 2019). This may, in turn, further exacerbate psychopathological disorders such as depression and anxiety (Kuss et al., 2017). Indeed, research suggests that disordered gaming, like other behavioural disorders (e.g., gambling), can co-occur with problematic behaviours or substance use (Burleigh, Griffiths, et al., 2019). Additionally, disordered gaming appears to interact and/or co-occur with other conditions, which may result in complications for both risk assessment and diagnosis (Burleigh, Griffiths, et al., 2019). Therefore, it is important to consider the influence gaming has on individuals who have (or are at-risk of) disordered behaviours (Stavropoulos, Gomez, et al., 2020).

Co-occurrence of Addictive Behaviours

Co-occurrence occurs when two or more potentially addictive behaviours (behavioural and/or substance-related) are engaged in concurrently or in close temporal proximity. In a recent review of co-occurrence of GD with other disordered behaviours, it was found that the presence of co-occurring disordered behaviour – or substance use – was linked with the symptomology of GD (Burleigh, Griffiths, et al., 2019). For example, Na et al. (2017) found that South Korean adults who engaged in both problematic alcohol use and problematic gaming exhibited higher cigarette smoking rates than those who engaged in problematic alcohol use or problematic gaming alone. This was also supported by Ream et al.'s study (2011) who investigated an American sample of adult gamers who had significant correlations between substance use and problematic videogame use, noting that the substances were often consumed while gaming.

The overlap in potentially addictive behaviours appears to create a cycle of reciprocity (Gossop, 2001; Haylett et al., 2004; Martin et al., 2014), in which mutual exacerbation occurs between two or more disordered behaviours. This may explain why individuals who experience more than one disordered behaviour display poorer outcomes in relation to physical and mental wellbeing (Burleigh et al., 2018; Martin et al., 2014; Urbanoski et al., 2007). Consequently, the mutual exacerbation can create complications within clinical symptomology – confounding accurate assessment, diagnosis, and treatment of psychiatric disorders (Najt et al., 2011). Similarly, GD behaviour may exacerbate existing disordered behaviours (e.g., substance use), causing symptomology of each behaviour to alternate – and therefore effecting treatment efficacy (Freimuth et al., 2008). Therefore, clinicians and scholars should be aware of the way in which disordered behaviours may influence or enforce various aspects of a presenting disorder (e.g., GD), and consider how co-occurrence and contextual factors (e.g., coping strategies) may be linked the onset, course, and outcomes of interventions.

Although there is an association between coping, co-occurrence, and GD, additional research is needed into how these may be influenced across varying cultural contexts (Ream et al., 2011). There is research to suggest that co-occurring disordered behaviour or substance use can vary based on geographical location (Burleigh, Griffiths, et al., 2019), and that one's country of origin can moderate disordered gaming (Stavropoulos et al., 2019). Consequently, the field would benefit from the exploration of the cultural nuances found in co-occurring disordered behaviours, coping strategies, and gaming behaviour (Stavropoulos, Baynes, et al., 2020).

Gaming and Culture

Scholars have consistently asserted that culture can influence psychopathology (Charlton & Danforth, 2007; O'Farrell et al., 2020; Stavropoulos, Baynes, et al., 2020). Further research indicates that it can linked to the experience and understanding of psychosocial, addictive, and psychopathological disorders (Anderson et al., 2017). Moreover, several studies have explored cross-cultural variations in videogame playing behaviour, suggesting that the culture context the individual is based in can aggravate GD severity (Király et al., 2019; Laconi et al., 2017). Therefore, it is important that the field develops an understanding of how GD may be experienced across differing regions, in an attempt to better understand the development and maintenance of disordered gaming behaviours (Pontes, Stavropoulos, et al., 2017; Stavropoulos et al., 2019; Stavropoulos, Baynes, et al., 2020).

In a broader context, culture might be described as patterns of behaviour that are explicitly and implicitly acquired and are communicated through symbols and/or practices, which are shared by those who accompany a collective/social identity (Triandis, 1996). There has been research conducted into the way cultures accept and interreact with technology, with Hofstede's (1980, 1991) proposed cultural dimensions being reliable in the field of information technology (Chen & Nath, 2016; Straub et al., 1997). Hofstede's cultural dimensions (Hofstede, 1980, 1991) attempt to categorise dominant cultures by systematically differentiating them from each other across six dimensions: power/distance, femininity/masculinity, uncertainty/avoidance, individualism/collectivism, long-term orientation, and indulgence. The present study focuses on cultures which present with high individualism as opposed to collectivism through the lens of Hofstede's proposed cultural dimensions. Individualistic societies tend to be more loosely socially connected, and individuals in these cultures tend to identify as an 'I' rather than a 'we'. Consequently, they tend to prioritise themselves and their immediate families rather than those with whom they are unfamiliar (Hofstede, 1980, 1991).

Hofstede's (1980, 1991) cultural dimensions provide a general understanding of the way in which a national culture expects, perceives, and assesses the values of its members. However, the theory has been criticised because it oversimplifies national culture – neglecting multicultural trends and individual differences found within each culture (Ladhari et al., 2011). Nevertheless, there have been a number of studies which have considered cross-cultural comparisons in the GD literature (e.g., O'Farrell et al., 2020; Stavropoulos, Baynes, et al., 2020), with a specific focus on the dichotomy between individualistic and collectivist cultures. Consequently, the nuance of either culture is not explored in depth. This is an important factor to consider because research suggests that within individualistic cultures, substance use and behaviours can differ depending on the geographical location of the culture (Burleigh, Griffiths, et al., 2019). For example, the United Nations' 'World Drug Report 2020' (United Nations, 2020) estimates that 1.3% of Australians use amphetamines, while England (including Wales) and New Zealand have rates of 0.6% and 0.8%, respectively. In addition, estimates of problematic behaviours and their co-occurrence can also differ across culturally diverse groups of individuals (Burleigh, Griffiths, et al., 2019; Strizek et al., 2020). Thus, the choice to include Australia, England (including Wales), and New Zealand within the present study is not arbitrary; as these countries are considered developed nations and share a similar cultural heritage, with English being the primary language spoken, and each being considered individualistic countries (Hofstede Insights, 2022). Moreover, they are countries where gaming is common leisure activity, however they demonstrate different substance use factors indicating intra-cultural difference despite their similar cultural heritage and individualist influences. Therefore, understanding the way in which cultural context may influence problematic substance use, behaviours, and subsequent co-occurrence is of particular importance.

Due to the intra-cultural differences found in behaviour and substance use, factors which influence coping styles (e.g., denial, escapism) within each country may also vary. This influences the way individuals use videogames in relation to life stressors and the potential of co-occurring problematic use. A recent review by Burleigh et al. (Burleigh, Griffiths, et al., 2019) reported four studies which considered coping in relation to disordered gaming. This demonstrates the need for further empirical evidence to better understand how individuals may utilise coping in a gaming context as a risk or protective factor against co-occurrence. Therefore, to gain a better understanding of how cultural dimensions may apply to disordered gaming, and to address the need of nuanced investigation of intra-cultural dimensions, in the present study, three countries considered individualist is explored (Hofstede Insights, 2022), with a focus on gaming, personality factors, coping styles, and disordered substance use and/or behaviours and their potential co-occurrence.

The Present Study

There has been evidence to suggest that gamers can have varying experiences of disordered gaming behaviours (Stavropoulos, Pontes, et al., 2020; Tullett-Prado et al., 2021). These varying experiences have been suggested to be due to coping mechanisms and how they can act as risk or protective factor for the development and/maintenance of disordered behaviours (Schneider et al., 2018). Furthermore, coping mechanisms can also shed light on the way an individual interacts and or engages in disordered behaviours – with research suggesting that dysfunctional coping strategies can result in the influence of disordered behaviours through a cycle of co-occurrence and reciprocity (Kuss et al., 2017). A particular area of interest is how this may manifest across different countries. A number of studies have considered the dichotomy between individualistic and collectivist countries (Charlton & Danforth, 2007; O'Farrell et al., 2020; Stavropoulos, Baynes, et al., 2020), focusing on the individualistic/collectivist attributes (e.g., competitiveness) that citizens in each country possess and how they differ. However, in doing so, they have overlooked the nuanced differences in disordered behaviours, personality factors, coping strategies, and the potential of co-occurrence found across similar countries in very different geographical locations (Burleigh, Griffiths, et al., 2019). This is an important facet to consider because understanding the interplay of these potential risk and protective factors within each of these countries will aid identifying and preventing disordered behaviours.

Researchers have explored a number of these facets (e.g., gaming and coping; Burleigh, Griffiths et al., 2019) using a variable-centred approach. This is an approach which provides specific information on the importance of each factor on the outcome variable (Li et al., 2017). However, these methods can be somewhat flawed when the assumption of homogeneity is applied to the sample (Cerniglia et al., 2019). Therefore, the present study considers a person-centred approach which is suited to examining the similarities and differences across participants, while considering how variables interact with one another (Masyn, 2013). This approach has a number of advantages because it can: (i) assess whether distinct groups of individuals can be identified through naturalistic grouping of factors; (ii) offer complex combinations among all possible factors at all possible levels of each factor; and (iii) be clinically appropriate because decisions concerning assessment and treatments often focus on the individual rather than on the variable or factor (Hallquist & Wright, 2014). In conjunction with the person-centred approach, the present study utilises latent profile analysis (LPA) to identify groups of individuals within each country that have similar profiles for multiple dimensions of psychopathology and disordered behaviours. LPA is used to define unobserved subgroups based on observed variables without specifying the number of profiles in advance. Therefore, it is believed to be a more appropriate method to address research questions that are exploratory in nature and to understand the diversity and complexity of multiple risk factors within psychopathology (Pontes & Griffiths, 2015).

Consequently, the present study seeks to identify profiles of individuals characterized by unique patterns of disordered behaviours (e.g., gambling, substance use, etc.), personality factors (e.g., neuroticism), co-occurrence, and coping strategies across individualised countries. It is hypothesised that (i) a profile with higher co-occurrence across all disordered behaviours will be identified (H_1); (ii) a profile with risk of disordered behaviours will be identified (H_2); (iii) dysfunctional coping strategies, low agreeableness, low emotional stability, and low conscientiousness will be strongly associated with the profiles that have higher scores on disordered behaviours (i.e., behavioural and substance use variables), and least strongly associated with profiles with low risk of disordered behaviours (H_3); and (iv) a profile of disordered behaviours differentiating between countries will be identified (H_4).

Method

Participants and Procedure

Participant data were collected from September 2019 to September 2021 across four universities in three countries: United Kingdom (Nottingham Trent University), New Zealand (Auckland University of Technology), and Australia (Victoria University and University of the Sunshine Coast). Flyers and online advertisements were used around each campus. The inclusion criteria for this sample were: (i) being aged 18 years or over; and (ii) currently residing in the country where the survey was taken (i.e., UK, NZ, AU). The UK sample comprised of 561 participants, including 416 women (M_{age}= 19.8 years; SD = 1.47) and 139 men (M_{age} = 20.7 years; SD = 2.68 years), aged between 18 and 36 years (M_{age} = 20 years; SD = 1.88). The NZ sample comprised 170 participants, including 88 women (M_{age}= 26.6 years; SD = 8.83) and 80 men (M_{age} = 25.6 years; SD = 9.07 years), aged between 18 and 65 years (M_{age} = 26.1 years; SD = 8.89). Lastly, the AU sample comprised 1185 participants, including 428 women (M_{age}= 28.2 years; SD = 10.2) and 772 men (M_{age} = 28.8 years; SD = 8.94 years), aged between 18 and 64 years (M_{age} = 28.5 years; SD = 9.35). Additional sociodemographic information is shown in Table 1. All participants were given information prior to the study, including data use, potential risks, and benefits, along with their right to withdraw from the study until data analysis. The study was approved by each of the university's ethics committees.

Table 1

Demographics and Videogame Use Information

Sociodemographic variables		Total (N=1916) (561, 170, 1185) *(UK, NZ, AU)*
Gender	Prefer not to say / Other	**43** *(6, 2, 30)*
Country	United Kingdom	**561**
	New Zealand	**170**
	Australia	**1185**
Marital Status	Same-sex civil partnership / married	**235** *(3, 27, 205)*
	Separated, but still legally in a same-sex civil partnership / married	**13** *(0, 15, 8)*
	Civil partnership has been dissolved / divorced	**32** *(2, 5, 25)*
	Never registered a same-sex civil partnership / married	**1302** *(459, 125, 718)*

	Prefer not to say / other	**334** *(97, 8, 229)*
Qualification	Postgraduate degree (e.g., MA, PhD)	**107** *(0, 25, 62)*
	Degree (e.g., BA, BSc)	**884** *(506, 44, 334)*
	Professional qualification (e.g., teaching, nursing, accountancy)	**372** *(28, 2, 342)*
	Other vocational / work related qualifications	**98** *(0, 4, 94)*
	Foundation degree / Progression diploma / Advanced diploma / Certificate or equivalent	**77** *(3, 13, 61)*
	A levels / AS levels / VCEs / Higher diploma or equivalent	**10** *(0, 10, 0)*
	GCSEs / CSEs / O levels or equivalent	**62** *(0, 62, 0)*
	No qualifications or education	**5** *(0, 4, 1)*
	Prefer not to say/Other	**301** *(4, 6, 291)*
Plays videogames?	Yes	**1640** *(384, 141, 1115)*
	No	**276** *(177, 29, 70)*

Measures

Internet Gaming Disorder Scale – Short Form 9 (IGDS9-SF)

The nine-item IGDS9-SF (Pontes & Griffiths, 2015) was used to assess the severity of GD symptoms by examining an individual's offline and online behaviours. Items include: *"Do you systematically fail when trying to control or cease your gaming activity?"* and *"Have you jeopardized or lost an important relationship, job or career opportunity because of your gaming activity?".* Participants respond to each item on a five-point scale from 1 (*never*) to 5 (*very often*). The final GD score is calculated by summing up the individual's answers and ranges from 9 to 45, with higher scores indicating higher severity of gaming disorder behaviours. The scale has been shown to be a reliable measure with a Cronbach's α of .88 (Pontes & Griffiths, 2015). In the present study, the scale showed very good reliability (Cronbach's α = .88).

Problem Gambling Severity Index (PGSI)

The nine-item PGSI (Ferris & Wynne, 2001) was used to assess problem gambling over the past 12 months (e.g., *"Have you gone back on another day to try to win back the money you lost?"*). Participants respond to items on a four-point scale ranging from 0 (*never*) to 3 (*always*). The total score is obtained by summing up each of the answers given and can range from 0 to 27, with higher scores indicating greater gambling severity. The final score relates to one of four gambling domains: non-problem gambler=0; Low-risk gambler=1–2; Moderate-risk gambler=3–7; Problem gambler=8 or above. This has been shown to be a reliable scale with a Cronbach's α of .76 (Ferris & Wynne, 2001). In the present study, the scale showed excellent reliability (Cronbach's α = .94).

Internet Disorder Scale 9–Short Form (IDS9-SF)

The nine-item IDS9-SF (Pontes & Griffiths, 2017) was used to assess problematic internet use behaviours over the past 12 months (e.g., *"Do you feel more irritability, anxiety and/or sadness when you try to either reduce or stop using the internet?"*). Responses are scored on a five-point scale ranging from 1 (*never*) to 5 (*very often*). The final score is calculated by adding each item score which gives a total score ranging from 9 to 45. Higher scores indicate a greater severity of disordered internet use. The IDS9-SF has been shown to be a reliable scale with a Cronbach's α of .96 (Pontes & Griffiths, 2017). In the present study, the scale showed very good reliability (Cronbach's α = .89).

The Bergen Social Media Addiction Scale (BSMAS)

The BSMAS (Andreassen et al., 2016) is an adapted version of the Bergen Facebook Addiction Scale (BFAS; Andreassen, Torsheim, Brunborg, & Pallesen, 2012) and includes six items assessing addictive social media use (e.g., *Facebook, Instagram, Twitter*) in the past 12 months. Each item reflects a core addiction element (e.g., withdrawal: *"How often have you become restless or troubled if you have been prohibited from using social media?"*), and is scored on a five-point scale ranging from 1 (*very rarely*) to 5 (*very often*) and can have a total score between 6 and 30. A higher score indicates a greater risk of social media addiction. The BSMAS has very good reliability (Cronbach's α = .88; Andreassen et al., 2016). In the present study, the scale showed very good reliability (Cronbach's α = .89).

Bergen-Yale Sex Addiction Scale (BYSAS)

The six-item BYSAS (Andreassen et al., 2018) was used to assess participants' problematic sexual activity over the last 12 months (e.g., *"How often … have you spent thinking about sex or masturbation?"*). Each response is scored on a five-point scale, with scores ranging from 0 (*very rarely*) to 4 (*very often*). To obtain the total score, the scores on each item are summed. The total score can range from 0 to 24, with a higher total score indicating a greater risk of sex addiction. The BYSAS has been found to be a reliable scale with a Cronbach's α of .82 (Andreassen et al., 2018). In the present study, the scale showed very good reliability (Cronbach's α = .84).

Bergen Shopping Addiction Scale (BSAS)

The seven-item BSAS was used to assess for problematic shopping behaviour (Andreassen et al., 2015). Participants respond to each item (e.g., *"I think about shopping or buying things all the time"*) on a five-point Likert scale from 0 (*completely disagree*) to 4 (*completely agree*). The final score is calculated by summing up the individuals' answers and ranges from 0 to 28, with higher scores indicating greater risk of shopping addiction. The BSAS has been found to be a reliable scale with a Cronbach's α of .87 (Andreassen et al., 2015). In the present study, the scale showed excellent reliability (Cronbach's α = .90).

Exercise Addiction Inventory–Revised (EAI-R)

The six-item EAI-R was used to assess addictive exercise (Szabo et al., 2019). Participants respond to each item (e.g., *"Over time I have increased the amount of exercise I do in a day"*) on a six-point Likert scale from 1 (*strongly disagree*) to 6 (*strongly agree*). The final score is calculated by summing up the individual's answers and ranges from 6 to 36, with higher scores indicating greater risk of exercise addiction. The EAI-R has been found to be a reliable scale with a Cronbach's α of .90 (Szabo et al., 2019). In the present study, the scale showed very good reliability (Cronbach's α = .85).

Cigarette Dependency Scale–5 (CDS)

The five-item CDS-5 (Etter et al., 2003) was used to assess the degree to which participants were dependent on cigarettes. Each item is scored on a five-point scale and assesses their cigarette use (e.g., *"Please rate your addiction to cigarettes on a scale of 0 to 100?"*) and habits (e.g., *"Usually, how soon after waking up do you some your first cigarette?"*). Questions 1 to 3 are open questions (e.g., "On average, how many cigarettes do you smoke per day?") where a participant can write their response. The response is then converted into a five-point scale (e.g., "8 cigarettes per day" equates to a score of 2 [6-10 cigarettes per day]). Questions 4 and 5 require typical responses with scores ranging from 1 (*totally disagree*) to 5 (*fully agree*). Questions 3 and 4 are both reverse coded, where the lower point is scored as 5 and the higher point is scored as 1 (e.g., *"For you, quitting smoking would be "Impossible"* [5] to *"Very Easy"* [1]). The final score is calculated by summing up the answers and ranges from 5 to 25, with higher scores indicating higher severity of cigarette dependant behaviours. The CDS-5 has been found to be a reliable scale with a Cronbach's α of .83 (Etter et al., 2003). However, in the present study, the scale showed lower reliability (Cronbach's α = .68).

Alcohol Use Disorder Identification Test (AUDIT)

The ten-item AUDIT (Saunders et al., 1993) was used to assess alcohol consumption, drinking behaviours, and alcohol-related problems (e.g., *"How often do you have six or more drinks on the one occasion?"*). Items 1 to 8 are rated on a five-point scale, which are scored from 0 (e.g., *"Never"*) to 4 (e.g., *"Daily or almost daily"*), whereas Items 9 and 10 are rated on a three-point scale and are scored as 0 (*"No"*), 2 (*"Yes, but not in the past"*), and 4 (*"Yes, during the past year"*). The total score comprises the summing of each of the selected item scores. The total score can range from 0 to 40. A score of 8 or more indicates hazardous drinking. A score of 13 or more in women, and 15 or more in men, may indicate alcohol dependence. The AUDIT has demonstrated good reliability. For example, in a systematic review by Meneses-Gaya et al. (2009) across ten studies the average Cronbach's alpha was .80. In the present study, the scale showed very good reliability (Cronbach's α = .87).

Drug Abuse Screen Test - 10 (DAST)

The ten-item DAST-10 (Skinner, 1982) was used to assess drug use behaviours in the past 12 months (e.g., *"Do you feel bad or guilty about your drug use?"*). Each item is rated on a dichotomized scale (yes/no answers). Each "Yes" answer is scored with 1, while each "No" answer is score with 0 – except for Question 3 for which a “No” is scored with 1 while “Yes” is scored with 0. The total score ranges from 0 to 10: 0=no problems; 1-2=low problems; 3-5=moderate problems; 6-8=substantial problems; 9-10=severe problems. In a systematic review on the psychometric properties of the DAS, Yudko, Lozhkina, and Fotus (2007) reported it to be a reliable measure with multiple studies citing a Cronbach’s α of over .90. In the present study, the scale demonstrated very good reliability (Cronbach’s α = .83).

Brief Coping Orientation to Problems Experienced (Brief-COPE)

The 30-item Brief-COPE (Carver et al., 1997) was used to assess coping behaviours individuals employed when experiencing stressful situations. Participants are asked to think about a recent stressful event in their life and how they coped within that situation. The Brief-COPE is rated on a four-point scale: 1 (*I haven’t been doing this at all*), 2 (*I’ve been doing his a little*), 3 (*I’ve been doing this a medium amount*), and 4 (*I’ve been doing this a lot*). The Brief-COPE has a total of 15 two-item subscales (e.g., self-distraction, substance use, humour). The subscale scores are then added together to give a score ranging from 2-8. A higher score on the subscale represents a higher utilisation of the related coping behaviour. These smaller subscales form a super-ordinate domain coping style. These are: emotion-focused coping (EFCope; scoring from 10 to 40; Cronbach’s α of .83), dysfunctional coping (DCope; scoring from 12 to 48; Cronbach’s α of .82), and problem-focused coping (PFCope; scoring from 6-24; Cronbach’s α of .76). The internal consistency estimates of the current study reflect the previously reported estimates in Carver’s (1997) paper (which ranged between .50 to .90), thus we consider the psychometric properties to be acceptable.

Ten Item Personality Inventory (TIPI)

The 10-item TIPI (Gosling et al., 2003) was used to briefly assess personality traits. The TIPI assesses extraversion, agreeableness, conscientiousness, emotional stability, and openness to experiences. Participants are asked to agree or disagree with a statement using a seven-point Likert scale from 1 (*disagree strongly*) to 7 (*agree strongly*). Each even number item (e.g., 2, 4, 6, etc.) is reverse scored and then the items are paired off into each of the five subscales. These two items are then averaged to give the total score of that subscale with higher scores indicating more pronounced personality traits. The original TIPI (Gosling et al., 2003) showed low-to-moderate Cronbach's alphas (α = 0.40-0.68), which is a common range within short scales (Ziegler et al., 2014). The present study had a Cronbach’s α ranging between .29 (Agreeableness) to .79 (Extraversion). As such, to better investigate the reliability of the present scale a McDonald’s coefficient omega was calculated at .52, 95% CI[.46-.58], indicating adequate internal consistency.

Data Analysis

First, the missing data imputation was calculated for the study variables and followed by descriptive statistics. In order to test the hypotheses, an LPA was conducted, a strategy which is appropriate for continuous indicators (Muthen & Muthen, 2000). The LPA investigates whether relatively homogeneous groups (i.e., profiles) can be identified based on observed values (Oberski, 2016). This shows whether structural groups exist in the data, where participants show similarities and differences with each other.

To examine whether and to what extent disordered behaviours differed across individualised countries, an LPA was conducted in Rstudio using tidyLPA (Rosenberg et al., 2018). For the LPA, disordered behaviours and substance use, personality, and coping domain variables were included. More specifically, scores of disordered gaming, internet use, social media, shopping, gambling, sex, exercise, drug use, alcohol use, and cigarette use were included, alongside scores on the five domains of personality (i.e., extraversion, agreeableness, conscientiousness, emotional stability, & openness to experience) and the three sub-domains of coping (i.e., problem-focused coping, emotion-focused coping, and dysfunctional coping). Within LPA, a range of models are predicted, and within these models an increasing number of profiles are tested. The Bayesian information criterion (BIC) and Akaike information criteria (AIC) indicate the fit of the model used, with the lower numbers indicating a better fit (Weller et al., 2020). Entropy indicates how well the model classifies participants into different profiles without overlap in or exclusion from other profiles. As such, lower entropy scores indicate that participants can be classified into more than one profile; therefore, entropy scores of 0.80 and over are recommended (Weller et al., 2020). Lastly, the bootstrap likelihood ratio test (BLRT) indicates whether models with one additional profile outperform the previous model.

To further validate the assessment of differences between the classes and to investigate the extent of these differences, a collection of multivariate analyses of variance (MANOVAs) was used between the identified profiles of each cohort and their effect sizes (Burns & Burns, 2008; Everitt et al., 2011). Following this, a pairwise comparison was conducted on the appropriate profiles and variables to investigate the specific differences between the selected profiles.

Results

The LPA was conducted using the equal variances and covariances fixed to zero model (i.e., EEI). This model demonstrated a better fit for the data and interpretability when compared to other LPA models. As seen in Table 2, the BIC suggested a four-model class across each of the cohorts. The BIC is considered the most reliable fit statistic in LCA (Weller et al., 2020). Therefore, a four-profile model was used. It is also important to note the four-profile model had adequate entropy (i.e., above the cut-off of .80; Weller et al., 2020), indicating that participants were assigned to profiles effectively.

Table 2

Model fit indices of latent profile analyses for all models compared in UK cohort.

Cohort	Classes	AIC	BIC	Entropy	Prob min	Prob max	% min	% max	BLRT *p*-value
UK	1	28710.87	28866.74	1.00	1.00	1.00	1.00	1.00	
UK	2	27955.39	28193.52	0.77	0.91	0.95	0.42	0.58	0.01
UK	3	27257.83	27578.23	0.85	0.92	1.00	0.05	0.52	0.01
UK	***4***	***27095.99***	***27498.66***	***0.79***	***0.84***	***1.00***	***0.05***	***0.39***	***0.01***
NZ	1	8737.85	8850.74	1.00	1.00	1.00	1.00	1.00	
NZ	2	8423.71	8596.18	0.94	0.93	0.99	0.18	0.82	0.01
NZ	3	8287.44	8519.49	0.94	0.92	1.00	0.07	0.74	0.01
NZ	***4***	***8170.85***	***8462.48***	***0.91***	***0.91***	***1.00***	***0.06***	***0.57***	***0.01***
AU	1	60585.91	60768.70	1.00	1.00	1.00	1.00	1.00	
AU	2	58451.02	58730.28	0.84	0.93	0.97	0.33	0.67	0.01
AU	3	57974.18	58349.91	0.76	0.86	0.91	0.25	0.38	0.01
AU	***4***	***56963.68***	***57435.89***	***0.81***	***0.85***	***0.96***	***0.10***	***0.35***	***0.01***

Note. The selected model specification bolded, and the selected model italicized.

Figures 1-3 show a graphical representation of each of the three cohorts and their four-profile model. The x-axis provides the names of each of the behaviours, personality factors, and coping style variables. The y-axis provides the standardised mean score of each profile in relation to each variable. Each cohort appeared to exhibit two profiles that averaged higher on disordered behaviours and dysfunctional coping strategies, and two profiles that averaged lower across disordered behaviours and dysfunctional coping strategies. Therefore, the two profiles which displayed higher scores on the disordered behaviour measures and on the dysfunctional coping strategies were classified as risk profiles. The two risk profiles were classified as 'at-risk' (i.e., the profile which typically demonstrated high disordered behaviour scores and lower substance use and dysfunctional coping scores in comparison to the 'high-risk' profile) and 'high risk' (i.e., the profile which demonstrated consistent high disordered substance use scores and a higher dysfunctional coping score, in comparison to at-risk). This process was done visually and was dependent on the scores obtained, and therefore a somewhat subjective choice; nevertheless, it is warranted in order to communicate the data effectively. The remaining profiles were classified as 'low-risk' profiles. These were spilt into low-risk extraversion and low-risk introversion, as each cohort demonstrated a low-risk profile with higher extraversion and lower extraversion (i.e., introversion). However, in line with the hypotheses, the present paper will consider the at-risk and high-risk profiles.

UK Cohort

Figure 1 shows four profiles found in the UK cohort. The at-risk profile was the larger of the two risk profiles and comprised 220 participants (38.86% of UK cohort), while the high-risk profile comprised 26 participants (4.59% of UK cohort). In the UK Cohort, it can be seen that the high-risk profile demonstrated a consistently higher standardised difference from the sample mean (z) than the at-risk profile, except on social media use (high-risk: $z = 0.42$; at-risk: $z = 0.66$). In addition, individuals with the high-risk profile scored lower on personality factors (bar emotion stability; high-risk: $z = 0.03$; at-risk: $z = -0.39$) and scored lower on problem-focused ($z = -0.04$) and emotion-focused ($z = 0.04$) coping strategies when compared to the sample mean of the at-risk profile ($z = 0.14$, $z = 0.26$, respectively). Both the at-risk and high-risk profiles demonstrated a clear reliance on dysfunctional coping strategies ($z = 0.61$, $z = 0.64$, respectively). Further details in relation to the UK cohort can be seen in Table 3

Table 3

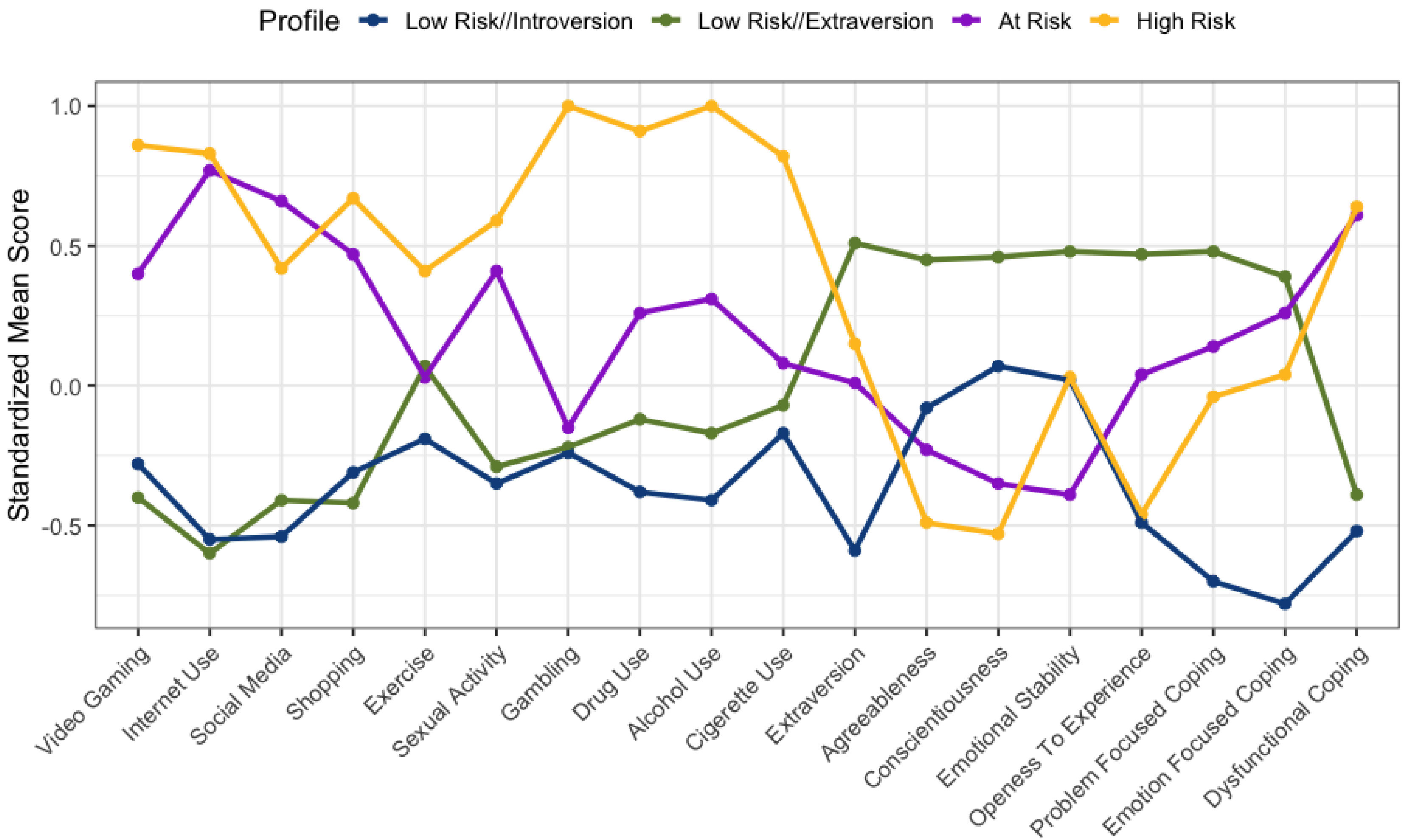
Standardised Score from the Sample Mean in UK Cohort

Variable	At-risk	High-Risk	Low-risk/Extraversion	Low-risk/Introversion
Video Gaming	0.40	0.86	-0.40	-0.28
Shopping	0.47	0.67	-0.42	-0.31
Sexual Activity	0.41	0.59	-0.29	-0.35
Social Media	0.66	0.42	-0.41	-0.54
Internet Use	0.77	0.83	-0.60	-0.55
Drug Use	0.26	0.91	-0.12	-0.38
Alcohol Use	0.31	1.00	-0.17	-0.41
Cigarette Use	0.08	0.82	-0.07	-0.17
Exercise	0.03	0.41	0.07	-0.19

Gambling	-0.15	1.00	-0.22	-0.24
Extraversion	0.01	0.15	0.51	-0.59
Agreeableness	-0.23	-0.49	0.45	-0.08
Conscientiousness	-0.35	-0.53	0.46	0.07
Emotional Stability	-0.39	0.03	0.48	0.02
Openness To Experience	0.04	-0.46	0.47	-0.49
Problem Focused Coping	0.14	-0.04	0.48	-0.70
Emotion Focused Coping	0.26	0.04	0.39	-0.78
Dysfunctional Coping	0.61	0.64	-0.39	-0.52

Figure 1

Standardized Mean Score Graph of the United Kingdom (UK) Cohort



New Zealand Cohort

Figure 2 shows the four profiles found in the NZ cohort. As in the previous analysis, there was a noticeable difference seen between the at-risk and high-risk profiles. The at-risk profile comprised 34 participants (20% of NZ cohort), while the high-risk profile comprised 10 participants (5.88% of NZ cohort). Within the NZ cohort, the at-risk profile demonstrated three higher standardised scores from the sample mean across gaming (z = 0.68), internet use (z = 1.00), and social media use (z = 1.00) in comparison to the high-risk profile (z = 0.51, 0.62, 0.67, respectively). As with the UK cohort, the high-risk cohort demonstrated a higher standardized difference from the sample mean across substance use (ranging from z = 0.96-1.00), whereas the at-risk profile demonstrated lower scores (ranging from z = -0.23 to 0.11). In addition, the high-risk profile had a low conscientious score (z = -1.30) and a high openness to experience score (z = 0.57), in contrast to the at-risk profile (z = -0.55, -0.12, respectively). Furthermore, both the at-risk and high-risk profiles demonstrated a high standardized difference from the sample mean (z = 0.93, z = 1.00, respectively). Further details in relation to the NZ cohort can be seen in Table 4.

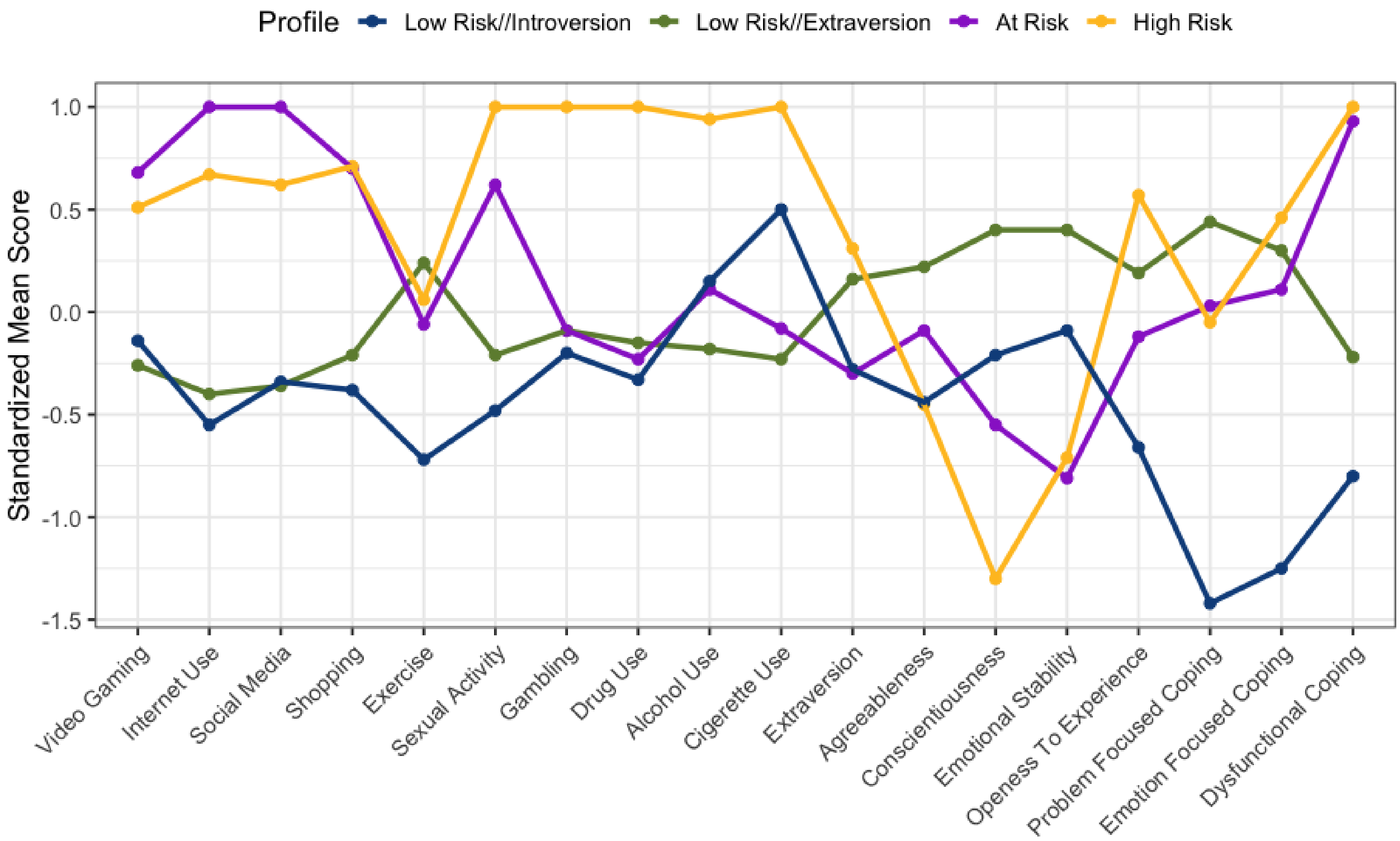
Table 4

Standardised Score from the Sample Mean in NZ Cohort

Variable	At-risk	High-Risk	Low-risk/Extraversion	Low-risk/Introversion
Video Gaming	0.68	0.51	-0.14	-0.28
Shopping	0.70	0.71	-0.38	-0.31
Sexual Activity	0.62	1.00	-0.48	-0.35
Social Media	1.00	0.62	-0.34	-0.54
Internet Use	1.00	0.67	-0.55	-0.55
Drug Use	-0.23	1.00	-0.33	-0.38
Alcohol Use	0.11	0.94	0.15	-0.41
Cigarette Use	-0.08	1.00	0.50	-0.17
Exercise	-0.06	0.06	-0.72	-0.19
Gambling	-0.09	1.00	-0.20	-0.24
Extraversion	-0.30	0.31	-0.28	-0.59
Agreeableness	-0.09	-0.45	-0.44	-0.08
Conscientiousness	-0.55	-1.30	-0.21	0.07
Emotional Stability	-0.81	-0.71	-0.09	0.02
Openness To Experience	-0.12	0.57	-0.66	-0.49
Problem Focused Coping	0.03	-0.05	-1.42	-0.70
Emotion Focused Coping	0.11	0.46	-1.25	-0.78
Dysfunctional Coping	0.93	1.00	-0.80	-0.52

Figure 2

Standardized Mean Score Graph of the New Zealand (NZ) Cohort



Australian Cohort

Figure 3 shows the four profiles found in the AU cohort. As in the previous two analyses, there was a noticeable difference between the at-risk and high-risk profiles. The at-risk profile comprised 314 participants (26.49% of AU cohort), while the high-risk profile comprised 115 participants (9.70% of AU cohort). As with the two previous cohorts, the AU cohort demonstrated a consistently high standardised score from the sample mean in both the at-risk and high-risk profiles. The AU cohort's at-risk profile demonstrated higher standardised scores from the sample mean across gaming ($z = 0.85$), internet use ($z = 0.99$), social media use ($z = 0.76$), and shopping ($z = 0.60$). The high-risk profile consistently had a higher standardised score from the sample mean across substance related behaviours (ranging from $z = 0.86$ to $z = 1.00$). In regard to personality variables, both the at-risk ($z = -0.41$) and high-risk profiles ($z = -0.63$) scored quite low on conscientiousness and scored quite high in dysfunctional coping strategies ($z = 0.68$, $z = 0.96$, respectively). Further details in relation to the AU cohort can be seen in Table 5.

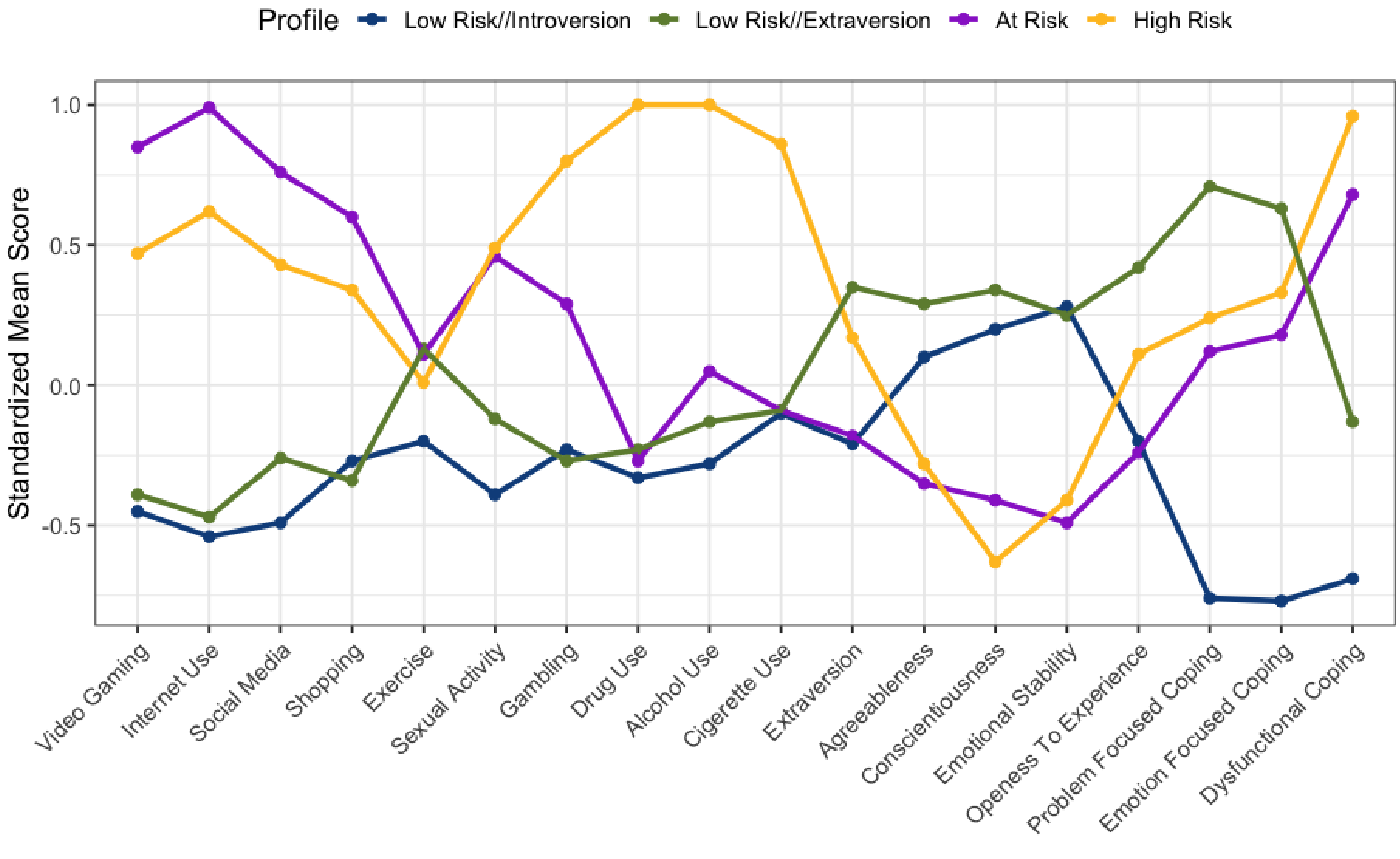
Table 5

Standardised score from the sample mean in AU Cohort

Variable	At-risk	High-Risk	Low-risk/Extraversion	Low-risk/Introversion
Video Gaming	0.85	0.47	-0.39	-0.45
Shopping	0.60	0.34	-0.34	-0.27
Sexual Activity	0.46	0.49	-0.12	-0.39
Social Media	0.76	0.43	-0.26	-0.49
Internet Use	0.99	0.62	-0.47	-0.54
Drug Use	-0.27	1.00	-0.23	-0.33
Alcohol Use	0.05	1.00	-0.13	-0.28
Cigarette Use	-0.09	0.86	-0.09	-0.10
Exercise	0.11	0.01	0.13	-0.20
Gambling	0.29	0.80	-0.27	-0.23
Extraversion	-0.18	0.17	0.35	-0.21
Agreeableness	-0.35	-0.28	0.29	0.10
Conscientiousness	-0.41	-0.63	0.34	0.20
Emotional Stability	-0.49	-0.41	0.25	0.28
Openness To Experience	-0.24	0.11	0.42	-0.2
Problem Focused Coping	0.12	0.24	0.71	-0.76
Emotion Focused Coping	0.18	0.33	0.63	-0.77
Dysfunctional Coping	0.68	0.96	-0.13	-0.69

Figure 3

Standardized Mean Score Graph of the Australian (AU) Cohort



At-risk Profile Across Cohorts

To investigate if the at-risk profiles differed significantly from each cohort, a one-way multivariate analysis of variance (MANOVA) was performed. A MANOVA was used to determine the difference of the at-risk cohort group on the behavioural (e.g., video gaming, internet use), substance (i.e., drug, alcohol, and cigarette use), personality (e.g., extraversion, agreeableness), and coping variables (i.e., problem-focused, emotion-focused, and dysfunctional coping). The three groups investigated were: (i) UK (at-risk profile), (ii) NZ (at-risk profile), and (iii) AU (at-risk profile). There was a statistically significant difference between the groups on the combined dependent variables (i.e., behaviour, substance, personality, and coping), $F(36, 1098) = 3.93$, $p<0.001$; Pillai's trace = .229, partial $\eta^2 = .114$. Follow-up univariate Welch ANOVAs using Hochberg correction showed there was a statistically significant group difference in scores in video gaming ($F[2, 87.9] = 13.6$, $p = <0.001$), internet use ($F[2, 91.7] = 12.3$, $p<0.001$), gambling ($F[2, 91.2] = 16.2$, $p<0.001$), and drug use ($F[2, 100] = 22.9$, $p<0.001$). Games Howell pairwise comparisons (adjusted Tukey p-value) were then conducted between the group's significant variables (i.e., video gaming, internet use, gambling, and drug use). Significant differences were observed (see Table 6).

Table 6

At-risk Profile Post-hoc Games Howell Pairwise Comparisons

Variables	Cohort 1	Cohort 2	Estimate	Confidence low	Confidence high	Adjusted *p*-value
Drug Use	AU	NZ	-0.002	-0.171	0.167	1.00
Drug Use	***AU***	***UK***	***0.538***	***0.350***	***0.727***	***<.001***
Drug Use	***NZ***	***UK***	***0.541***	***0.305***	***0.776***	***0.001***
Gambling	***AU***	***NZ***	***-0.390***	***-0.702***	***-0.078***	***0.011***
Gambling	***AU***	***UK***	***-0.442***	***-0.625***	***-0.260***	***<.001***
Gambling	NZ	UK	-0.052	-0.328	0.223	0.889
Internet Use	***AU***	***NZ***	***0.410***	***0.0580***	***0.763***	***0.019***
Internet Use	***AU***	***UK***	***-0.244***	***-0.411***	***-0.076***	***0.002***
Internet Use	***NZ***	***UK***	***-0.655***	***-1.014***	***-0.295***	***<.001***
Video Gaming	AU	NZ	-0.183	-0.745	0.378	0.707
Video Gaming	***AU***	***UK***	***-0.481***	***-0.697***	***-0.265***	***<.001***
Video Gaming	NZ	UK	-0.298	-0.868	0.272	0.419

Note. With adjusted Tukey p-value. Bold and italicised rows indicate significance.

High-risk Profile Across Cohorts

To investigate if the high-risk profiles differed significantly from each cohort, a one-way multivariate analysis of variance (MANOVA) was performed. The three groups investigated were: (i) UK (high-risk profile), (ii) NZ (high-risk profile), and (iii) AU (high-risk profile). There was a statistically significant difference between the groups on the combined dependent variables (i.e., behaviour, substance, personality, and coping), $F(36, 264) = 3.96$, $p<0.001$; Pillai's trace = .702, partial $\eta^2 = .351$. Follow-up univariate Welch ANOVAs, using Hochberg correction, showed that there was a statistically significant group difference in scores in gambling ($F[2, 21] = 59.2$, $p<0.001$) and drug use ($F[2, 100] = 21$, $p<0.001$). Games Howell pairwise comparisons (adjusted Tukey *p*-value) were then conducted between the group's significant variables (i.e., gambling and drug use). Significant differences were observed (see Table 7).

Table 7

High-risk Profile Post-hoc Games Howell Pairwise Comparisons

Variables	Cohort 1	Cohort 2	Estimate	Confidence low	Confidence high	Adjusted *p*-value
Drug Use	***AU***	***UK***	***-1.672***	***-2.454***	***-0.89***	***<.001***
Drug Use	AU	NZ	0.638	-0.117	1.393	0.101
Drug Use	***UK***	***NZ***	***2.311***	***1.314***	***3.308***	***<.001***
Gambling	***AU***	***UK***	***3.230***	***2.525***	***3.935***	***<.001***
Gambling	AU	NZ	0.968	-1.863	3.800	0.626
Gambling	UK	NZ	-2.262	-5.108	0.584	0.124

Note. With adjusted Tukey p-vale. Bold and italicised rows indicate significance.

Discussion

In the present study, firstly, the latent profiles found within the different individualistic countries of Australia, New Zealand, and the United Kingdom were explored. Secondly, these profiles were compared across the aforementioned countries to investigate the potential differences between high-risk and at-risk groups by exploring how gaming, problematic behaviour and substance use, personality factors, and coping mechanisms were reported within these individualistic countries, as opposed to the often-examined individual/collectivist dichotomy.

The findings suggest that H_1 was partially supported. More specifically, it was found that across each cohort, there was a profile (i.e., high-risk profile) in which individuals scored consistently higher across substance use variables (i.e., drug use, alcohol use, cigarette use) with varying elevated levels of behavioural variables (e.g., gaming, social media use). Similarly, a profile with elevated levels across behavioural and substance use was also found within each profile. Individuals with this profile consistently scored lower than individuals with the high-risk profile – but higher than individuals with the low-risk profiles. Therefore, H_2 was supported, which suggests that each cohort contains a profile which demonstrated at-risk scores, i.e., scores which were lower than the highest profile but were higher than low-risk profiles. The profiles identified as at-risk and high-risk demonstrated consistently higher scores on dysfunctional coping strategies, and lower scores on conscientiousness. In addition, scores on emotional stability remained low in both the risk profiles and low-risk profiles, therefore partially supporting H_3. Lastly, H_4 was partially supported. More specifically, while the at-risk profile demonstrated significant differences between cohorts, these differences were not present across all variables.

Risk Profiles Across Cohorts

The results of the LPA provided some support for H_4, which suggested that within each cultural cohort, a set of unique risk factors would be present. The at-risk profile made up 39.2%, 20%, and 25.5% of total UK, NZ, and AU cohorts, respectively, while the high-risk profiles made up 4.6%, 5.8%, and 9.7%, respectively.

Behaviour, Substance Use, and Co-occurrence

In regard to drug use scores in the at-risk group, the UK cohort demonstrated higher scores than both the AU and NZ cohorts, while the AU and NZ cohorts did not show any significant differences. This suggests the UK cohort may have experienced higher rates of substance use. In regard to behaviours, the AU cohort demonstrated significantly higher scores on gambling and gaming, while each cohort varied in relation to disordered internet use. In regard to the high-risk sample, the UK cohort demonstrated higher scores on substance use when compared with both the AU and NZ cohorts. The AU cohort scored significantly higher on gambling than the UK cohort. These findings suggest that, within the present at-risk sample, there are nuances in how each cohort experienced behavioural and substance use disorders. This is in line with previous literature suggesting that a country can influence specific risk behaviours (Király et al., 2019; Laconi et al., 2017), with the present study suggesting that this is not limited to countries that have different cultural norms. There is evidence to suggest that individualistic and collectivist countries can influence how the individual experiences and manifests disordered behaviours (Andreetta et al., 2020). However, as seen in the present study, this is also apparent in country that share many intracultural similarities.

Understanding how individuals interact within their country and how their country may contribute to the manifestation and prevalence of disordered behaviours has important implications for at-risk individuals because the literature suggests that cultural paradigms may influence specific co-occurring problematic behaviours among at-risk individuals (Andreetta et al., 2020). Within the current cohorts in the present study, the results suggested that the UK cohort demonstrated a higher risk in relation to substance abuse, whereas the AU cohort demonstrated a higher risk of gambling. Understanding the potential co-occurring at-risk and high-risk behaviours associated with substance use or gambling may allow researchers to better contextualise and explore issues of co-occurrence across these specific individualistic country by considering the specific intracultural nuances. Co-occurrence is prevalent across multiple different countries, both individualistic and collectivist (Burleigh, Griffiths, et al., 2019), and research has shown that co-occurrence is related to, and thus, may complicate the diagnosis and treatment of clinical disorders (Najt et al., 2011). Therefore, it is important that clinicians have access to empirical data that will aid in the creation of early interventions which are tailored to at-risk groups, with a focus on the known co-occurring issues experienced within their country. While the differences in the engagement of substance use and behaviours are apparent, it should be noted that the cohorts shared similarities in both personality and coping style.

Personality Factors

In regard to the personality factors assessed within the at-risk cohorts, only individuals with higher extraversion scores were found to score consistently higher across all three at-risk cohorts – however, it should be noted that within the UK at-risk cohort, individuals scored higher on "openness to experience" when compared to the standardised mean of the other cohorts. The remainder of the personality factors (i.e., agreeableness, conscientiousness, emotional stability, and openness to experience) were found to be negatively associated with the at-risk profile. Emotional stability was found to be the lowest scored personality trait across all three at-risk cohorts. In regard to the high-risk cohorts, it was found that individuals consistently scored lower on conscientiousness across all cohorts. Similarly, there were lower scores on agreeableness when compared to the standardised means scores of other personality factors. There have been a number of studies which have considered personality in relation to both problematic substance use and behaviours (Chew, 2022; Hussain & Pontes, 2019), and the present findings suggest that within each risk profile cohort, there are consistent personality factors which are present. Indeed, the present results support that consistent personality factors can be seen across countries, and that some personality factors (e.g., low conscientiousness, extraversion) could be considered risk factors in relation to problematic behaviours and substance use (Chew, 2022; Hussain & Pontes, 2019).

It is well established that high levels of extraversion and low levels of conscientiousness can, and often are, used as a predictors for disordered behaviours (Lui & Rollock, 2020). The present study also supports the established literature on disordered behaviour. However, while there appears to be consistency in a majority of the personality factors in relation to addictive behaviours, it is interesting that extraversion is consistently high despite being tested on a high majority of gamers – when previous research suggests that extraversion is typically lower in gamers (Chew, 2022). This result may be due to the type of gamers surveyed. There is a large body of research which focused on individuals who play Massively Multiplayer Online Role-Playing Games (MMORPGs). Their findings suggest that more introverted individuals play these games in order to fulfil fantasies which they perhaps cannot fulfil in their offline life (Burleigh et al., 2018). However, videogames have evolved significantly in the past decade; new and more competitive gaming genres (e.g., Battle Royale games, Multiplayer Online Battle Arena [MOBA] games) have become increasingly popular (Laconi et al., 2017). It could be that the gamers surveyed in the present cohorts were more outgoing and competitive and therefore scored more highly on extraversion as a result. This may also be reflected in the substance use behaviour of these cohorts, as preliminary data suggest that competitive gamers consume substances with stimulating effects (Škařupová et al., 2018). This may also be associated with the low scores in agreeableness that were found among the at-risk and high-risk cohorts because low agreeableness is associated with competitive and antagonistic attitudes (Kaufman et al., 2019). How personality factors may influence individuals' engagement with different videogame genres is beyond the scope of the present study. However, the present study highlights the need to investigate the ambiguity found in relation to extraversion further.

Emotional stability appeared as the lowest scored trait across each of the at-risk and high-risk cohorts. However, it should be noted that the UK cohort appeared to have higher emotional stability within the high-risk profile, although this was not significantly higher than the other two cohorts. Nevertheless, poor emotional stability (i.e., neuroticism) indicates that individuals in the at-risk group may be more emotionally reactive, and therefore find it more difficult to cope with stressful situations (Kaufman et al., 2019). It then follows that those who have poor emotional stability are more likely to develop emotion-focused and dysfunctional coping strategies as they are more emotionally reactive.

Coping

In regard to coping, the findings suggest that coping style appeared to be associated with disordered behaviour, and similar to personality factors, this appeared to be consistent across cohorts. It was found that within both the at-risk and the high-risk profiles, individuals consistently scored higher on dysfunctional coping strategies relative to the sample mean, and higher than both problem-focused and emotion-focused coping. Therefore, the present findings support the broader literature that associates poor coping strategies with potentially addictive behaviours (Burleigh, Griffiths, et al., 2019). The high-risk cohort consistently scored higher on dysfunctional coping compared to their at-risk counterparts, which suggests that the coping strategies used are likely well established. This could indicate negative long-term effects on mental well-being (Loton et al., 2016) and the exacerbation of co-occurring behaviours (Kuss et al., 2017) as demonstrated by consistently high scores across disordered behaviour and substance use. For example, it has been documented that individuals, and particularly gamers, utilise strategies such as escapism to cope with stressors in life (Melodia et al., 2022). While this is not a maladaptive strategy in and of itself, if relied upon without other strategies, it may worsen symptomology (Kardefelt-Winther, 2014; Loton et al., 2016). Therefore, it is important that when considering disordered behaviours, such as gaming, a focus on how individuals cope with life stressors, and their reason for playing videogames (e.g., stress release, escapism), should be considered irrespective of country or perceived risk level. Indeed, a better understanding of coping strategies and how individuals with different personalities approach life stressors would be beneficial for both at-risk and high-risk groups.

Implications and Future Directions

The present results suggest that individuals within the at-risk profile would likely benefit from psychoeducation as a potential preventative strategy. In addition, psychoeducation which considers coping strategies may be efficacious despite varying cultural backgrounds because each present cohort displayed consistent coping profiles. More specifically, informing at-risk and high-risk individuals about adaptive coping strategies and co-occurrence would be beneficial (Lee et al., 2018), in conjunction with an understanding of cultural manifestations and shared clinical features (e.g., personality factors; Ream et al., 2011) of problematic behaviours and/or substance use could increase resilience. The present results also suggest that individuals within all high-risk cohorts scored highly across disordered substance use and some addictive behaviours, which may indicate co-occurrence (Burleigh, Kuss, et al., 2019). The present research suggests that when considering potential substance and behavioural addictions, a more nuanced understanding should be considered. A number of studies have considered the effect of co-occurring addictive disorders on treatment efficacy, suggesting that treatment efficacy can be increased when considering not only the primary disorder, but also other secondary problematic disordered behaviour (Burleigh, Kuss, et al., 2019; Kuss & Pontes, 2019). Indeed, research in the field of substance abuse has gained traction when considering an integrated treatment approach (Carrà et al., 2015; Roncero et al., 2017). The present research suggests that high rates of potentially addictive substances and behaviours are present in large samples of at-risk and high-risk gamers, which suggests that co-occurrence is as well. Therefore, scholars should also investigate the efficacy of integrated treatment paradigms when engaging at-risk and high-risk gamers.

Limitations and Strengths

There are some limitations that should be acknowledged. Firstly, the measure used to assess personality factors contained only two questions per personality domain, which results in the scale having an adequate omega coefficient. As a result, the conclusions drawn in relation to personality should be interpreted with caution, and future research should consider more psychometrically robust personality measures. Furthermore, the study employed self-report measures for each cohort; therefore, participants may not accurately represent their behaviours related to substance use or problematic behaviours, which may lead to biased reporting. Second, the present study utilised a cross-sectional design, and therefore temporal and casual relationships cannot be argued empirically. Third, it is worth noting that the NZ cohort and the number of non-gamers within the whole sample was quite small, which means that the results cannot (and should not) be generalised to the wider general population and may not apply to non-gamers. Fourth, the labels for each group (e.g., high risk, low risk) were decided based on a visual inspection of the data, and thus are subjective in nature. Lastly, while the present study contained three individualistic countries, generalisation to other individualistic countries (e.g., USA) may be limited, as individuals in these countries may have different risk factors unique to that specific country. However, this is also one of the strengths of the present study. The present study had a diverse sample from three individualistic countries, which had large to medium sample sizes within each cohort. The present study considered a number of different risk factors using an LPA analysis, and also provided evidence on how individuals with these profiles may or may not differ within similar cultural settings. The study also provides valuable insight into the gaming community and further adds to the call for stronger research into treatment paradigms (Andreetta et al., 2020).

Conclusions

While evidence suggests that a minority of gamers are affected by GD, there appears to be an at-risk cohort who may utilise gaming as a maladaptive coping strategy and other accompanying potentially addictive behaviour or substance use may be exacerbated as a result (Pontes, 2018), the manifestation of which can be influenced based on cultural elements (Andreetta et al., 2020). Therefore, when considering gamers from similar countries, it is important to be cognisant of the variations found in the manifestations of GD and accompanying potentially addictive behaviours to allow for more precise identification of at-risk behaviours, which will result in more favourable treatment outcomes for those who are at-risk or high-risk individuals. Similarly, it is vital that future studies continue to investigate how cultural factors, individual factors, and their interactions may impact gamers as the present study suggests that factors can vary, even within countries which are more individualistically orientated.

Part III: General Discussion

Chapter 7

General Discussion

The present doctoral research thesis investigated the neurophysiological underpinnings of gaming disorder (GD), and the way in which co-occurrence can influence and correlate with GD in a clinical and a multi-cultural context. The unique contribution of knowledge was (i) the assessment of the neurophysiological expression of gamers using a novel spiking neural network (SNN) methodology; (ii) exploring co-occurrence in gamers and substance abstinent gamers; and (iii) exploring co-occurrence in gamers across three different individualistic countries (i.e., Australia, New Zealand, and the United Kingdom).

In order to contextualise the aims of the present doctoral thesis, the literature was systematically reviewed, with a focus on co-occurrence, EEG methodologies, and the use of ML algorithms within EEG resting state data. The first review presented in Chapter 1 aimed to determine the co-occurrence of potentially addictive behaviours with problematic and disordered gaming, and to explore the potential risk factors in the development and maintenance of co-occurrence within gaming disorder. The findings suggested that there were few empirical studies examining the (i) co-occurrence of gaming disorder with other addictive behaviours, (ii) longitudinal risk of disordered gaming with co-occurring addictive behaviours, and (iii) mechanisms of co-occurrence in disordered gaming with co-occurring potentially addictive behaviours. Furthermore, the findings suggested that that disordered gaming can co-occur with a variety of other addictive behaviours (e.g., alcohol use disorder or social media addiction). The reviewed literature suggested that gamers engage in a number of potentially addictive behaviours including substance use which can have detrimental outcomes on health and wellbeing. While a majority of the reviewed studies considered prevalence rates from a range of geographical locations, there are fewer studies which investigated individual and environmental risk factors. Therefore, the first chapter contextualized the understanding of co-occurrence and gaming within the present research project.

The second review in Chapter 2 contextualized and explored the methodological use of EEG within the GD field. This was done in an attempt to better understand how resting state EEG methodologies have been utilized, and therefore give insight into the current neurophysiological understanding of the presentation of GD. The results suggested individuals with GD have raised delta and theta activity and reduced beta activity, with coherence analysis suggesting altered brain activity in the mid-to-high frequency range. Individuals with internet addiction (IA) demonstrated raised gamma activity, and reduced beta and delta activity. The reason Chapter 2 also considered IA was to illustrate the differences between GD and IA and their neurophysiological expression. This was an important distinction because several problematic gaming labels (e.g., 'pathological video gaming'; Lemmens et al., 2011) have fallen under the IA umbrella (Kuss et al, 2014). The results of the review suggest that the altered brain activity found in GD/IA may represent distinct underlying neurophysiological markers or traits – which importantly – further supported the research suggested that they were unique constructs.

This ensured that utilizing the EEG methodology in Chapter 4 would yield results in relation to GD and not IA. As with previous research in the field, it was suggested that the findings of EEG studies should be replicated and/or explored in a wider variety of cultural contexts in order to strengthen the neurophysiological bases of GD. This was an important factor, as each of the EEG papers reviewed within Chapter 2 were from either China or South Korea. This indicated a dearth of resting state EEG methodologies employed in the western GD field; therefore, the present doctoral research project also filled this empirical gap by utilising a resting state EEG methodology in a western sample.

The third and last review chapter was presented in Chapter 3. This investigated the use of machine learning (ML) methodologies within the GD field. Chapters 2 and 3 illustrated that there is an increased need to better understand, conceptualise, and assess GD. The topic of assessment and prediction has long been explored by data analysts, experimental scientists, and psychologists. In recent years, the advent of artificial intelligence (AI) technology has brought new insights into the discussions regarding analysis and assessment (Orrù et al., 2020). Chapter 3 explored how ML methodologies had been employed within the GD field, with the aim of providing contemporary information on the use of ML techniques and findings in relation to GD. Therefore, providing an up-to-date summary of ML techniques currently employed and the subsequent findings within the scope of GD. The findings suggested that ML should be utilised in the assessment and prediction of GD. It was found that a wide variety of ML techniques were utilized in psychometric studies and reported high accuracy in differentiating disordered gamers from recreational gamers.

Furthermore, studies which investigated neurophysiological and physiological data utilized similar ML techniques, and all reported high accuracy, indicating that the use of neurophysiological in conjunction with EEG data would be a novel avenue of research for the present doctoral research project. The review concluded that future research should consider utilising ML to investigate other areas within the GD field, such as the detrimental aspects of co-occurrence in disordered behaviour and substance use. They highlight a further need to investigate potential applications of ML and related techniques in the detection and prediction of GD. Therefore, the present doctoral research project utilised an approach which combined resting-state EEG with a novel ML methodology within a western sample to contribute to the neurophysiological conceptualisation and understanding of GD, as detailed within the first empirical study.

The first empirical study presented in Chapter 4 (i) utilised the *NeuCube* SNN architecture within the GD field, thereby utilizing a novel AI-related methodology to discriminate recreational and problematic gaming behaviour; and (ii) investigated gamers using resting state EEG data to better understand the neurophysiological expression of recreational and problematic gaming. Resting state EEG data was collected from 16 participants, which was then analysed with the *NeuCube* – an SNN architecture. The results indicated that the *NeuCube* was able to accurately discriminate between recreational gamers and problematic gamers (within the current sample) with a high success rate. However, these results were not statistically significant when averaged and explored using a repeated measures ANOVA. This may be due to the limitations of averaging data points to conduct the analysis, and in doing so losing spatial and temporal data. Nevertheless, the results from the NeuCube suggest that recreational gamers and problematic gamers appear to have different resting state brain activity, suggesting that problematic play, and by extension disordered gaming, may alter an individual's neurophysiology. This provides evidence that GD has a neurophysiological underpinning and therefore should be considered as a disordered behaviour because it can alter neurophysiological expression. Understanding the different neurophysiological expressions of recreational and problematic gamers could aid in the early detection and classification of GD, and the *NeuCube* appears to be a viable tool to use to investigate these differences.

The second empirical study presented in Chapter 5 explored how gamers experienced co-occurrence in a general and a clinical sample. Chapter 4 suggested that recreational and problematic gamers appear to have different resting state neurophysiology depending on their involvement in videogames. Therefore, Chapter 5 sought to better understand the presentation of gamers in a non-clinical and clinical (substance abstinent) cohort, therefore, giving insight into the similarities and differences in mechanisms of disordered behaviour between GD and substance use disorder. A cross-sectional survey was conducted with a clinical sample of 64 substance abstinent participants and a control group comprised of 138 (convenience-sample) participants. The scores were standardised, and the control group was matched to the clinical cohort. The results suggested that gamers shared common at-risk behaviours (seen in both the clinical and non-clinical group). More specifically, problematic behaviours were more pronounced in abstinent substance use gamers, and more so in poly-substance use gamers.

The findings suggest that maladaptive coping style and co-occurrence appear in both groups. More specifically, dysfunctional coping strategies were found across both groups, and the maladaptive coping was found to be higher in the substance-abstinent gamers. This finding suggests that poly-substance users (i.e., individuals who take more than one illicit substance concurrently) may be at a higher risk of developing a repetitive use of videogames, representing a unique risk factor within gamers abstaining from substance use. This is an important finding because it highlights the complexities of clinical symptomology, and the way in which co-occurring use may manifest other potential underlying risk factors (Najt et al., 2011). Indeed, previous research has evidenced the co-occurrence of substance use and other addictive behaviours (Kotyuk et al., 2020). Chapter 5 adds to the discourse suggesting that there can be overlaps in problematic/disordered behaviours and substance use. Taken together, Chapters 3 and 4 illustrate that GD has both a neurophysiological underpinning and demonstrates observable maladaptive behaviours which mirror other disordered behaviours such as substance abuse disorder.

The US National Institute of Mental Health (NIMH) advocates using Research Domain Criteria (RDoC) and a multidimensional approach that includes observable behaviour and neurophysiological measurements to understand complex human behaviours and the mental disorder continuum (Clark et al., 2017). Chapters 4 and 5 established that there appears to be an empirical basis for both the neurophysiology and behavioural expression of GD, lending support to its inclusion in the ICD-11 and DSM-5 (American Psychiatric Association, 2013; World Health Organization, 2019). Furthermore, they demonstrated that gamers may have varying experiences due to the coping mechanisms they employed, with the studies suggesting that dysfunctional coping strategies can result in aggravation of disordered behaviours through a cycle of reciprocity (i.e., co-occurrence). However, it has been noted that co-occurrence (e.g., substance-use) can manifest in different ways due to cultural influences (Burleigh, Griffiths, et al., 2019). As Chapters 4 and 5 focused on smaller groups from different geographical locations, it was then important to understand how co-occurrence and maladaptive coping strategies may present themselves across different individual-oriented countries.

Indeed, the identification of individuals who may be at risk of developing maladaptive coping strategies – and the way in which their geographical location, and problematic behaviours such as GD or substance use may influence it – may have implications in both a research and clinical setting. Therefore, the aim with Chapter 6 was to identify profiles of individuals characterized by unique patterns of disordered behaviours (e.g., gambling, substance use), personality factors (e.g., neuroticism), co-occurrence, and coping strategies across individualised countries (i.e., Australia, New Zealand, and the United Kingdom). A cross-sectional survey was distributed across four different universities in three different countries. The total samples across Australia, New Zealand, and the United Kingdom were 1185, 170, and 561, respectively. A latent profile analysis (LPA) was conducted to investigate the potential differences between high-risk and at-risk groups by exploring how gaming, problematic behaviour and substance use, personality factors, and coping mechanisms were reported within these individualistic cultures.

The findings suggest that across each cohort, there was a consistent high-risk profile in which individuals scored consistently higher across substance use variables with varying elevated levels of behavioural variables (e.g., gaming). In addition to this, each cohort contained a profile which demonstrated at-risk scores (i.e., scores which were lower than the highest profile, but were higher than low-risk profiles). Both the high-risk and at-risk profiles consistently demonstrated higher scores on dysfunctional coping strategies, and lower scores on conscientiousness. In addition, scores on emotional stability were low in both the risk profiles and low-risk profiles. Therefore, there appears to be an at-risk cohort present in each country which score highly across multiple problematic behaviour measures. Considering their high scores in relation to dysfunctional coping strategies and gaming, they may utilise gaming as a maladaptive coping strategy, and as a result other accompanying potentially addictive behaviour or substance use may be influenced (Pontes, 2018).

The findings also suggested that the manifestation of substance use (e.g., alcohol, cigarette use, etc.) and problematic behaviours (e.g., gambling, gaming, sexual activity, etc.) can be influenced by the country that the participant resides in, as indicated by the differing risk-factors (e.g., problematic sexual behaviour is scored higher in the NZ high-risk cohort compared to the AU and UK high-risk cohorts) found within each cohort (Andreetta et al., 2020). Therefore, when considering gamers from individually-oriented countries, it is important to be cognisant of the variations found in the manifestations of GD and accompanying potentially addictive behaviours – and the co-occurrence of those behaviours – to allow for more precise identification of at-risk behaviours, which will result in more favourable treatment outcomes for those who are considered to be an at-risk or high-risk individual.

Methodology

In the present doctoral research project, quantitative research methods were employed, integrating novel ML methodologies in conjunction with EEG data. In the first empirical chapter (Chapter 4), EEG data were collected from a number of participants. There are several advantages to utilising EEG data over other neuroimaging techniques. For example, collecting EEG data does not require invasive scanning; it is more mobile than other neuroimaging machine (e.g., *f*MRI); it is also more accessible; and has a lower financial cost to utilise (Burleigh et al., 2020). In addition to this, EEG can capture spatial temporal brain data (STBD) when the human brain is activated by cognitive tasks, or even when it is at rest. It has also been used to investigate various disorders, with spectral and coherence analyses being employed to investigate addiction (Houston & Ceballos, 2013). Furthermore, EEG is capable of recording said STBD with high temporal resolution, allowing it to detect changes across the brain in milliseconds (Doborjeh et al., 2016). EEG is also able to detect and capture changes associated with perception and cognitive function, such as memory and attention. Consequently, EEG data analysis can be a complex task, and as such a wide range of methodologies have been used to interpret the data, such as AI-related approaches (Burleigh et al., 2020). Therefore, the use of EEG to collect neurophysiological data within Chapter 4 seemed appropriate due to the mobility, cost effectiveness, and its use within the behavioural addiction field.

Furthermore, EEG has been used with ML methodologies to improve classification of disorders using neurophysiological data (Drysdale et al., 2017). More specifically, ML methodologies have been used to improve prognosis and diagnosis in mood disorders using neurophysiological data (McGinnis et al., 2018; Tekin Erguzel et al., 2015). In recent years, there has also been preliminary use of SNN models and methodologies in conjunction with EEG data to analyse and interpret substance abuse data (Doborjeh et al., 2016; Doborjeh & Kasabov, 2016). When using SNN models (to analyse and interpret EEG-related STBD), results have demonstrated superior classification accuracy when compared with more traditional ML techniques such as support vector machine or logistic regression (Doborjeh et al., 2016). Therefore, given these methods appear to be under-utilised in the GD field (see Chapter 2 [i.e., Burleigh et al., 2020] and Chapter 3, for review), the present doctoral research project evaluated the efficacy of a novel ML SNN model in conjunction with complex STBD.

Moreover, deeper modelling insight into neural circuitry, information processing, and plasticity in brain areas is important in building an understanding between disordered gaming symptoms at the neural level and the resulting behavioural disorder of an individual. In order to provide novel insights into the potential use of neural networks and to identify specific neurological behaviour and disordered behaviour, in Chapter 4, a novel computational framework of brain-inspired SNN (i.e., the *NeuCube*) was applied to resting EEG data to investigate the differences between recreational and problematic gamers. Indeed, the use of a SNN, which considers both the *space* and *time* components of STBD, was an appropriate tool for the investigation of the neurophysiological presentation of gamers investigated in Chapter 4.

In addition to the aforementioned methods, self-report surveys were collected and analysed in both Chapters 5 and 6. While Chapter 5 contained a clinical sample which had been clinically evaluated, the general cohort in Chapter 5 and the cohorts in Chapter 6 were collected from the general public. Therefore, additional caution is advised when interpreting results as the self-reported measures used do not indicate a clinical diagnosis. However, it should be noted that self-report measures are commonplace in psychological research and have a number of benefits to being used (Frankfort-Nachmias et al., 2015). For example, self-reported surveys are a cost-effective way to reach a wider sample as they do not require professional training for distribution or administration. Moreover, they are anonymous, and allow for participants to consider their responses.

However, there are several associated disadvantages. Self-report surveys must include simple and easy to understand questions, which may result in the questions being limited in their depth. Furthermore, researchers cannot follow up open-ended questions, and there is a limited amount of control to the environment when a participant is completing the survey, which may lead to distractions (Frankfort-Nachmias et al., 2015). Nevertheless, it has been suggested that there is not a significant difference between self-rating and clinical ratings regarding disordered behaviours. Therefore, self-report measures may closely reflect a participant's symptomology in relation to a disordered behaviour (Jackson et al., 1998). Furthermore, it is common practice within clinical psychology to utilise psychometric screening tools to evaluate a patient's mental health prior to treatment (Bernstein et al., 2020). Moreover, self-reported symptom severity has been used to discriminate between participants with and without clinically diagnosed disorders (Jackson et al., 1998), which supports the use of self-report measures for screening and initial evaluation. This demonstrates the efficacy of self-report measures as an appropriate tool when assessing an individual's behaviour, and therefore was a suitable tool to use within the empirical chapters when assessing problematic behaviours in both clinical and non-clinical samples.

Limitations, Implications, and Future Research

There are a number of limitations within the present doctoral research project. The following section highlights a number of these, in addition to the ones presented throughout the empirical chapters. It should be noted that each empirical chapter was of a cross-sectional design and while the respective results offer insights into the associations between the assessed variables, a causal relationship cannot be determined. Consequently, longitudinal research should be considered to provide insight into the variables' effects over time. This will allow researchers to better understanding the neurophysiological underpinnings of GD and how the factors identified in the empirical chapters may change over time. This may offer insight into the development and maintenance of disordered behaviours.

In regard to ML models, there are still technical challenges when using a SNN architecture, such as the NeuCube. For example, there is currently no robust information theory supporting the design and implementation of SNN, the choice of network structure (e.g., the placement of input neurons), and the additional hyperparameter for each application (e.g., classifying mood disorders, or behaviour disorders) is based on heuristic measures and expert opinion (Tan et al., 2020). Therefore, it is difficult to generalise and optimise the operation in a number of different settings (e.g., clinical settings). Consequently, additional research is needed into the use and parameter optimisation of SNNs, making them more accessible to the scientific and clinical communities. Nevertheless, the use of the *NeuCube* within GD has practical implications for the field because it paves the way for SNNs being used in the classification and prediction of various disordered behaviours, such as gambling disorder.

Future research should investigate other behavioural disorders to further test the accuracy and sensitivity of the *NeuCube* within the addiction field. In addition to this, replicating the findings presented in Chapter 4 is also an important direction to consider because this will strengthen the hypothesis that behavioural addictions such as GD appear to have a specific neurophysiological basis similar to other substance use addictions (Park et al., 2021). In doing so, the *NeuCube* may become a valuable tool in the predication and/or assessment of disordered behaviour. However, additional research is needed to assess the viability of such an idea.

It should also be noted that, as pointed out in Chapter 4, there was no control group used within that empirical study (i.e., participants who did not play videogames). Unfortunately, due to the global COVID-19 pandemic, it was not possible to collect participants during the projected data collection phase. However, a study which was conducted using microstate EEG found that there were no significant differences between recreational gamers and healthy controls (Wang et al., 2021). Consequently, it was decided that the use of a single recreational gamer cohort would be viable. However, future research should address this gap by implementing control groups to investigate the difference in resting state data using SNN.

The research within the present project has implications for the conceptual underpinnings of GD, its classification, and prediction in a research setting. Firstly, in Chapter 4, STBD in conjunction with the SNN architecture the *NeuCube* was used, providing a unique opportunity to better understand the complex interactions of space and time in EEG data. Indeed, the study presented in Chapter 4 represents the first foray into using this particular method in the disordered behaviour field (to the author's knowledge), offering a novel step forward in the use of AI-related methodologies. However, further investigating differences of the connectivity weights within the SNN using traditional statistical methods will require appropriate sample size. Nevertheless, using the *NeuCube* within this context has implications for understanding the neurophysiological expression of GD. It has been suggested that behavioural disorders have a neurophysiological basis similar to that of substance use (Park et al., 2021), and the present research project suggests that this too may be the case with GD. In addition to this, it also paves the way for SNNs to be used in the classification and prediction of other behavioural disorders.

The findings also have extended implications in the behavioural presentation of GD in clinical cohorts, which should be considered in clinical research. In Chapter 5, previous research which focuses on co-occurrence (Walther et al., 2012), and coping (Schneider et al., 2018) was expanded on, and as recommended by previous research, utilised a clinical population sample (Burleigh et al., 2019). In Chapter 5, the effect of co-occurring disordered behaviour on the association of dysfunctional coping strategies was emphasised, resulting in a cycle of reciprocity (Gossop, 2001; Haylett et al., 2004; Martin et al., 2014). This has important implications for clinical research because it highlights the need for assessment of multiple risk factors associated with disordered behaviours and suggests that clinicians and researchers should be aware of the different types of co-occurrences which may accompany specific disordered behaviours (Burleigh et al., 2019). This adds to the growing literature that suggests that clinicians need to consider underlying co-occurring disorders which may require an integrated treatment approach (Carrà et al., 2015; Roncero et al., 2017). Therefore, additional research is needed into specific aspects of gaming in order to ascertain the way in which it may facilitate co-occurrence because gamers were found to score significantly higher across disordered behaviour measures when compared to healthy controls.

In regard to gaming populations, there is a need for more research into the impacts of problematic gaming in gamer populations who suffer clinical symptomology, such as substance use disorder (Burleigh, Griffiths, et al., 2019). Interestingly, the findings in Chapter 5 indicated that while disordered gaming scores were not significantly different between non-clinical and clinical cohorts, the results suggested that other behaviours, such as problematic sexual activity, may instead play a replacement role in gamers. Therefore, future research should investigate problematic behaviours with larger clinical samples, examining a variety of substance uses with a focus on specific co-occurring usage, whilst considering the onset and length of use in relation to the development of other problematic behaviours.

In regard to coping, Chapters 5 and 6 further expanded previous work in regard to coping strategies (Loton et al., 2016; Plante et al., 2019; Schneider et al., 2018), highlighting that dysfunctional coping styles influence the association between psychopathology, personality, and videogame use. Indeed, in Chapter 5, these findings are extended to a sample of gamers and substance-abstinent gamers. While the results presented in Chapter 6 support that high-risk gamers (i.e., from a general sample) consistently scored higher on dysfunctional coping compared to their at-risk counterparts, which suggests that the maladaptive coping strategies used are likely well established. These findings have implications for preventive efforts for gamers whether it be those with at-risk behaviours or clinical symptomology. For example, research should consider exploring the effectiveness of psychoeducation within gamer populations.

Psychoeducation has been shown to be a useful tool for substance users in treatment as substance users often lack insight into their symptomology (Ekhtiari et al., 2017), and in Chapter 6 it was suggested that psychoeducation may be an efficacious approach despite varying cultural backgrounds as consistent coping strategies were present across different countries. Therefore, a psychoeducation approach should be investigated to aid a wide range of different gamers in learning the risks of co-occurrence and replacement behaviours and which coping styles are implicated in the process. This could be done by investigating the over-time development and/or maintenance of these coping strategies, with a specific focus on identifying specific known risk factors (e.g., co-occurrence) and gaming-related elements (e.g., playstyle or game genre) that may act as risk or resilience factors in the development of maladaptive coping.

Taken together, the present studies suggests that co-occurring behaviours within GD and other disordered behaviours may be enforced through dysfunctional coping strategies (Heggeness et al., 2020; Kuss et al., 2017). Moreover, the present doctoral thesis offers a novel insight into the links between maladaptive coping and potential co-occurrence within in a clinical sample, and samples across multiple cultures. It demonstrates that when considering potential substance and behavioural addictions, a more nuanced understanding should be considered, one that not only considers any primary presenting behaviours, but also considers potentially problematic secondary behaviours; therefore offering an integrated treatment approach (Carrà et al., 2015; Roncero et al., 2017). In addition to this, research has suggested there is an effect of co-occurring addictive disorders on treatment efficacy, indicating that treatment efficacy can be increased when considering not only the primary disorder, but also other secondary problematic disordered behaviour (Burleigh, Kuss, et al., 2019; Kuss & Pontes, 2019). Therefore, clinicians should consider an integrated treatment approach; a paradigm which has gained traction in the substance abuse field (Carrà et al., 2015; Roncero et al., 2017). However, what is less clear from the empirical chapters is the extent to which gaming activities themselves differ across individual-oriented countries and how co-occurrence and maladaptive coping behaviours may influence adverse outcomes in a range of gamers. While it is possible that perceptions and nuanced risk-factors around videogame use may differ across studies due to the geographical location of the participants included (Lee & Wohn, 2012; Stavropoulos, Baynes, et al., 2020), further multi-cultural data are required to investigate this theory.

Summary and Conclusion

The present doctoral research project sought to further understand the conceptualisation of GD using multiple systematic research methods of the present literature, the use of neurophysiological EEG data, a ML approach which utilised a novel SNN architecture (i.e., the *NeuCube*), and the use of surveys to reach a clinical cohort and three cohort spanning three different countries in an effort to investigate the way in which co-occurrence may influence gamers and at-risk gamers. This was achieved by exploring the similarities and differences in the neurophysiological expressions of recreational gamers and problematic gamers. The findings presented in Chapter 4 supported the hypothesis that problematic gamers experience different neurophysiological symptoms than those who recreational game. Not only that, but it also utilised a novel ML methodology to be used in the classification of problematic gaming, which has the potential to be used as a cost-effective method of classification when used in conjunction with EEG spatial-temporal brain data.

In Chapter 5, results were presented from a study investigating the mechanisms underlying the difference between recreational and problematic gamers (in both a general and clinical setting), focusing on co-occurrence and coping strategies. The findings identified similarities between each cohort, suggesting that maladaptive coping strategies were significantly associated to gaming scores, and that gamers appeared to experience co-occurrence more so than their non-gamer counterparts. To better understand the profile of these at-risk groups, the next study presented in Chapter 6 used large-scale cross-sectional sample, finding that at-risk and high-risk gamers may utilise gaming as a maladaptive coping strategy and other accompanying potentially addictive behaviour, or substance use may be influenced as a result. Moreover, the findings also suggested that the manifestation of these factors can be influenced by the countries in which an individual resides because within the present research each individualistic country appeared to vary in dominate risk factors within the at-risk groups (e.g., the AU and NZ cohort scored more highly within the at-risk group for problematic gaming use compared to the UK at-risk profile, see Chapter 6).

Taken together, the present doctoral project further clarified the conceptualisation of GD, utilising a neurophysiological underpinning which is further supported with observed behaviour as suggested by the NIMH. It provides a novel and effective method of analysing and identifying GD in individuals, thereby contributing to the identification and potential diagnosis of GD. In addition, it places an emphasis on the importance of understanding co-occurrence and specific at-risk factors (e.g., coping) which may contribute to the development and maintenance of problematic or disordered gaming in a clinical sample. Moreover, it asserts that when assessing co-occurrence within different individualistic societies, clinicians and researchers alike should consider the potential unique risks that specific location (e.g., a higher rate of alcohol use in one individualistic country may not be reflected in another individualistic country) in order to provide an integrated treatment approach. In sum, the findings offer a multidimensional conceptualisation of GD, drawing parallels with other disordered behaviours and substance use, and further supporting the GD classification as a multi-faceted behavioural disorder.

References

Aarseth, E., Bean, A. M., Boonen, H., Carras, M. C., Coulson, M., Das, D., Deleuze, J., Dunkels, E., Edman, J., Ferguson, C. J., Haagsma, M. C., Bergmark, K. H., Hussain, Z., Jansz, J., Kardefelt-Winther, D., Kutner, L., Markey, P., Nielsen, R. K. L., Prause, N., … 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/http://dx.doi.org/10.1556/2006.5.2016.088

Abbott, L. (1999). Lapicque's introduction of the integrate-and-fire model neuron (1907). *Brain Research Bulletin*, *50*(5–6), 303–304. https://doi.org/10.1016/S0361-9230(99)00161-6

Abhang, P. A., Gawali, B. W., & Mehrotra, S. C. (2016). Technical aspects of brain rhythms and speech parameters. In *Introduction to EEG- and Speech-Based Emotion Recognition* (pp. 51–79). Elsevier. https://doi.org/10.1016/B978-0-12-804490-2.00003-8

Acion, L., Kelmansky, D., van der Laan, M., Sahker, E., Jones, D., & Arndt, S. (2017). Use of a machine learning framework to predict substance use disorder treatment success. *PLOS ONE*, *12*(4), e0175383. https://doi.org/10.1371/journal.pone.0175383

Adams, B. L. M., Stavropoulos, V., Burleigh, T. L., Liew, L. W. L., Beard, C. L., & Griffiths, M. D. (2019). Internet gaming disorder behaviours in emergent adulthood: A pilot study examining the interplay between anxiety and family cohesion. *International Journal of Mental Health and Addiction*, *17*(4), 828–844. https://doi.org/10.1007/s11469-018-9873-0

Aggarwal, S., Saluja, S., Gambhir, V., Gupta, S., & Satia, S. P. S. (2020). Predicting likelihood of psychological disorders in PlayerUnknown's Battlegrounds (PUBG) players from Asian countries using supervised machine learning. *Addictive Behaviours*, *101*, 106132. https://doi.org/10.1016/j.addbeh.2019.106132

Akoglu, H. (2018). User's guide to correlation coefficients. *Turkish Journal of Emergency Medicine*, *18*(3), 91–93. https://doi.org/10.1016/j.tjem.2018.08.001

Aldao, A., Nolen-Hoeksema, S., & Schweizer, S. (2010). Emotion-regulation strategies across psychopathology: A meta-analytic review. *Clinical Psychology Review*, *30*(2), 217–237. https://doi.org/10.1016/j.cpr.2009.11.004

American Academy of Pediatrics. Committee on Public Education. (2001). American Academy of Pediatrics: Children, adolescents, and television. *Pediatrics*.

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). American Psychiatric Association. https://doi.org/10.1176/appi.books.9780890425596

Anderson, C. W., Stolz, E. A., & Shamsunder, S. (1998). Multivariate autoregressive models for classification of spontaneous electroencephalographic signals during mental tasks. *IEEE Transactions on Biomedical Engineering*, *45*(3), 277–286. https://doi.org/10.1109/10.661153

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

Andreassen, C. S., 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 Behaviours*, *30*(2), 252–262. https://doi.org/10.1037/adb0000160

Andreassen, C. S., Griffiths, M. D., Gjertsen, S. R., Krossbakken, E., Kvam, S., & Pallesen, S. (2013). The relationships between behavioural 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

Andreassen, C. S., Griffiths, M. D., Hetland, J., & Pallesen, S. (2012). Development of a work addiction scale. *Scandinavian Journal of Psychology*, *53*(3), 265–272. https://doi.org/10.1111/j.1467-9450.2012.00947.x

Andreassen, C. S., Griffiths, M. D., Pallesen, S., Bilder, R. M., Torsheim, T., & Aboujaoude, E. (2015). The Bergen shopping addiction scale: Reliability and validity of a brief screening test. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.01374

Andreassen, C. S., Pallesen, S., Griffiths, M. D., Torsheim, T., & Sinha, R. (2018). The development and validation of the Bergen–Yale sex addiction scale with a large national sample. *Frontiers in Psychology*, *9*, 1–15. https://doi.org/10.3389/fpsyg.2018.00144

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

Andreetta, J., Teh, J., Burleigh, T. L., Gomez, R., & Stavropoulos, V. (2020). Associations between comorbid stress and Internet Gaming Disorder symptoms: Are there cultural and gender variations? *Asia-Pacific Psychiatry*, *12*(2). https://doi.org/10.1111/appy.12387

Aresi, G., Cleveland, M. J., Beccaria, F., & Marta, E. (2021). Variations in acceptability of heavy alcohol use and gender double standards across drinking cultures. A U.S.A. – Italy study. *Journal of Ethnicity in Substance Abuse*, 1–17. https://doi.org/10.1080/15332640.2021.1956391

Armsden, G. C., & Greenberg, M. T. (1987). The inventory of parent and peer attachment: Individual differences and their relationship to psychological well-being in adolescence. *Journal of Youth and Adolescence*. https://doi.org/10.1007/BF02202939

Babor, T. F., Higgins-Biddle, J. C., Saunders, J. B., & Monteiro, M. G. (2001). *The alcohol use disorders identification test* (pp. 1-37). Geneva: World Health Organization.

Baker, J. P., & Berenbaum, H. (2007). Emotional approach and problem-focused coping: A comparison of potentially adaptive strategies. *Cognition & Emotion*, *21*(1), 95–118. https://doi.org/10.1080/02699930600562276

Barry, R. J., Clarke, A. R., Hajos, M., McCarthy, R., Selikowitz, M., & Dupuy, F. E. (2010). Resting-state EEG gamma activity in children with Attention-Deficit/Hyperactivity Disorder. *Clinical Neurophysiology*, *121*(11), 1871–1877. https://doi.org/10.1016/j.clinph.2010.04.022

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*, *118*(12), 2765–2773. https://doi.org/10.1016/j.clinph.2007.07.028

Bavelier, D., Achtman, R. L., Mani, M., & Föcker, J. (2012). Neural bases of selective attention in action video game players. *Vision Research*, *61*, 132–143. https://doi.org/10.1016/j.visres.2011.08.007

Beard, K. W., & Wolf, E. M. (2001). Modification in the proposed diagnostic criteria for internet addiction. *CyberPsychology & Behaviour*, *4*(3), 377–383. https://doi.org/10.1089/109493101300210286

Bengio, Y., Lee, D.-H., Bornschein, J., Mesnard, T., & Lin, Z. (2015). Towards biologically plausible deep learning. *ArXiv Preprint*. http://arxiv.org/abs/1502.04156

Bernstein, D. A., Teachman, B. A., Olatunji, B. O., & Lilienfeld, S. O. (2020). *Introduction to clinical psychology: Bridging science and practice* (9th ed.). Cambridge University Press. https://doi.org/10.1017/9781108676908

Bibbey, A., Phillips, A. C., Ginty, A. T., & Carroll, D. (2015). Problematic Internet use, excessive alcohol consumption, their comorbidity and cardiovascular and cortisol reactions to acute psychological stress in a student population. *Journal of Behavioral Addictions*, *4*(2), 44–52. https://doi.org/10.1556/2006.4.2015.006

Bioulac, S., Arfi, L., & Bouvard, M. P. (2008). Attention deficit/hyperactivity disorder and video games: A comparative study of hyperactive and control children. *European Psychiatry*, *23*(2), 134–141. https://doi.org/10.1016/j.eurpsy.2007.11.002

Bishop, C. (2006). *Pattern recognition and machine learning*. Springer-Verlag.

Bishop, J., Johnston, L., Wolfe, K., & Mull, J. (2015). *Psychological and social implications surrounding internet and gaming addiction* (J. Bishop, Ed.). IGI Global. https://doi.org/10.4018/978-1-4666-8595-6

Bjelland, I., Dahl, A. A., Haug, T. T., & Neckelmann, D. (2002). The validity of the hospital anxiety and depression scale. *Journal of Psychosomatic Research*, *52*(2), 69–77. https://doi.org/10.1016/S0022-3999(01)00296-3

Brand, J. E., Jervis, J., Huggins, P. M., & Wilson, T. W. (2019a). *Digital Australia 2020*. IGEA. https://igea.net/wp-content/uploads/2019/08/DA20-Report-FINAL-Aug19.pdf

Brand, J. E., Jervis, J., Huggins, P. M., & Wilson, T. W. (2019b). *Digital New Zealand 2020*. IGEA. https://igea.net/wp-content/uploads/2019/09/DNZ20-Final-Report-2019.pdf

Brand, M., Laier, C., & Young, K. S. (2014). Internet addiction: Coping styles, expectancies, and treatment implications. *Frontiers in Psychology*, *5*, 1256. https://doi.org/10.3389/fpsyg.2014.01256

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

Breiman, L. (2001). Random forests. *Machine Learning*, *45*, 5–32. https://doi.org/10.1023/A:1010933404324

Buckner, J. D., Zvolensky, M. J., Farris, S. G., & Hogan, J. (2014). Social anxiety and coping motives for cannabis use: The impact of experiential avoidance. *Psychology of Addictive Behaviours*, *28*(2), 568–574. https://doi.org/http://dx.doi.org/10.1037/a0034545

Burdzovic Andreas, J., Lauritzen, G., & Nordfjærn, T. (2015). Co-occurrence between mental distress and poly-drug use: A ten-year prospective study of patients from substance abuse treatment. *Addictive Behaviours*, *48*, 71–78. https://doi.org/10.1016/j.addbeh.2015.05.001

Burleigh, T. L., Griffiths, M. D., Sumich, A., Stavropoulos, V., & Kuss, D. J. (2019). A systematic review of the co-occurrence of gaming disorder and other potentially addictive behaviours. *Current Addiction Reports*, *6*(4), 383–401. https://doi.org/10.1007/s40429-019-00279-7

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 Behaviours*, *107*, 106429. https://doi.org/10.1016/j.addbeh.2020.106429

Burleigh, T. L., Kuss, D. J., Sumich, A., & Griffiths, M. D. (2019). Exploring the implications of co-occurrence within Internet Addiction and Gaming Disorder. In Z. Demetrovics (Ed.), *6th International Conference on Behavioral Addictions (ICBA2019)* (Vol. 8, Issue Supplement 1, pp. 1–220). Journal of Behavioral Addictions. https://doi.org/10.1556/JBA.8.2019.Suppl.1

Burleigh, T. L., Stavropoulos, V., Liew, L. W. L., Adams, B. L. M., & Griffiths, M. D. (2018). Depression, internet gaming disorder, and the moderating effect of the gamer-avatar relationship: An exploratory longitudinal study. *International Journal of Mental Health and Addiction*, *16*(1), 102–124. https://doi.org/10.1007/s11469-017-9806-3

Burns, R., & Burns, R. (2008). *Business research methods and statistics using SPSS*. Sage Publications.

Buzsáki, G., & Wang, X.-J. (2012). Mechanisms of gamma oscillations. *Annual Review of Neuroscience*, *35*(1), 203–225. https://doi.org/10.1146/annurev-neuro-062111-150444

Caetano, S. C., Kaur, S., Brambilla, P., Nicoletti, M., Hatch, J. P., Sassi, R. B., Mallinger, A. G., Keshavan, M. S., Kupfer, D. J., Frank, E., & Soares, J. C. (2006). Smaller cingulate volumes in unipolar depressed patients. *Biological Psychiatry*, *59*(8), 702–706. https://doi.org/10.1016/j.biopsych.2005.10.011

Caporale, N., & Dan, Y. (2008). Spike timing–dependent plasticity: A hebbian learning rule. *Annual Review of Neuroscience*, *31*(1), 25–46. https://doi.org/10.1146/annurev.neuro.31.060407.125639

Carlson, N. R., & Birkett, M. A. (2017). *Physiology of behaviour* (12th ed.). Pearson Education Limited.

Carrà, G., Bartoli, F., Brambilla, G., Crocamo, C., & Clerici, M. (2015). Comorbid addiction and major mental illness in Europe: A narrative review. *Substance Abuse*, *36*(1), 75–81.

https://doi.org/10.1080/08897077.2014.960551

Carver, C. S. (1997). You want to measure coping but your protocol' too long: Consider the brief cope. *International Journal of Behavioral Medicine*, *4*(1), 92–100. https://doi.org/10.1207/s15327558ijbm0401_6

Carver, C. S., & Scheier, M. F. (1981). *Attention and self-regulation: A control theory approach*. Springer.

Carver, C. S., Scheier, M. F., & Weintraub, J. K. (1989). Assessing coping strategies: A theoretically based approach. *Journal of Personality and Social Psychology*, *56*(2), 267–283. https://doi.org/10.1037/0022-3514.56.2.267

Cavalieri, D., McGovern, P. E., Hartl, D. L., Mortimer, R., & Polsinelli, M. (2003). Evidence for S. cerevisiae fermentation in ancient wine. *Journal of Molecular Evolution*, *57*, S226–S232. https://doi.org/10.1007/s00239-003-0031-2

Cerniglia, L., Griffiths, M. D., Cimino, S., De Palo, V., Monacis, L., Sinatra, M., & Tambelli, R. (2019). A latent profile approach for the study of internet gaming disorder, social media addiction, and psychopathology in a normative sample of adolescents. *Psychology Research and Behaviour Management*, *Volume 12*, 651–659. https://doi.org/10.2147/PRBM.S211873

Chamarro, A., Carbonell, X., Manresa, J. M., Munoz-Miralles, R., Ortega-Gonzalez, R., Lopez-Morron, M. R., Batalla-Martinez, C., & Toran-Monserrat, P. (2014). El Cuestionario de Experiencias Relacionadas con los Videojuegos (CERV): Un instrumento para detectar el uso problemático de videojuegos en adolescentes españoles. *Adicciones*, *26*(4), 303. https://doi.org/10.20882/adicciones.31

Chang, C.-C., & Lin, C.-J. (2011). LIBSVM. *ACM Transactions on Intelligent Systems and Technology*, *2*(3), 1–27. https://doi.org/10.1145/1961189.1961199

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

Charlton, J. P., & Danforth, I. D. W. (2010). Validating the distinction between computer addiction and engagement: Online game playing and personality. *Behaviour & Information Technology*, *29*(6), 601–613. https://doi.org/10.1080/01449290903401978

Charzyńska, E., Sussman, S., & Atroszko, P. A. (2021). Profiles of potential behavioural addictions' severity and their associations with gender, personality, and well-being: A person-centered approach. *Addictive Behaviours*, *119*(May), 106941. https://doi.org/10.1016/j.addbeh.2021.106941

Chen, L., & Nath, R. (2016). Understanding the underlying factors of Internet addiction across cultures: A comparison study. *Electronic Commerce Research and Applications*, *17*, 38–48. https://doi.org/10.1016/j.elerap.2016.02.003

Chew, P. K. H. (2022). A meta-analytic review of Internet gaming disorder and the Big Five personality factors. *Addictive Behaviours*, *126*(November 2021), 107193. https://doi.org/10.1016/j.addbeh.2021.107193

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

Clark, L. A., Cuthbert, B., Lewis-Fernández, R., Narrow, W. E., & Reed, G. M. (2017). Three Approaches to Understanding and Classifying Mental Disorder: ICD-11, DSM-5, and the National Institute of Mental Health's Research Domain Criteria (RDoC). *Psychological Science in the Public Interest*, *18*(2), 72–145. https://doi.org/10.1177/1529100617727266

Cleary, M., Hunt, G. E., Matheson, S., & Walter, G. (2009). Psychosocial treatments for people with co-occurring severe mental illness and substance misuse: Systematic review. *Journal of Advanced Nursing*, *65*(2), 238-258. https://doi.org/10.1111/j.1365-2648.2008.04879.x

Coëffec, A., Romo, L., Cheze, N., Riazuelo, H., Plantey, S., Kotbagi, G., & Kern, L. (2015). Early substance consumption and problematic use of video games in adolescence. *Frontiers in Psychology*, *6*(501). https://doi.org/10.3389/fpsyg.2015.00501

Colder Carras, M., & Kardefelt-Winther, D. (2018). When addiction symptoms and life problems diverge: A latent class analysis of problematic gaming in a representative multinational sample of European adolescents. *European Child & Adolescent Psychiatry*, *27*(4), 513–525. https://doi.org/http://dx.doi.org/10.1007/s00787-018-1108-1

Conners, C. K., Erhardt, D., Epstein, J. N., Parker, J. D. A., Sitarenios, G., & Sparrow, E. (1999). Self-ratings of ADHD symptoms in adults I: Factor structure and normative data. *Journal of Attention Disorders*. https://doi.org/10.1177/108705479900300303

Connor, J. P., Symons, M., Feeney, G. F. X., Young, R. M., & Wiles, J. (2007). The application of machine learning techniques as an adjunct to clinical decision making in alcohol dependence treatment. *Substance Use & Misuse*, *42*(14), 2193–2206. https://doi.org/10.1080/10826080701658125

Connor, K. M., & Davidson, J. R. T. (2003). Development of a new resilience scale: The Connor-Davidson Resilience Scale (CD-RISC). *Depression and Anxiety*, *18*(2), 76–82. https://doi.org/10.1002/da.10113

Coutin-Churchman, P., Moreno, R., Añez, Y., & Vergara, F. (2006). Clinical correlates of quantitative EEG alterations in alcoholic patients. *Clinical Neurophysiology*, *117*(4), 740–751. https://doi.org/10.1016/j.clinph.2005.12.021

Cunningham-Williams, R. M., Cottler, L. B., Compton, W. M., Spitznagel, E. L., & Ben-Abdallah, A. (2000). Problem gambling and comorbid psychiatric and substance use disorders among drug users recruited from drug treatment and community settings. *Journal of Gambling Studies*, *16*(4), 347–376. https://doi.org/10.1023/A:1009428122460

D'Hondt, F., Billieux, J., & Maurage, P. (2015). Electrophysiological correlates of problematic Internet use: Critical review and perspectives for future research. *Neuroscience & Biobehavioral Reviews*, *59*, 64–82. https://doi.org/10.1016/j.neubiorev.2015.10.005

Dance, A. (2016). Smart drugs: A dose of intelligence. *Nature*, *531*(7592), S2–S3. https://doi.org/10.1038/531S2a

De Benedictis, A., Duffau, H., Paradiso, B., Grandi, E., Balbi, S., Granieri, E., Colarusso, E., Chioffi, F., Marras, C. E., & Sarubbo, S. (2014). Anatomo-functional study of the temporo-parieto-occipital region: Dissection, tractographic and brain mapping evidence from a neurosurgical perspective. *Journal of Anatomy*, *225*(2), 132–151. https://doi.org/10.1111/joa.12204

de Meneses-Gaya, C., Zuardi, A. W., Loureiro, S. R., & Crippa, J. A. S. (2009). Alcohol use disorders identification test (AUDIT): An updated systematic review of psychometric properties. *Psychology & Neuroscience*, *2*(1), 83–97. https://doi.org/10.3922/j.psns.2009.1.12

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

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

Demetrovics, Z., Szeredi, B., & Rózsa, S. (2008). The three-factor model of Internet addiction: the development of the Problematic Internet Use Questionnaire. *Behaviour Research Methods*.

Derogatis, L. R., Lipman, R. S., Rickels, K., Uhlenhuth, E. H., & Covi, L. (1974). The Hopkins symptom checklist (HSCL): A self-report symptom inventory. *Behavioral Science*. https://doi.org/10.1002/bs.3830190102

DeSalvo, K. B., Bloser, N., Reynolds, K., He, J., & Muntner, P. (2006). Mortality prediction with a single general self-rated health question: A meta-analysis. In *Journal of General Internal Medicine*. https://doi.org/10.1111/j.1525-1497.2005.00291.x

Dickman, S. J. (1990). Functional and dysfunctional impulsivity: Personality and cognitive correlates. *Journal of Personality and Social Psychology*. https://doi.org/10.1037/0022-3514.58.1.95

Doborjeh, M. G., Wang, G. Y., Kasabov, N. K., Kydd, R., & Russell, B. (2016). A spiking neural network methodology and system for learning and comparative analysis of EEG data from healthy versus addiction treated versus addiction not treated subjects. *IEEE Transactions on Biomedical Engineering*, *63*(9), 1830–1841. https://doi.org/10.1109/TBME.2015.2503400

Doborjeh, M., & Kasabov, N. (2016). Personalised modelling on integrated clinical and EEG spatio-temporal brain data in the NeuCube spiking neural network system. *2016 International Joint Conference on Neural Networks (IJCNN)*, 1373–1378. https://doi.org/10.1109/IJCNN.2016.7727358

Doborjeh, Z., Doborjeh, M., Crook-Rumsey, M., Taylor, T., Wang, G. Y., Moreau, D., Krägeloh, C., Wrapson, W., Siegert, R. J., Kasabov, N., Searchfield, G., & Sumich, A. (2020). Interpretability of spatiotemporal dynamics of the brain processes followed by mindfulness intervention in a brain-inspired spiking neural network architecture. *Sensors*, *20*(24), 7354. https://doi.org/10.3390/s20247354

Doborjeh, Z., Doborjeh, M., Taylor, T., Kasabov, N., Wang, G. Y., Siegert, R., & Sumich, A. (2019). Spiking neural network modelling approach reveals how mindfulness training rewires the brain. *Scientific Reports*, *9*(1), 6367. https://doi.org/10.1038/s41598-019-42863-x

Doborjeh, Z., Kasabov, N., Gholami Doborjeh, M., & Sumich, A. (2018). Modelling peri-perceptual brain processes in a deep learning spiking neural network architecture. *Scientific Reports*, *8*(1), 8912. https://doi.org/10.1038/s41598-018-27169-8

Dong, G.-H., Wang, M., Zheng, H., Wang, Z., Du, X., & Potenza, M. N. (2021). Disrupted prefrontal regulation of striatum-related craving in Internet gaming disorder revealed by dynamic causal modeling: Results from a cue-reactivity task. *Psychological Medicine*, *51*(9), 1549–1561. https://doi.org/10.1017/S003329172000032X

Dong, G.-H., Wang, Z., Dong, H., Wang, M., Zheng, Y., Ye, S., Zhang, J., & Potenza, M. N. (2020). More stringent criteria are needed for diagnosing Internet gaming disorder: Evidence from regional brain features and whole-brain functional connectivity multivariate pattern analyses. *Journal of Behavioral Addictions*, *9*(3), 642–653. https://doi.org/10.1556/2006.2020.00065

Dong, G., DeVito, E., Huang, J., & Du, X. (2012). Diffusion tensor imaging reveals thalamus and posterior cingulate cortex abnormalities in Internet gaming addicts. *Journal of Psychiatric Research*, *46*(9), 1212–1216. https://doi.org/http://dx.doi.org/10.1016/j.jpsychires.2012.05.015

Dong, G., Liu, X., Zheng, H., Du, X., & Potenza, M. N. (2019). Brain response features during forced break could predict subsequent recovery in Internet gaming disorder: A longitudinal study. *Journal of Psychiatric Research*, *113*, 17–26. https://doi.org/10.1016/j.jpsychires.2019.03.003

Dong, G., Wang, L., Du, X., & Potenza, M. N. (2018). Gender-related differences in neural responses to gaming cues before and after gaming: Implications for gender-specific vulnerabilities to Internet gaming disorder. *Social Cognitive and Affective Neuroscience*, *13*(11), 1203–1214. https://doi.org/10.1093/scan/nsy084

Dong, G., Wang, Z., Wang, Y., Du, X., & Potenza, M. N. (2019). Gender-related functional connectivity and craving during gaming and immediate abstinence during a mandatory break: Implications for development and progression of Internet gaming disorder. *Progress in Neuro-Psychopharmacology & Biological Psychiatry*, *88*, 1–10. https://doi.org/10.1016/j.pnpbp.2018.04.009

Dong, G., Zheng, H., Liu, X., Wang, Y., Du, X., & Potenza, M. N. (2018). Gender-related differences in cue-elicited cravings in Internet gaming disorder: The effects of deprivation. *Journal of Behavioral Addictions*, *7*(4), 953–964. https://doi.org/10.1556/2006.7.2018.118

Donnellan, M. B., Oswald, F. L., Baird, B. M., & Lucas, R. E. (2006). The mini-IPIP scales: Tiny-yet-effective measures of the Big Five factors of personality. *Psychological Assessment*. https://doi.org/10.1037/1040-3590.18.2.192

Döpfner, M., & Lehmkuhl, G. (1998). *DISYPS-KJ: Diagnostik-System für psychische Störungen im Kindes- und*

Jugendalter nach ICD-10 und DSM-IV; klinische Diagnostik - Elternurteil - Erzieher- und Lehrerurteil - Selbsturteil ; Manual (2nd ed.). Huber. https://books.google.co.uk/books?id=iFA-PAAACAAJ

Döring, N., & Bortz, J. (1993). Psychometrische Einsamkeitsforschung: Deutsche Neukonstruktion der UCLA Loneliness Scale. *Diagnostica*.

Dowd, D. A., Keough, M. T., Jakobson, L. S., Bolton, J. M., & Edgerton, J. D. (2020). A longitudinal examination of gambling subtypes in young adulthood. *International Gambling Studies*, *20*(2), 185–199. https://doi.org/10.1080/14459795.2019.1697343

Drabant, E. M., McRae, K., Manuck, S. B., Hariri, A. R., & Gross, J. J. (2009). Individual differences in typical reappraisal use predict amygdala and prefrontal responses. *Biological Psychiatry*, *65*(5), 367–373. https://doi.org/10.1016/j.biopsych.2008.09.007

Dreier, M., Wölfling, K., Duven, E., Giralt, S., Beutel, M. E., & Müller, K. W. (2017). Free-to-play: About addicted whales, at risk dolphins and healthy minnows. Monetarization design and Internet gaming disorder. *Addictive Behaviours*, *64*, 328–333. https://doi.org/10.1016/j.addbeh.2016.03.008

Drysdale, A. T., Grosenick, L., Downar, J., Dunlop, K., Mansouri, F., Meng, Y., Fetcho, R. N., Zebley, B., Oathes, D. J., Etkin, A., Schatzberg, A. F., Sudheimer, K., Keller, J., Mayberg, H. S., Gunning, F. M., Alexopoulos, G. S., Fox, M. D., Pascual-Leone, A., Voss, H. U., … Liston, C. (2017). Resting-state connectivity biomarkers define neurophysiological subtypes of depression. *Nature Medicine*, *23*(1), 28–38. https://doi.org/10.1038/nm.4246

Duda, R. O., Hart, P. E., & Stork, D. G. (2000). *Pattern classification* (2nd ed.). Wiley-Interscience.

Dunbar, A. B., & Taylor, J. R. (2016). Inhibition of protein synthesis but not β-adrenergic receptors blocks reconsolidation of a cocaine-associated cue memory. *Learning & Memory*, *23*(8), 391–398. https://doi.org/10.1101/lm.042838.116

Dybek, I., Bischof, G., Grothues, J., Reinhardt, S., Meyer, C., Hapke, U., John, U., Broocks, A., Hohagen, F., & Rumpf, H.-J. (2006). The reliability and validity of the alcohol use disorders identification test (AUDIT) in a German general practice population sample. *Journal of Studies on Alcohol*.

Dye, M. W. G., Green, C. S., & Bavelier, D. (2009). The development of attention skills in action video game players. *Neuropsychologia*, *47*(8–9), 1780–1789. https://doi.org/10.1016/j.neuropsychologia.2009.02.002

Ehlers, C. L., Wall, T. L., & Schuckit, M. A. (1989). EEG spectral characteristics following ethanol administration in young men. *Electroencephalography and Clinical Neurophysiology*, *73*(3), 179–187. https://doi.org/10.1016/0013-4694(89)90118-1

Eichenbaum, H., Yonelinas, A. P., & Ranganath, C. (2007). The medial temporal lobe and recognition memory. *Annual Review of Neuroscience*, *30*(1), 123–152. https://doi.org/10.1146/annurev.neuro.30.051606.094328

Ekhtiari, H., Rezapour, T., Aupperle, R. L., & Paulus, M. P. (2017). Neuroscience-informed psychoeducation for addiction medicine: A neurocognitive perspective. In T. Calvey & W. Daniels (Eds.), *Brain Research* *in Addiction* (Vol. 235, pp. 239–264). Elsevier. https://doi.org/10.1016/bs.pbr.2017.08.013

Elliott, A. (2021). *The Routledge Social Science Handbook of AI* (A. Elliott, Ed.). Routledge. https://doi.org/10.4324/9780429198533

Engels, R. C. M. E., Finkenauer, C., Meeus, W., & Deković, M. (2001). Parental attachment and adolescents' emotional adjustment: The associations with social skills and relational competence. *Journal of Counseling Psychology*. https://doi.org/10.1037/0022-0167.48.4.428

Erevik, E. K., Torsheim, T., Andreassen, C. S., Krossbakken, E., Vedaa, Ø., & Pallesen, S. (2019). The associations between low-level gaming, high-level gaming and problematic alcohol use. *Addictive Behaviours Reports*, *10*, 100186. https://doi.org/10.1016/j.abrep.2019.100186

Estévez, A., Jáuregui, P., Sánchez-Marcos, I., López-González, H., & Griffiths, M. D. (2017). Attachment and emotion regulation in substance addictions and behavioural addictions. *Journal of Behavioral Addictions*, *6*(4), 534–544. https://doi.org/10.1556/2006.6.2017.086

Etter, J.-F., Le Houezec, J., & Perneger, T. V. (2003). A self-administered questionnaire to measure dependence on cigarettes: The cigarette dependence scale. *Neuropsychopharmacology*, *28*(2), 359–370. https://doi.org/10.1038/sj.npp.1300030

Everitt, B., Landau, S., Leese, M., & Stahl, D. (2011). *Cluster analysis* (5th ed.). John Wiley & Sons.

Faber, R. J., & O'Guinn, T. C. (2002). A clinical screener for compulsive buying. *Journal of Consumer Research*. https://doi.org/10.1086/209315

Fairburn, C. G., & Beglin, S. J. (1994). Assessment of eating disorder psychopathology: Interview or self-report questionnaire. *International Journal of Eating Disorders*.

Fargues, M. B., Lusar, A. C., Jordania, C. G., & Sánchez, X. C. (2009). Validación de dos escalas breves para evaluar la adicción a Internet y el abuso de móvil. *Psicothema*.

Ferreri, F., Bourla, A., Mouchabac, S., & Karila, L. (2018). e-Addictology: An overview of new technologies for assessing and intervening in addictive behaviours. *Frontiers in Psychiatry*, *9*(MAR), 1–10. https://doi.org/10.3389/fpsyt.2018.00051

Ferris, J. A., & Wynne, H. J. (2001). *The Canadian problem gambling index*. Canadian Centre on Substance Abuse.

Fioravanti, G., & Casale, S. (2015). Evaluation of the psychometric properties of the italian internet addiction test. *Cyberpsychology, Behaviour, and Social Networking*, *18*(2), 120–128. https://doi.org/10.1089/cyber.2014.0493

Foa, E. B., Huppert, J. D., Leiberg, S., Langner, R., Kichic, R., Hajcak, G., & Salkovskis, P. M. (2002). The obsessive-compulsive inventory: Development and validation of a short version. *Psychological Assessment*, *14*(4), 485–496. https://doi.org/10.1037/1040-3590.14.4.485

Fossati, A., Feeney, J. A., Donati, D., Donini, M., Novella, L., Bagnato, M., Acquarini, E., & Maffei, C. (2003).

On the dimensionality of the attachment style questionnaire in Italian clinical and non clinical participants. *Journal of Social and Personal Relationships*, *20*(1), 55–79. https://doi.org/10.1177/0265407503020001187

Frankfort-Nachmias, C., Nachmias, D., & DeWaard, J. (2015). *research methods in the social sciences* (8th ed.). Worth Publishers.

Freimuth, M., Waddell, M., Stannard, J., Kelley, S., Kipper, A., Richardson, A., & Szuromi, I. (2008). Expanding the scope of dual diagnosis and co-addictions: Behavioral addictions. *Journal of Groups in Addiction and Recovery*, *3*(3–4), 137–160. https://doi.org/10.1080/15560350802424944

Friedrich, S., Antes, G., Behr, S., Binder, H., Brannath, W., Dumpert, F., Ickstadt, K., Kestler, H. A., Lederer, J., Leitgöb, H., Pauly, M., Steland, A., Wilhelm, A., & Friede, T. (2021). Is there a role for statistics in artificial intelligence? *Advances in Data Analysis and Classification*. https://doi.org/10.1007/s11634-021-00455-6

Gallarin, M., & Alonso-Arbiol, I. (2013). Dimensionality of the inventory of parent and peer attachment: Evaluation with the Spanish version. *The Spanish Journal of Psychology*, *16*, E55. https://doi.org/10.1017/sjp.2013.47

Gallimberti, L., Buja, A., Chindamo, S., Rabensteiner, A., Terraneo, A., Marini, E., Pérez, L. J. G., & Baldo, V. (2016). Problematic use of video games and substance abuse in early adolescence: A cross-sectional study. *American Journal of Health Behaviour*, *40*(5), 594–603. https://doi.org/10.5993/AJHB.40.5.6

Goldstein, R. Z., & Volkow, N. D. (2011). Dysfunction of the prefrontal cortex in addiction: Neuroimaging findings and clinical implications. *Nature Reviews Neuroscience*, *12*(11), 652–669. https://doi.org/10.1038/nrn3119

Gonzalez, J., Alba, G., Pereda, E., Mañas, S., González, A., & Méndez, L. (2015). Electroencephalography signatures of attention-deficit/hyperactivity disorder: Clinical utility. *Neuropsychiatric Disease and Treatment*, 2755. https://doi.org/10.2147/NDT.S51783

Gosling, S. D., Rentfrow, P. J., & Swann, W. B. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in Personality*, *37*(6), 504–528. https://doi.org/10.1016/S0092-6566(03)00046-1

Gossop, M. (2001). A web of dependence. *Addiction*, *96*(5), 677–678. https://doi.org/10.1046/j.1360-0443.2001.9656771.x

Gossop, M., Marsden, J., & Stewart, D. (2002). Dual dependence: Assessment of dependence upon alcohol and illicit drugs, and the relationship of alcohol dependence among drug misusers to patterns of drinking, illicit drug use and health problems. *Addiction*, *97*(2), 169–178. https://doi.org/10.1046/j.1360-0443.2002.00028.x

Goudriaan, A. E., Oosterlaan, J., de Beurs, E., & van den Brink, W. (2006). Psychophysiological determinants and concomitants of deficient decision making in pathological gamblers. *Drug and Alcohol Dependence*, *84*(3), 231–239. https://doi.org/10.1016/j.drugalcdep.2006.02.007

Grant, B. F., Goldstein, R. B., Saha, T. D., Chou, S. P., Jung, J., Zhang, H., Pickering, R. P., Ruan, W. J., Smith, S. M., Huang, B., & Hasin, D. S. (2015). Epidemiology of DSM-5 alcohol use disorder. *JAMA Psychiatry*, *72*(8), 757. https://doi.org/10.1001/jamapsychiatry.2015.0584

Gratz, K., & Roemer, L. (2004). Multidimensional assessment of emotion regulation and dysregulation. *Journal of Psychopathology and Behavioral Assessment*, *26*, 41-54. https://doi.org/10.1023/B:JOBA.0000007455.08539.94

Gregg, L., Haddock, G., Emsley, R., & Barrowclough, C. (2014). Reasons for substance use and their relationship to subclinical psychotic and affective symptoms, coping, and substance use in a nonclinical sample. *Psychology of Addictive Behaviours*, *28*(1), 247–256. https://doi.org/http://dx.doi.org/10.1037/a0034761

Griffiths, M. D., & Meredith, A. (2009). Videogame addiction and its treatment. *Journal of Contemporary Psychotherapy*, *39*(4), 247–253. https://doi.org/10.1007/s10879-009-9118-4

Griffiths, M. D., Rooij, A. J., Kardefelt-Winther, D., Starcevic, V., Király, O., Pallesen, S., Müller, K., Dreier, M., Carras, M., Prause, N., King, D. L., Aboujaoude, E., Kuss, D. J., Pontes, H. M., Lopez Fernandez, O., Nagygyorgy, K., Achab, S., Billieux, J., Quandt, T., … Demetrovics, Z. (2016). Working towards an international consensus on criteria for assessing internet gaming disorder: A critical commentary on Petry et al . (2014). *Addiction*, *111*(1), 167–175. https://doi.org/10.1111/add.13057

Griffiths, M., Parke, J., & Wood, R. (2002). Excessive gambling and substance abuse: is there a relationship? *Journal of Substance Use*, *7*(4), 187–190. https://doi.org/10.1080/14659890215688

Griffiths, M., & Sutherland, I. (1998). Adolescent gambling and drug use. *Journal of Community and Applied Social Psychology*, *8*(6), 423–427. https://doi.org/10.1002/(SICI)1099-1298(199811/12)8:6<423::AID-CASP499>3.0.CO;2-B

Gross, J. J. (2002). Emotion regulation: Affective, cognitive, and social consequences. *Psychophysiology*, *39*(3), S0048577201393198. https://doi.org/10.1017/S0048577201393198

Grüsser, S. M., Thalemann, R., & Griffiths, M. D. (2007). Excessive computer game playing: Evidence for addiction and aggression? *CyberPsychology & Behaviour*. https://doi.org/10.1089/cpb.2006.9956

Gutiérrez, A. E., Fernández, D. H., Gonzalvo, I. S., Bilbao, P. J., Estévez, A., Herrero, D., Sarabia, I., & Jáuregui, P. (2014). - Mediating role of emotional regulation between impulsive behaviour in gambling. *Adicciones*, *26*(4), 282–290. https://doi.org/http://dx.doi.org/10.20882/adicciones.26

Hafeez, T., Umar Saeed, S. M., Arsalan, A., Anwar, S. M., Ashraf, M. U., & Alsubhi, K. (2021). EEG in game user analysis: A framework for expertise classification during gameplay. *PLOS ONE, 16*(6), e0246913. https://doi.org/10.1371/journal.pone.0246913

Hall, W., Degenhardt, L., & Teesson, M. (2009). Reprint of “Understanding comorbidity between substance use, anxiety and affective disorders: Broadening the research base.” *Addictive Behaviours*, *34*(10), 795–

799. https://doi.org/10.1016/j.addbeh.2009.03.040

Hallquist, M. N., & Wright, A. G. C. (2014). Mixture modeling methods for the assessment of normal and abnormal personality, part I: Cross-sectional models. *Journal of Personality Assessment*, *96*(3), 256–268. https://doi.org/10.1080/00223891.2013.845201

Hannun, A., Case, C., Casper, J., Catanzaro, B., Diamos, G., Elsen, E., Prenger, R., Satheesh, S., Sengupta, S., Coates, A., & Ng, A. Y. (2014). Deep Speech: Scaling up end-to-end speech recognition. *ArXiv Preprint*. http://arxiv.org/abs/1412.5567

Harris, C. R., Millman, K. J., van der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., Kern, R., Picus, M., Hoyer, S., van Kerkwijk, M. H., Brett, M., Haldane, A., del Río, J. F., Wiebe, M., Peterson, P., … Oliphant, T. E. (2020). Array programming with NumPy. *Nature*, *585*(7825), 357–362. https://doi.org/10.1038/s41586-020-2649-2

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning* (2nd ed.). Springer New York. https://doi.org/10.1007/978-0-387-84858-7

Hausenblas, H. A., & Downs, D. S. (2002). How much is too much? The development and validation of the exercise dependence scale. *Psychology and Health*. https://doi.org/10.1080/0887044022000004894

Haylett, S. A., Stephenson, G. M., & Lefever, R. M. H. (2004). Covariation in addictive behaviours: A study of addictive orientations using the shorter PROMIS questionnaire. *Addictive Behaviours*, *29*(1), 61–71. https://doi.org/10.1016/S0306-4603(03)00083-2

Heggeness, L. F., Bean, C. A. L., Kalmbach, D. A., & Ciesla, J. A. (2020). Cognitive risk, coping-oriented substance use, and increased avoidance tendencies among depressed outpatients: A prospective investigation. *Journal of Clinical Psychology*, jclp.22978. https://doi.org/10.1002/jclp.22978

Hellman, M., & Rolando, S. (2013). Collectivist and individualist values traits in Finnish and Italian adolescents' alcohol norms. *Drugs and Alcohol Today*, *13*(1), 51–59. https://doi.org/10.1108/17459261311310853

Hemenover, S. H., & Bowman, N. D. (2018). Video games, emotion, and emotion regulation: Expanding the scope. *Annals of the International Communication Association*, *42*(2), 125–143. https://doi.org/10.1080/23808985.2018.1442239

Hervás, Gonzalo; Jódar, R. (2008). Adaptación al castellano de la Escala de Dificultades en la Regulación Emocional. *Clínica y Salud*.

Hilbert, A., de Zwaan, M., & Braehler, E. (2012). How frequent are eating disturbances in the population? Norms of the eating disorder examination-questionnaire. *PLoS ONE*. https://doi.org/10.1371/journal.pone.0029125

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis*, *15*(3), 199–236. https://doi.org/10.1093/pan/mpl013

Hofstede, G. (1980). *Culture's consequences: International differences in work-related values.* Sage Publications.

Hofstede, G. (1991). *Culture and organisations: International cooperation and its importance for survival*. Harper Collins.

Hofstede Insights. (2022). *Country comparison*. https://www.hofstede-insights.com/country-comparison/australia,new-zealand,the-uk/

Houston, R. J., & Ceballos, N. A. (2013). Human neurophysiology: EEG and quantitative EEG in addiction research. In *Biological research on addiction* (pp. 379–390). Elsevier. https://doi.org/10.1016/B978-0-12-398335-0.00038-8

Howland, R. H., Shutt, L. S., Berman, S. R., Spotts, C. R., & Denko, T. (2011). The emerging use of technology for the treatment of depression and other neuropsychiatric disorders. *Annals of Clinical Psychiatry*, *23*(1), 48–62. http://www.ncbi.nlm.nih.gov/pubmed/21318196

Hughes, J. R., Fingar, J. R., Budney, A. J., Naud, S., Helzer, J. E., & Callas, P. W. (2014). Marijuana use and intoxication among daily users: An intensive longitudinal study. *Addictive Behaviours*, *39*(10), 1464–1470. https://doi.org/10.1016/j.addbeh.2014.05.024

Hussain, Z., & Pontes, H. M. (2019). Personality, Internet addiction, and other technological addictions: A psychological examination of personality traits and technological addictions. In I. R. M. Association (Ed.), *Substance abuse and addiction: Breakthroughs in research and practice* (pp. 236–262). IGI Global. https://doi.org/10.4018/978-1-5225-7666-2.ch012

Huys, Q. J. M., Maia, T. V, & Frank, M. J. (2016). Computational psychiatry as a bridge from neuroscience to clinical applications. *Nature Neuroscience*, *19*(3), 404–413. https://doi.org/10.1038/nn.4238

Hyman, S. E., Malenka, R. C., & Nestler, E. J. (2006). Neural mechanisms of addiction: The role of reward-related learning and memory. *Annual Review of Neuroscience*, *29*(1), 565–598. https://doi.org/10.1146/annurev.neuro.29.051605.113009

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

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 Behaviours*, *81*, 157–166. https://doi.org/10.1016/j.addbeh.2018.02.017

Ivory, A. H., Ivory, J. D., & Lanier, M. (2017). Video game use as risk exposure, protective incapacitation, or inconsequential activity among university students. *Journal of Media Psychology*, *29*(1), 42–53. https://doi.org/10.1027/1864-1105/a000210

Jackson, J. L., O'Malley, P. G., & Kroenke, K. (1998). Clinical predictors of mental disorders among medical outpatients: Validation of the “S4” model. *Psychosomatics*, *39*(5), 431–436. https://doi.org/10.1016/S0033-3182(98)71302-7

Jacobs, D. F. (1986). A general theory of addictions: A new theoretical model. *Journal of Gambling Behaviour*, *2*(1), 15–31. https://doi.org/10.1007/BF01019931

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/http://dx.doi.org/10.1111/adb.12246

Jiang, Z., & Shi, M. (2016). Prevalence and co-occurrence of compulsive buying, problematic Internet and mobile phone use in college students in Yantai, China: Relevance of self-traits. *BMC Public Health*, *16*(1), 1211. https://doi.org/10.1186/s12889-016-3884-1

Jones, C. M., Scholes, L., Johnson, D., Katsikitis, M., & Carras, M. C. (2014). Gaming well: Links between videogames and flourishing mental health. *Frontiers in Psychology*, *5*, 8. https://doi.org/10.3389/fpsyg.2014.00260

Kalina, K., & Vacha, P. (2013). Dual diagnoses in therapeutic communities for addicts -- possibilities and limits of integrated treatment. *Adiktologie*, *13*(2), 144–164.

Kandel, D. B., & Davies, M. (1982). Epidemiology of depressive mood in adolescents: An empirical study. *Archives of General Psychiatry*, *39*(10), 1205–1212. http://www.ncbi.nlm.nih.gov/pubmed/7125850

Kardefelt-Winther, D. (2014). The moderating role of psychosocial well-being on the relationship between escapism and excessive online gaming. *Computers in Human Behaviour*, *38*, 68–74. https://doi.org/10.1016/j.chb.2014.05.020

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

Kasabov, N., & Capecci, E. (2015). Spiking neural network methodology for modelling, classification and understanding of EEG spatio-temporal data measuring cognitive processes. *Information Sciences*, *294*, 565–575. https://doi.org/10.1016/j.ins.2014.06.028

Kasabov, N., Dhoble, K., Nuntalid, N., & Indiveri, G. (2013). Dynamic evolving spiking neural networks for on-line spatio- and spectro-temporal pattern recognition. *Neural Networks*, *41*, 188–201. https://doi.org/10.1016/j.neunet.2012.11.014

Kasabov, N. K. (2014). NeuCube: A spiking neural network architecture for mapping, learning and understanding of spatio-temporal brain data. *Neural Networks*, *52*, 62–76. https://doi.org/10.1016/j.neunet.2014.01.006

Kaufman, S. B., Yaden, D. B., Hyde, E., & Tsukayama, E. (2019). The light vs. dark triad of personality:

Contrasting two very different profiles of human nature. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.00467

Kautz, M., Charney, D. S., & Murrough, J. W. (2017). Neuropeptide Y, resilience, and PTSD therapeutics. *Neuroscience Letters*, *649*, 164–169. https://doi.org/10.1016/j.neulet.2016.11.061

Kemper, H. C. G., Ooijendijk, W. T. M., & Stiggelbout, M. (2000). Consensus over de Nederlandse norm voor gezond bewegen. *Tijdschrift Voor Gezondheidswetenschappen*.

Kessler, R. C., Adler, L., Ames, M., Demler, O., Faraone, S., Hiripi, E., Howes, M. J., Jin, R., Secnik, K., Spencer, T., Ustun, T. B., & Walters, E. E. (2005). The World Health Organization adult ADHD self-report scale (ASRS): A short screening scale for use in the general population. *Psychological Medicine*, *35*(2), 245–256. https://doi.org/10.1017/S0033291704002892

Kessler, R. C., Hwang, I., Labrie, R., Petukhova, M., Sampson, N. A., Winters, K. C., & Shaffer, H. J. (2008). DSM-IV pathological gambling in the National Comorbidity Survey Replication. *Psychological Medicine*. https://doi.org/10.1017/S0033291708002900

Khantzian, E. J. (1985). The self-medication hypothesis of addictive disorders: Focus on heroin and cocaine dependence. *American Journal of Psychiatry*, *142*(11), 1259–1264. https://doi.org/10.1176/ajp.142.11.1259

Kim, H., Ha, J., Chang, W.-D., Park, W., Kim, L., & Im, C.-H. (2018). Detection of craving for gaming in adolescents with internet gaming disorder using multimodal biosignals. *Sensors*, *18*(2), 102. https://doi.org/10.3390/s18010102

Kim, H., Kim, L., & Im, C.-H. C.-H. (2019). Machine-learning-based detection of craving for gaming using multimodal physiological signals: validation of test-retest reliability for practical use. *Sensors*, *19*(16), 3475. https://doi.org/10.3390/s19163475

Kim, K. I., Kim, J. H., & Won, H. T. (1984). *Korean manual of symptom checklist-90- revision*. Jung Ang Juk Sung Publisher.

Kim, K., & Kim, W. S. (2001). Korean-BAS/bis scale. *Korean Journal Health Psychology*, *6*(2), 19–37.

Kim, Y. J., Lee, J.-Y., Oh, S., Park, M., Jung, H. Y., Sohn, B. K., Choi, S.-W., Kim, D. J., & Choi, J.-S. (2017). Associations between prospective symptom changes and slow-wave activity in patients with Internet gaming disorder. *Medicine*, *96*(8), e6178. https://doi.org/10.1097/MD.0000000000006178

King, D. L., Chamberlain, S. R., Carragher, N., Billieux, J., Stein, D., Mueller, K., Potenza, M. N., Rumpf, H. J., Saunders, J., Starcevic, V., Demetrovics, Z., Brand, M., Lee, H. K., Spada, M., Lindenberg, K., Wu, A. M. S., Lemenager, T., Pallesen, S., Achab, S., … Delfabbro, P. H. (2020). Screening and assessment tools for gaming disorder: A comprehensive systematic review. *Clinical Psychology Review*, *77*, 101831. https://doi.org/10.1016/j.cpr.2020.101831

King, D. L., & Delfabbro, P. H. (2014). The cognitive psychology of Internet gaming disorder. *Clinical Psychology Review*, *34*(4), 298–308. https://doi.org/10.1016/j.cpr.2014.03.006

King, D. L., Delfabbro, P. H., Wu, A. M. S. S., Doh, Y. Y., Kuss, D. J., Pallesen, S., Mentzoni, R., Carragher, N., & Sakuma, H. (2017). Treatment of Internet gaming disorder: An international systematic review and CONSORT evaluation. *Clinical Psychology Review*, *54*(November 2016), 123–133. https://doi.org/10.1016/j.cpr.2017.04.002

King, D. L., Delfabbro, P. H., Zwaans, T., & Kaptsis, D. (2013). Clinical features and axis I comorbidity of Australian adolescent pathological Internet and video game users. *Australian & New Zealand Journal of Psychiatry*, *47*(11), 1058–1067. https://doi.org/10.1177/0004867413491159

Király, O., Bőthe, B., Ramos-Diaz, J., Rahimi-Movaghar, A., Lukavska, K., Hrabec, O., Miovsky, M., Billieux, J., Deleuze, J., Nuyens, F., Karila, L., Griffiths, M. D., Nagygyörgy, K., Urbán, R., Potenza, M. N., King, D. L., Rumpf, H.-J., Carragher, N., & Demetrovics, Z. (2019). Ten-item Internet gaming disorder test (IGDT-10): Measurement invariance and cross-cultural validation across seven language-based samples. *Psychology of Addictive Behaviours*, *33*(1), 91–103. https://doi.org/10.1037/adb0000433

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, Behaviour, and Social Networking*, *17*(12), 749–754. https://doi.org/10.1089/cyber.2014.0475

Kircaburun, K., Pontes, H. M., Stavropoulos, V., & Griffiths, M. D. (2020). A brief psychological overview of disordered gaming. *Current Opinion in Psychology*, *36*, 38–43. https://doi.org/10.1016/j.copsyc.2020.03.004

Klein, V., Rettenberger, M., Boom, K.-D., & Briken, P. (2014). A validation study of the German version of the hypersexual behaviour inventory (HBI). *Psychotherapie Psychosomatik Medizinische Psychologie, 64*(03-04), 136-140. https://doi.org/10.1055/s-0033-1357133.

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

Ko, C., Yen, J.-Y., Yen, C., Chen, C. C., Weng, C., & Chen, C. C. (2008). The Association between Internet addiction and problematic alcohol use in adolescents: The problem behaviour model. *CyberPsychology & Behaviour*, *11*(5), 571–576. https://doi.org/10.1089/cpb.2007.0199

Konkolÿ Thege, B., Colman, I., El-guebaly, N., Hodgins, D. C., Patten, S. B., Schopflocher, D., Wolfe, J., & Wild, T. C. (2015). Substance-related and behavioural addiction problems: Two surveys of Canadian adults. *Addiction Research & Theory*, *23*(1), 34–42. https://doi.org/10.3109/16066359.2014.923408

Konkolÿ Thege, B., Hodgins, D. C., & Wild, T. C. (2016). Co-occurring substance-related and behavioural addiction problems: A person-centered, lay epidemiology approach. *Journal of Behavioral Addictions*, *5*(4), 614–622. https://doi.org/10.1556/2006.5.2016.079

Kotyuk, E., Magi, A., Eisinger, A., Király, O., Vereczkei, A., Barta, C., Griffiths, M. D., Székely, A., Kökönyei, G., Farkas, J., Kun, B., Badgaiyan, R. D., Urbán, R., Blum, K., & Demetrovics, Z. (2020). Co-occurrences of substance use and other potentially addictive behaviours: Epidemiological results from the psychological and genetic factors of the addictive behaviours (PGA) Study. *Journal of Behavioral Addictions*, *9*(2), 272–288. https://doi.org/10.1556/2006.2020.00033

Kounios, J., Fleck, J. I., Green, D. L., Payne, L., Stevenson, J. L., Bowden, E. M., & Jung-Beeman, M. (2008). The origins of insight in resting-state brain activity. *Neuropsychologia*, *46*(1), 281–291. https://doi.org/10.1016/j.neuropsychologia.2007.07.013

Kuhn, M. (2008). Building predictive models in R using the caret package. *Journal of Statistical Software*, *28*(5). https://doi.org/10.18637/jss.v028.i05

Kuss, D., Dunn, T. J., Wölfling, K., Müller, K. W., Hędzelek, M., Marcinkowski, J., Hędzelek, M., Marcinkowski, J., Hędzelek, M., & Marcinkowski, J. (2017). Excessive internet use and psychopathology: The role of coping. *Clinical Neuropsychiatry*, *14*(1), 73–81. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85014318858&partnerID=40&md5=b8531bcec872196c6a3096dc98a23a38

Kuss, D. J., & Billieux, J. (2017). Technological addictions: Conceptualisation, measurement, etiology and treatment. *Addictive Behaviours*, *64*, 231–233. https://doi.org/10.1016/j.addbeh.2016.04.005

Kuss, D. J., & Griffiths, M. D. (2012a). Internet gaming addiction: A systematic review of empirical research. *International Journal of Mental Health and Addiction*, *10*(2), 278–296. https://doi.org/10.1007/s11469-011-9318-5

Kuss, D. J., & Griffiths, M. D. (2012b). Internet and gaming addiction: A systematic literature review of neuroimaging studies. *Brain Sciences*, *2*(3), 347–374. https://doi.org/10.3390/brainsci2030347

Kuss, D. J., Griffiths, M. D., Karila, L., & Billieux, J. (2014). Internet addiction: A systematic review of epidemiological research for the last decade. *Current Pharmaceutical Design*, *20*(25), 4026–4052. https://doi.org/10.2174/13816128113199990617

Kuss, D. J., Griffiths, M. D., & Pontes, H. M. (2017). DSM-5 diagnosis of Internet gaming disorder: Some ways forward in overcoming issues and concerns in the gaming studies field. *Journal of Behavioral Addictions*, *6*(2), 133–141. https://doi.org/10.1556/2006.6.2017.032

Kuss, D. J., Louws, J., & Wiers, R. W. (2012). Online gaming addiction? Motives predict addictive play behaviour in massively multiplayer online role-playing games. *Cyberpsychology, Behaviour, and Social Networking*, *15*(9), 480–485. https://doi.org/http://dx.doi.org/10.1089/cyber.2012.0034

Kuss, D. J., & Pontes, H. M. (2019). *Internet addiction. Evidence-based practice in psychotherapy*. Hogrefe Publishing.

Kuss, D. J., Pontes, H. M., & Griffiths, M. D. (2018). Neurobiological correlates in Internet gaming disorder: A systematic literature review. *Frontiers in Psychiatry*, *9*(MAY), 1–12. https://doi.org/10.3389/fpsyt.2018.00166

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 Behaviour*, *29*(5), 1987–1996. https://doi.org/10.1016/j.chb.2013.04.002

La Greca, A. M., & Stone, W. L. (2005). Social anxiety scale for children-revised: Factor structure and concurrent validity. *Journal of Clinical Child Psychology*. https://doi.org/10.1207/s15374424jccp2201_2

Laconi, S., Pirès, S., & Chabrol, H. (2017). Internet gaming disorder, motives, game genres and psychopathology. *Computers in Human Behaviour*, *75*, 652–659. https://doi.org/10.1016/j.chb.2017.06.012

Ladhari, R., Pons, F., Bressolles, G., & Zins, M. (2011). Culture and personal values: How they influence perceived service quality. *Journal of Business Research*, *64*(9), 951–957. https://doi.org/10.1016/j.jbusres.2010.11.017

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer.

Lee, D., Kelly, K. R., & Edwards, J. K. (2006). A closer look at the relationships among trait procrastination, neuroticism, and conscientiousness. *Personality and Individual Differences*, *40*(1), 27–37. https://doi.org/10.1016/j.paid.2005.05.010

Lee, H. J., Tran, D. D., & Morrell, H. E. R. R. (2018). Smoking, ADHD, and problematic video game use: A structural modeling approach. *Cyberpsychology, Behaviour, and Social Networking*, *21*(5), 281–286. https://doi.org/10.1089/cyber.2017.0429

Lee, J.-Y., Choi, C.-H., Park, M., Park, S., & Choi, J.-S. (2022). Enhanced resting-state EEG source functional connectivity within the default mode and reward-salience networks in internet gaming disorder. *Psychological Medicine*, 1–9. https://doi.org/10.1017/S0033291722000137

Lee, J.-Y., Choi, J.-S., & Kwon, J. S. (2019). Neurophysiological mechanisms of resilience as a protective factor in patients with internet gaming disorder: A resting-state EEG coherence study. *Journal of Clinical Medicine*, *8*(1), 49. https://doi.org/10.3390/jcm8010049

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

Lee, J. Y., Park, S. M., Kim, Y. J., Kim, D. J., Choi, S.-W., Kwon, J. S., & Choi, J.-S. (2017). Resting-state EEG activity related to impulsivity in gambling disorder. *Journal of Behavioral Addictions*, *6*(3), 387–395. https://doi.org/10.1556/2006.6.2017.055

Lee, Y.-H., & Wohn, D. Y. (2012). Are there cultural differences in how we play? Examining cultural effects on playing social network games. *Computers in Human Behaviour*, *28*(4), 1307–1314. https://doi.org/10.1016/j.chb.2012.02.014

Lemmens, J. S., Valkenburg, P. M., & Peter, J. (2009). Development and validation of a game addiction scale for adolescents. *Media Psychology*. https://doi.org/10.1080/15213260802669458

Lemmens, J. S., Valkenburg, P. M., & Peter, J. (2011a). The effects of pathological gaming on aggressive behaviour. *Journal of Youth and Adolescence*. https://doi.org/10.1007/s10964-010-9558-x

Lemmens, J. S., Valkenburg, P. M., & Peter, J. (2011b). Psychosocial causes and consequences of pathological gaming. *Computers in Human Behaviour*, *27*(1), 144–152. https://doi.org/http://dx.doi.org/10.1016/j.chb.2010.07.015

Leung, L. (2008). Leisure boredom, sensation seeking, self-esteem, and addiction: Symptoms and patterns of cell phone use. In Konijn, E.A., Utz, S., Tanis, M., & Barnes, S.B. (Eds.), *Mediated Interpersonal Communication*. Routledge. https://doi.org/10.4324/9780203926864

Ley, C., Martin, R. K., Pareek, A., Groll, A., Seil, R., & Tischer, T. (2022). Machine learning and conventional statistics: making sense of the differences. *Knee Surgery, Sports Traumatology, Arthroscopy*, *30*(3), 753–757. https://doi.org/10.1007/s00167-022-06896-6

Li, D., Li, X., Zhao, L., Zhou, Y., Sun, W., & Wang, Y. (2017). Linking multiple risk exposure profiles with adolescent Internet addiction: Insights from the person-centered approach. *Computers in Human Behaviour*, *75*, 236–244. https://doi.org/10.1016/j.chb.2017.04.063

Liew, L. W. L., Stavropoulos, V., Adams, B. L. M., Burleigh, T. L., & Griffiths, M. D. (2018). Internet gaming disorder: The interplay between physical activity and user–avatar relationship. *Behaviour & Information Technology*, *37*(6), 558–574. https://doi.org/10.1080/0144929X.2018.1464599

Lin, E., Lin, C.-H., & Lane, H.-Y. (2020). Precision psychiatry applications with pharmacogenomics: artificial intelligence and machine learning approaches. *International Journal of Molecular Sciences*, *21*(3), 969. https://doi.org/10.3390/ijms21030969

Linn, K. A., Gaonkar, B., Doshi, J., Davatzikos, C., & Shinohara, R. T. (2016). Addressing confounding in predictive models with an application to neuroimaging. *The International Journal of Biostatistics*, *12*(1), 31–44. https://doi.org/10.1515/ijb-2015-0030

Loton, D., Borkoles, E., Lubman, D., & Polman, R. (2016). Video game addiction, engagement and symptoms of stress, depression and anxiety: The mediating role of coping. *International Journal of Mental Health and Addiction*, *14*(4), 565–578. https://doi.org/10.1007/s11469-015-9578-6

Lovibond, P. F., & Lovibond, S. H. (1995). The structure of negative emotional states: Comparison of the depression anxiety stress scales (DASS) with the Beck depression and anxiety inventories. *Behaviour Research and Therapy*, *33*(3), 335–343. https://doi.org/10.1016/0005-7967(94)00075-U

Lu, D. W., Wang, J. W., & Huang, A. C. W. (2010). Differentiation of Internet addiction risk level based on autonomic nervous responses: The Internet-addiction hypothesis of autonomic activity. *Cyberpsychology, Behaviour, and Social Networking*, *13*(4), 371–378. https://doi.org/10.1089/cyber.2009.0254

Lui, P. P., & Rollock, D. (2020). Addictive personality and substance abuse disorders (SUD). In B.J. Carducci, C.S. Nave, J.S. Mio & R.E. Riggio (Eds.), *The Wiley Encyclopedia of Personality and Individual Differences* (pp. 81–87). Wiley. https://doi.org/10.1002/9781119547181.ch278

Maass, W. (1997). Networks of spiking neurons: The third generation of neural network models. *Neural Networks*, *10*(9), 1659–1671. https://doi.org/10.1016/S0893-6080(97)00011-7

Mak, K. K., Lee, K., & Park, C. (2019). Applications of machine learning in addiction studies: A systematic review. *Psychiatry Research*, *275*, 53–60. https://doi.org/10.1016/j.psychres.2019.03.001

Malik, S., Wells, A., & Wittkowski, A. (2015). Emotion regulation as a mediator in the relationship between attachment and depressive symptomatology: A systematic review. *Journal of Affective Disorders*, *172*, 428–444. https://doi.org/10.1016/j.jad.2014.10.007

Marmet, S., Studer, J., Rougemont-Bücking, A., & Gmel, G. (2018). Latent profiles of family background, personality and mental health factors and their association with behavioural addictions and substance use disorders in young Swiss men. *European Psychiatry*, *52*, 76–84. https://doi.org/10.1016/j.eurpsy.2018.04.003

Martens, M., Assema, P. van, & Brug, J. (2005). Why do adolescents eat what they eat? Personal and social environmental predictors of fruit, snack and breakfast consumption among 12– 14-year-old Dutch students. *Public Health Nutrition*. https://doi.org/10.1079/phn2005828

Martin, R. J., Usdan, S., Cremeens, J., & Vail-Smith, K. (2014). Disordered gambling and co-morbidity of psychiatric disorders among college students: An examination of problem drinking, anxiety and depression. *Journal of Gambling Studies*, *30*(2), 321–333. https://doi.org/10.1007/s10899-013-9367-8

Martínez-Loredo, V., Grande-Gosende, A., Fernández-Artamendi, S., Secades-Villa, R., & Fernández-Hermida, J. R. (2019). Substance use and gambling patterns among adolescents: Differences according to gender and impulsivity. *Journal of Gambling Studies*, *35*(1), 63–78. https://doi.org/10.1007/s10899-018-09824-x

Masyn, K. E. (2013). *Latent class analysis and finite mixture modelling*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199934898.013.0025

May, M. (2021). Eight ways machine learning is assisting medicine. *Nature Medicine*, *27*(1), 2–3. https://doi.org/10.1038/s41591-020-01197-2

Mcbride, J., & Derevensky, J. (2012). Internet gambling and risk-taking among students: An exploratory study. *Journal of Behavioral Addictions*, *1*(2), 50–58. https://doi.org/10.1556/JBA.1.2012.2.2

McBride, J., & Derevensky, J. (2009). Internet gambling behaviour in a sample of online gamblers. *International Journal of Mental Health and Addiction*, *7*(1), 149–167. https://doi.org/10.1007/s11469-008-9169-x

McBride, J., & Derevensky, J. (2017). Gambling and video game playing among youth. *Journal of Gambling Issues*, *2016*(34), 156–178. https://doi.org/10.4309/jgi.2016.34.9

McCrae, R. R., & Costa, P. T. (2004). A contemplated revision of the NEO five-factor inventory. *Personality and Individual Differences*. https://doi.org/10.1016/S0191-8869(03)00118-1

McGinnis, R. S., McGinnis, E. W., Hruschak, J., Lopez-Duran, N. L., Fitzgerald, K., Rosenblum, K. L., &

Muzik, M. (2018). Rapid anxiety and depression diagnosis in young children enabled by wearable sensors and machine learning. *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 3983–3986. https://doi.org/10.1109/EMBC.2018.8513327

McKinney, W. (2011). Pandas: A foundational Python library for data analysis and statistics. *Python for High Performance and Scientific Computing*, *14*(9), 1–9.

McMahon, E. M., Corcoran, P., McAuliffe, C., Keeley, H., Perry, I. J., & Arensman, E. (2013). Mediating effects of coping style on associations between mental health factors and self-harm among adolescents. *Crisis*, *34*(4), 242–250. https://doi.org/10.1027/0227-5910/a000188

Meerkerk, G.-J., Van Den Eijnden, R. J. J. M., Vermulst, A. A., & Garretsen, H. F. L. (2008). The compulsive Internet use scale (CIUS): Some psychometric properties. *CyberPsychology & Behaviour*. https://doi.org/10.1089/cpb.2008.0181

Melfsen, S. S. (1999). *Sozial ängstliche Kinder: Untersuchungen zum mimischen Ausdrucksverhalten und zur Emotionserkennung*. Tectum-Verlag. https://books.google.co.uk/books?id=rBdTSU3ewjsC

Melodia, F., Canale, N., & Griffiths, M. D. (2022). The role of avoidance coping and escape motives in problematic online gaming: A systematic literature review. *International Journal of Mental Health and Addiction*, *20*(2), 996–1022. https://doi.org/10.1007/s11469-020-00422-w

Mérelle, S. Y. M., Kleiboer, A. M., Schotanus, M., Cluitmans, T. L. M., Waardenburg, C. M., Kramer, D., van de Mheen, D., & van Rooij, A. J. (2017). Which health-related problems are associated with problematic video-gaming or social media use in adolescents? A large-scale cross-sectional study. *Clinical Neuropsychiatry*, *14*(1), 11–19. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85014377270&partnerID=40&md5=4e9b4b8ef0bb79cde9969d34298a717a

Mikulincer, M., Shaver, P. R., Sapir-Lavid, Y., & Avihou-Kanza, N. (2009). What's inside the minds of securely and insecurely attached people? The secure-base script and its associations with attachment-style dimensions. *Journal of Personality and Social Psychology*, *97*(4), 615–633. https://doi.org/10.1037/a0015649

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

Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G., PRISMA Group. (2009) Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Med*., *6(7),* e1000097. https://doi.org/10.1371/journal.pmed.1000097.

Monacis, L., de Palo, V., Sinatra, M., & Berzonsky, M. D. (2016). The revised identity style inventory: Factor structure and validity in italian speaking students. *Frontiers in Psychology*, *7(883)*. https://doi.org/10.3389/fpsyg.2016.00883

Monacis, L., Palo, V. de, Griffiths, M. D., & Sinatra, M. (2016). Validation of the Internet gaming disorder scale

– short-form (IGDS9-SF) in an Italian-speaking sample. *Journal of Behavioral Addictions*, *5*(4), 683–690. https://doi.org/10.1556/2006.5.2016.083

Monacis, L., Palo, V., Griffiths, M. D., Sinatra, M., De Palo, V., Griffiths, M. D., & Sinatra, M. (2017). Exploring individual differences in online addictions: The role of identity and attachment. *International Journal of Mental Health and Addiction*, *15*(4), 853–868. https://doi.org/10.1007/s11469-017-9768-5

Morisano, D., Babor, T. F., & Robaina, K. A. (2014). Co-occurrence of substance use disorders with other psychiatric disorders: Implications for treatment services. *NAD Publication*, *31*(1), 5–25. https://doi.org/10.2478/nsad-2014-0002

Mueller, A., Mitchell, J. E., Crosby, R. D., Gefeller, O., Faber, R. J., Martin, A., Bleich, S., Glaesmer, H., Exner, C., & de Zwaan, M. (2010). Estimated prevalence of compulsive buying in Germany and its association with sociodemographic characteristics and depressive symptoms. *Psychiatry Research*. https://doi.org/10.1016/j.psychres.2009.12.001

Müller, A., Claes, L., Smits, D., Gefeller, O., Hilbert, A., Herberg, A., Müller, V., Hofmeister, D., & De Zwaan, M. (2013). Validation of the German version of the exercise dependence scale. *European Journal of Psychological Assessment*. https://doi.org/10.1027/1015-5759/a000144

Müller, A., Loeber, S., Söchtig, J., Te Wildt, B., & De Zwaan, M. (2015). Risk for exercise dependence, eating disorder pathology, alcohol use disorder and addictive behaviours among clients of fitness centers. *Journal of Behavioral Addictions*, *4*(4), 273–280. https://doi.org/10.1556/2006.4.2015.044

Müller, M., & Montag, C. (2017). The relationship between internet addiction and alcohol consumption is influenced by the smoking status in male online video gamers. *Clinical Neuropsychiatry*, *14*(1), 34–43. https://www.clinicalneuropsychiatry.org/download/the-relationship-between-internet-addiction-and-alcohol-consumption-is-influenced-by-the-smoking-status-in-male-online-video-gamers/

Mumtaz, W., Vuong, P. L., Xia, L., Malik, A. S., & Rashid, R. B. A. (2017). An EEG-based machine learning method to screen alcohol use disorder. *Cognitive Neurodynamics*, *11*(2), 161–171. https://doi.org/10.1007/s11571-016-9416-y

Muris, P., Meesters, C., & van den Berg, F. (2003). The strengths and difficulties questionnaire (SDQ). *European Child & Adolescent Psychiatry*, *12*(1), 1–8. https://doi.org/10.1007/s00787-003-0298-2

Murphy, E. L., & Comiskey, C. M. (2013). Using chi-squared automatic interaction detection (CHAID) modelling to identify groups of methadone treatment clients experiencing significantly poorer treatment outcomes. *Journal of Substance Abuse Treatment*, *45*(4), 343–349. https://doi.org/10.1016/j.jsat.2013.05.003

Muthen, B., & Muthen, L. K. (2000). Integrating person-centered and variable-centered analyses: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research*, *24*(6), 882–891. https://doi.org/10.1111/j.1530-0277.2000.tb02070.x

Na, E., Lee, H., Choi, I., & Kim, D.-J. D.-J. D. D.-J. D.-J. (2017). Comorbidity of Internet gaming disorder and alcohol use disorder: A focus on clinical characteristics and gaming patterns. *American Journal on Addictions*, *26*(4), 326–334. https://doi.org/10.1111/ajad.12528

Najt, P., Fusar-Poli, P., & Brambilla, P. (2011). Co-occurring mental and substance abuse disorders: A review on the potential predictors and clinical outcomes. *Psychiatry Research*, *186*(2–3), 159–164. https://doi.org/10.1016/j.psychres.2010.07.042

Nicola, M. Di, Tedeschi, D., Risio, L. De, Pettorruso, M., Martinotti, G., Ruggeri, F., Swierkosz-Lenart, K., Guglielmo, R., Callea, A., Ruggeri, G., Pozzi, G., Giannantonio, M. Di, Janiri, L., Di Nicola, M., Tedeschi, D., De Risio, L., Pettorruso, M., Martinotti, G., Ruggeri, F., … Janiri, L. (2015). Co-occurrence of alcohol use disorder and behavioural addictions: Relevance of impulsivity and craving. *Drug and Alcohol Dependence*, *148*, 118–125. https://doi.org/10.1016/j.drugalcdep.2014.12.028

Nuyens, F., Deleuze, J., Maurage, P., Griffiths, M. D., Kuss, D. J., & Billieux, J. (2016). Impulsivity in multiplayer online battle arena gamers: Preliminary results on experimental and self-report measures. *Journal of Behavioral Addictions*, *5*(2), 351–356. https://doi.org/10.1556/2006.5.2016.028

O'Farrell, D. L., Baynes, K.-L., M. Pontes, H., D. Griffiths, M., & Stavropoulos, V. (2020). Depression and disordered gaming: Does culture matter? *International Journal of Mental Health and Addiction*, 333–348. https://doi.org/10.1007/s11469-020-00231-1

Oberski, D. (2016). Mixture models: Latent profile and latent class analysis. In J. Robertson & M. Kaptein (Eds.), *Modern Statistical Methods for HCI* (pp. 275–287). Springer. https://doi.org/10.1007/978-3-319-26633-6_12

Orrù, G., Monaro, M., Conversano, C., Gemignani, A., & Sartori, G. (2020). Machine learning in psychometrics and psychological research. *Frontiers in Psychology*, *10*(2970). https://doi.org/10.3389/fpsyg.2019.02970

Ouyang, W., & Wang, X. (2013). Joint deep learning for pedestrian detection. *Proceedings of the IEEE International Conference on Computer Vision*, 2056–2063.

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … McKenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews. *BMJ*, *372*, n160. https://doi.org/10.1136/bmj.n160

Pápay, O., Urbán, R., Griffiths, M. D., Nagygyörgy, K., Farkas, J., Kökönyei, G., Felvinczi, K., Oláh, A., Elekes, Z., & Demetrovics, Z. (2013). Psychometric properties of the problematic online gaming questionnaire short-form and prevalence of problematic online gaming in a national sample of adolescents. *Cyberpsychology, Behaviour, and Social Networking, 16*(5), 340-348. https://doi.org/10.1089/cyber.2012.0484

Park, J. H., Hong, J. S., Han, D. H., Min, K. J., Lee, Y. S., Kee, B. S., & Kim, S. M. (2017). Comparison of QEEG findings between adolescents with attention deficit hyperactivity disorder (ADHD) without comorbidity and ADHD comorbid with Internet gaming disorder. *Journal of Korean Medical Science*, *32*(3), 514. https://doi.org/10.3346/jkms.2017.32.3.514

Park, S. M., Jeong, B., Oh, D. Y., Choi, C.-H. H., Jung, H. Y., Lee, J.-Y. Y., Lee, D., & Choi, J.-S. S. (2021). Identification of major psychiatric disorders from resting-state electroencephalography using a machine learning approach. *Frontiers in Psychiatry*, *12*(707581). https://doi.org/10.3389/fpsyt.2021.707581

Park, S. M., Lee, J. Y., Kim, Y. J., Lee, J.-Y., Jung, H. Y., Sohn, B. K., Kim, D. J., & Choi, J.-S. (2017). Neural connectivity in Internet gaming disorder and alcohol use disorder: A resting-state EEG coherence study. *Scientific Reports*, *7*(1), 1333. https://doi.org/10.1038/s41598-017-01419-7

Park, S., Ryu, H., Lee, J.-Y., Choi, A., Kim, D.-J., Kim, S. N., & Choi, J.-S. (2018). Longitudinal changes in neural connectivity in patients with Internet gaming disorder: A resting-state EEG coherence study. *Frontiers in Psychiatry*, *9*(JUN). https://doi.org/10.3389/fpsyt.2018.00252

Parsons, T. D., McMahan, T., & Parberry, I. (2022). Classification of video game player experience using consumer-grade electroencephalography. *IEEE Transactions on Affective Computing*, *13*(1), 3–15. https://doi.org/10.1109/TAFFC.2020.2992437

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Müller, A., Nothman, J., Louppe, G., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830. http://arxiv.org/abs/1201.0490

Pedrero Pérez, E. J., Rodríguez Monje, M. T., Gallardo Alonso, F., Fernández Girón, M., Pérez López, M., & Chicharro Romero, J. (2007). Validación de un instrumento para la detección de trastornos de control de impulsos y adicciones: el MULTICAGE CAD-4. *Trastornos Adictivos*, *9*(4), 269–278. https://doi.org/10.1016/S1575-0973(07)75656-8

Peng, C.-Y., Chen, Y.-C., Cui, Y., Zhao, D.-L., Jiao, Y., Tang, T.-Y., Ju, S., & Teng, G.-J. (2016). Regional coherence alterations revealed by resting-state fMRI in post-stroke patients with cognitive dysfunction. *PLOS ONE*, *11*(7), e0159574. https://doi.org/10.1371/journal.pone.0159574

Petro, B., Kasabov, N., & Kiss, R. M. (2020). Selection and optimization of temporal spike encoding methods for spiking neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, *31*(2), 358–370. https://doi.org/10.1109/TNNLS.2019.2906158

Petry, N. M., Rehbein, F., Gentile, D. A., Lemmens, J. S., Rumpf, H. J., Mößle, T., Bischof, G., Tao, R., Fung, D. S. S., Borges, G., Auriacombe, M., González Ibáñez, A., Tam, P., & O'Brien, C. P. (2014). An international consensus for assessing Internet gaming disorder using the new DSM-5 approach. *Addiction, 109*(9), 1399-1406. https://doi.org/10.1111/add.12457

Petry, N. M., Rehbein, F., Gentile, D. A., Lemmens, J. S., Rumpf, H., Mößle, T., Bischof, G., Tao, R., Fung, D. S. S., Borges, G., Auriacombe, M., González-Ibáñez, A., Tam, P., & O'Brien, C. P. (2016). Griffiths et al.'s comments on the international consensus statement of internet gaming disorder: Furthering consensus or hindering progress? *Addiction*, *111*(1), 175–178. https://doi.org/10.1111/add.13189

Plante, C. N., Gentile, D. A., Groves, C. L., Modlin, A., & Blanco-Herrera, J. (2019). Video games as coping mechanisms in the etiology of video game addiction. *Psychology of Popular Media Culture.*, *8*(4), 385–394. https://doi.org/http://dx.doi.org/10.1037/ppm0000186

Pontes, H. M. (2017). Investigating the differential effects of social networking site addiction and Internet gaming disorder on psychological health. *Journal of Behavioral Addictions*, *6*(4), 601–610. https://doi.org/10.1556/2006.6.2017.075

Pontes, H. M. (2018). Making the case for video game addiction: Does it exist or not? In C. J. Ferguson (Ed.), *Video game influences on aggression, cognition, and attention* (pp. 41–57). Springer International Publishing. https://doi.org/10.1007/978-3-319-95495-0_4

Pontes, H. M., & Griffiths, M. D. (2015). Measuring DSM-5 internet gaming disorder: Development and validation of a short psychometric scale. *Computers in Human Behaviour, 45*, 137–143. https://doi.org/10.1016/j.chb.2014.12.006

Pontes, H. M., & Griffiths, M. D. (2017). The development and psychometric properties of the Internet disorder scale–short form (IDS9-SF). *Addicta: The Turkish Journal on Addictions*, *3*(3), 303-318. https://doi.org/10.15805/addicta.2016.3.0102

Pontes, H. M., Kuss, D. J., & Griffiths, M. D. (2017). Psychometric assessment of internet gaming disorder in neuroimaging studies: A Systematic Review. In C. Montag & M. Reuter (Eds.), *Internet addiction: Neuroscientific approaches and therapeutical implications including smartphone addiction* (2nd ed., pp. 181–208). Springer. https://doi.org/10.1007/978-3-319-46276-9_11

Pontes, H. M., Stavropoulos, V., & Griffiths, M. D. (2017). Measurement invariance of the internet gaming disorder scale–short-form (IGDS9-SF) between the United States of America, India and the United Kingdom. *Psychiatry Research*, *257*, 472–478. https://doi.org/10.1016/j.psychres.2017.08.013

Porjesz, B., Rangaswamy, M., Kamarajan, C., Jones, K. A., Padmanabhapillai, A., & Begleiter, H. (2005). The utility of neurophysiological markers in the study of alcoholism. *Clinical Neurophysiology*, *116*(5), 993–1018. https://doi.org/10.1016/j.clinph.2004.12.016

Potenza, M. N. (2018). Do gaming disorder and hazardous gaming belong in the ICD-11? Considerations regarding the death of a hospitalized patient that was reported to have occurred while a care provider was gaming. *Journal of Behavioral Addictions*, *7*(2), 206–207. https://doi.org/10.1556/2006.7.2018.42

Ptak, R. (2012). The frontoparietal attention network of the human brain. *The Neuroscientist*, *18*(5), 502–515. https://doi.org/10.1177/1073858411409051

Radloff, L. S. (1977). The CES-D scale: A self-report depression scale for research in the general population. *Applied Psychological Measurement* 1(3), 385-401. https://doi.org/10.1177/014662167700100306

Rangaswamy, M., Porjesz, B., Chorlian, D. B., Wang, K., Jones, K. A., Kuperman, S., Rohrbaugh, J., O'Connor, S. J., Bauer, L. O., Reich, T., & Begleiter, H. (2004). Resting EEG in offspring of male alcoholics: Beta frequencies. *International Journal of Psychophysiology*, *51*(3), 239–251.

https://doi.org/10.1016/j.ijpsycho.2003.09.003

Ream, G. L., Elliott, L. C., & Dunlap, E. (2011). Playing video games while using or feeling the effects of substances: associations with substance use problems. *International Journal of Environmental Research and Public Health*, *8*(10), 3979–3998. https://doi.org/10.3390/ijerph8103979

Ream, G. L., Elliott, L. C., & Dunlap, E. (2013). Trends in video game play through childhood, adolescence, and emerging adulthood. *Psychiatry Journal*, *2013*, 1–7. https://doi.org/10.1155/2013/301460

Rehbein, F., Psych, G., Kleimann, M., Mediasci, G., & Mößle, T. (2010). Prevalence and risk factors of video game dependency in adolescence: Results of a German nationwide survey. *Cyberpsychology, Behaviour, and Social Networking*. https://doi.org/10.1089/cyber.2009.0227

Reid, R. C., Li, D. S., Gilliland, R., Stein, J. A., & Fong, T. (2011). Reliability, validity, and psychometric development of the pornography consumption inventory in a sample of hypersexual men. *Journal of Sex and Marital Therapy*. https://doi.org/10.1080/0092623X.2011.607047

Reid, R. C., Li, D. S., Lopez, J., Collard, M., Parhami, I., Karim, R., & Fong, T. (2011). Exploring facets of personality and escapism in pathological gamblers. *Journal of Social Work Practice in the Addictions*, *11*(1), 60–74. https://doi.org/http://dx.doi.org/10.1080/1533256X.2011.547071

Rho, M. J., Jeong, J.-E., Chun, J.-W., Cho, H., Jung, D. J., Choi, I. Y., & Kim, D.-J. D.-J. (2016). Predictors and patterns of problematic Internet game use using a decision tree model. *Journal of Behavioral Addictions*, *5*(3), 500–509. https://doi.org/10.1556/2006.5.2016.051

Roncero, C., Grau-López, L., & Casas, M. (2017). Dual Disorders. *Addictive Disorders & Their Treatment*, *16*(4), 175–179. https://doi.org/10.1097/ADT.0000000000000113

Rosenberg, J., Beymer, P., Anderson, D., van Lissa, C. j., & Schmidt, J. (2018). tidyLPA: An R package to easily carry out latent profile analysis (LPA) using open-source or commercial software. *Journal of Open Source Software*, *3*(30), 978. https://doi.org/10.21105/joss.00978

Rosenberg, M. (1965). *Society and the adolescent self-image*. Princeton University Press.

Rosenblatt, F. (1958). The perceptron: A probabilistic model for information storage and organization in the brain. *Psychological Review*, *65*(6), 386–408. https://doi.org/10.1037/h0042519

Ruiz, P. (2017). Dual Disorders: A Worldwide Perspective. *Addictive Disorders & Their Treatment*, *16*(4), 151–154. https://doi.org/10.1097/ADT.0000000000000111

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A. C., & Fei-Fei, L. (2015). ImageNet large scale visual recognition challenge. *International Journal of Computer Vision*, *115*(3), 211–252. https://doi.org/10.1007/s11263-015-0816-y

Russell, D., Peplau, L. A., & Cutrona, C. E. (1980). The revised UCLA loneliness scale: Concurrent and discriminant validity evidence. *Journal of Personality and Social Psychology*, *39*(3), 472-480. https://doi.org/10.1037/0022-3514.39.3.472

Saletu-Zyhlarz, G. M. (2004). Differences in brain function between relapsing and abstaining alcohol-dependent patients, evaluated by EEG mapping. *Alcohol and Alcoholism*, *39*(3), 233–240. https://doi.org/10.1093/alcalc/agh041

Şalvarlı, Ş. İ., & Griffiths, M. D. (2019). The association between Internet gaming disorder and impulsivity: A systematic review of literature. *International Journal of Mental Health and Addiction, 20,* 92-118. https://doi.org/http://dx.doi.org/10.1007/s11469-019-00126-w

Saunders, J. B., Aasland, O. G., Babor, T. F., De La Fuente, J. R., & Grant, M. (1993). Development of the alcohol use disorders identification test (AUDIT): WHO collaborative project on early detection of persons with harmful alcohol consumption-II. *Addiction*, *88*(6), 791–804. https://doi.org/10.1111/j.1360-0443.1993.tb02093.x

Schiller, D., Kanen, J. W., LeDoux, J. E., Monfils, M.-H., & Phelps, E. A. (2013). Extinction during reconsolidation of threat memory diminishes prefrontal cortex involvement. *Proceedings of the National Academy of Sciences*, *110*(50), 20040–20045. https://doi.org/10.1073/pnas.1320322110

Schimmenti, A., Infanti, A., Badoud, D., Laloyaux, J., & Billieux, J. (2017). Schizotypal personality traits and problematic use of massivelymultiplayer online role-playing games (MMORPGs). *Computers in Human Behaviour*, *74*, 286–293. https://doi.org/10.1016/j.chb.2017.04.048

Schneider, L. A., King, D. L., & Delfabbro, P. H. (2018). Maladaptive coping styles in adolescents with Internet gaming disorder symptoms. *International Journal of Mental Health and Addiction*, *16*(4), 905–916. https://doi.org/10.1007/s11469-017-9756-9

Schreiber, L. R. N., Grant, J. E., & Odlaug, B. L. (2012). Emotion regulation and impulsivity in young adults. *Journal of Psychiatric Research*, *46*(5), 651–658. https://doi.org/10.1016/j.jpsychires.2012.02.005

Schrouff, J., Rosa, M. J., Rondina, J. M., Marquand, A. F., Chu, C., Ashburner, J., Phillips, C., Richiardi, J., & Mourão-Miranda, J. (2013). PRoNTo: Pattern recognition for neuroimaging toolbox. *Neuroinformatics*, *11*(3), 319–337. https://doi.org/10.1007/s12021-013-9178-1

Schwarzer, R. (1999). *Skalen zur erfassung von lehrer- und schülermerkmalen: dokumentation der psychometrischen verfahren im rahmen der wissenschaftlichen begleitung des modellversuchs selbstwirksame schulen*. Freie Universität Berlin. https://books.google.co.uk/books?id=CeWMAgAACAAJ

Senormanci, O., Konkan, R., Guclu, O., & Senormanci, G. (2014). Evaluation of coping strategies of male patients, being treated in internet addiction outpatient clinic in Turkey. *Journal of Mood Disorders*, *4*(1), 14. https://doi.org/10.5455/jmood.20131213042312

Shaffer, H. J., LaPlante, D. A., LaBrie, R. A., Kidman, R. C., Donato, A. N., & Stanton, M. V. (2004). Toward a syndrome model of addiction: Multiple expressions, common etiology. *Harvard Review of Psychiatry*, *12*(6), 367–374. https://doi.org/10.1080/10673220490905705

Shah, D., Wang, G. Y., Doborjeh, M., Doborjeh, Z., & Kasabov, N. (2019). Deep learning of EEG data in the

NeuCube brain-inspired spiking neural network architecture for a better understanding of depression. In T. Gedeon, K. W. Wong, & M. Lee (Eds.), *International Conference on Neural Information Processing* (pp. 195–206). Springer International Publishing. https://doi.org/10.1007/978-3-030-36718-3_17

Sharifat, H., Rashid, A. A., & Suppiah, S. (2018). Systematic review of the utility of functional MRI to investigate internet addiction disorder: Recent updates on resting state and task-based fMRI. *Malaysian Journal of Medicine and Health Sciences*, *14*(1), 21–33. https://medic.upm.edu.my/upload/dokumen/2018031608380404_MJMHS_Vol14_No1_Jan2018_0080_-_2nd_proof.pdf

Shen, X., Finn, E. S., Scheinost, D., Rosenberg, M. D., Chun, M. M., Papademetris, X., & Constable, R. T. (2017). Using connectome-based predictive modelling to predict individual behaviour from brain connectivity. *Nature Protocols*, *12*(3), 506–518. https://doi.org/10.1038/nprot.2016.178

Siddaway, A. P., Wood, A. M., & Hedges, L. V. (2019). How to do a systematic review: A best practice guide for conducting and reporting narrative reviews, meta-analyses, and meta-syntheses. *Annual Review of Psychology*, *70*(1), 747–770. https://doi.org/10.1146/annurev-psych-010418-102803

Škařupová, K., Blinka, L., & Ťápal, A. (2018). Gaming under the influence: An exploratory study. *Journal of Behavioral Addictions*, *7*(2), 493–498. https://doi.org/10.1556/2006.7.2018.27

Skinner, H. A. (1982). The drug abuse screening test. *Addictive Behaviours*, *7*(4), 363–371. https://doi.org/10.1016/0306-4603(82)90005-3

Šlamberová, R., Vrajová, M., Schutová, B., Mertlová, M., Macúchová, E., Nohejlová, K., Hrubá, L., Puskarčíková, J., & Bubeníková-Valešová, V Yamamotová, A. (2014). Prenatal methamphetamine exposure induces long-lasting alterations in memory and development of NMDA receptors in the hippocampus. *Physiological Research*, S547–S558. https://doi.org/10.33549/physiolres.932926

Smith, J. L., Mattick, R. P., Jamadar, S. D., & Iredale, J. M. (2014). Deficits in behavioural inhibition in substance abuse and addiction: A meta-analysis. In *Drug and Alcohol Dependence 145*, 1-33. https://doi.org/10.1016/j.drugalcdep.2014.08.009

Snyder, S. M., & Hall, J. R. (2006). A meta-analysis of quantitative EEG power associated with attention-deficit hyperactivity disorder. *Journal of Clinical Neurophysiology*, *23*(5), 441–456. https://doi.org/10.1097/01.wnp.0000221363.12503.78

So, K., & Sung, E. (2013). A validation study of the brief alcohol use disorder identification test (AUDIT): A brief screening tool derived from the AUDIT. *Korean Journal of Family Medicine*, *34*(1), 11. https://doi.org/10.4082/kjfm.2013.34.1.11

Son, K.-L., Choi, J.-S., Lee, J., Park, S. M., Lim, J.-A., Lee, J. Y., Kim, S. N., Oh, S., Kim, D. J., & Kwon, J. S. (2015). Neurophysiological features of Internet gaming disorder and alcohol use disorder: A resting-state EEG study. *Translational Psychiatry*, *5*(9), e628–e628. https://doi.org/10.1038/tp.2015.124

Song, K., Potenza, M. N., Fang, X., Gong, G., Yao, Y., Wang, Z., Liu, L., Ma, S., Xia, C., Lan, J., Deng, L., Wu, L., & Zhang, J. (2021). Resting-state connectome-based support-vector-machine predictive modelling of Internet gaming disorder. *Addiction Biology*, *26*(4), 10. https://doi.org/10.1111/adb.12969

Stadler, C., Janke, W., & Schmeck, K. (2002). *IVE: Inventar zur erfassung von impulsivität, risikoverhalten und empathie bei 9- bis 14-jährigen kindern: Manual*. Hogrefe. https://books.google.co.uk/books?id=iES6cQAACAAJ

Staiger, P. K., Richardson, B., Long, C. M., Carr, V., & Marlatt, G. A. (2013). Overlooked and underestimated? Problematic alcohol use in clients recovering from drug dependence. *Addiction*, *108*(7), 1188–1193. https://doi.org/10.1111/j.1360-0443.2012.04075.x

Starcevic, V., & Khazaal, Y. (2017). Relationships between behavioural addictions and psychiatric disorders: What is known and what is yet to be learned? *Frontiers in Psychiatry*, *8*(APR), 53. https://doi.org/10.3389/fpsyt.2017.00053

Statista. (2021). *Video game industry in the United Kingdom - statistics & facts*. https://www.statista.com/topics/1763/gaming-in-the-united-kingdom/#:~:text=Between 2019 and 2020%2C the,at 5.3 billion British pounds.

Stavropoulos, V., Adams, B. L. M. M., Beard, C. L., Dumble, E., Trawley, S., Gomez, R., & Pontes, H. M. (2019). Associations between attention deficit hyperactivity and internet gaming disorder symptoms: Is there consistency across types of symptoms, gender and countries? *Addictive Behaviours Reports*, *9*, 10. https://doi.org/http://dx.doi.org/10.1016/j.abrep.2018.100158

Stavropoulos, V., Baynes, K. L., O'Farrel, D. L., Gomez, R., Mueller, A., Yucel, M., & Griffiths, M. (2020). Inattention and disordered gaming: Does culture matter? *Psychiatric Quarterly*, *91*(2), 333–348. https://doi.org/10.1007/s11126-019-09702-8

Stavropoulos, V., Gomez, R., Mueller, A., Yucel, M., & Griffiths, M. (2020). User-avatar bond profiles: How do they associate with disordered gaming? *Addictive Behaviours*, *103*, 106245. https://doi.org/10.1016/j.addbeh.2019.106245

Stavropoulos, V., Kuss, D., Griffiths, M., & Motti-Stefanidi, F. (2016). A longitudinal study of adolescent internet addiction. *Journal of Adolescent Research*, *31*(4), 442–473. https://doi.org/10.1177/0743558415580163

Stavropoulos, V., Pontes, H. M., Gomez, R., Schivinski, B., & Griffiths, M. (2020). Proteus effect profiles: How do they relate with disordered gaming behaviours? *Psychiatric Quarterly*, *91*(3), 615–628. https://doi.org/10.1007/s11126-020-09727-4

Straub, D., Keil, M., & Brenner, W. (1997). Testing the technology acceptance model across cultures: A three country study. *Information & Management*, *33*(1), 1–11. https://doi.org/10.1016/S0378-7206(97)00026-8

Streiner, D. L., & Cairney, J. (2007). What's under the ROC? An introduction to receiver operating characteristics curves. *The Canadian Journal of Psychiatry*, *52*(2), 121–128. https://doi.org/10.1177/070674370705200210

Strizek, J., Atzendorf, J., Kraus, L., Monshouwer, K., Puhm, A., & Uhl, A. (2020). Perceived problems with adolescent online gaming: National differences and correlations with substance use. *Journal of Behavioral Addictions*, *9*(3), 629–641. https://doi.org/10.1556/2006.2020.00061

Sun, Y., Wang, H., & Bo, S. (2019). Altered topological connectivity of Internet addiction in resting-state EEG through network analysis. *Addictive Behaviours*, *95*, 49–57. https://doi.org/10.1016/j.addbeh.2019.02.015

Sussman, S. (2005). The relations of cigarette smoking with risky sexual behaviour among teens. *Sexual Addiction & Compulsivity*, *12*(2–3), 181–199. https://doi.org/10.1080/10720160500203732

Sussman, S., & Black, D. S. (2008). Substitute addiction: A concern for researchers and practitioners. *Journal of Drug Education*, *38*(2), 167–180. https://doi.org/10.2190/DE.38.2.e

Sussman, S., Lisha, N., & Griffiths, M. (2011). Prevalence of the addictions: A problem of the majority or the minority? *Evaluation & the Health Professions*, *34*(1), 3–56. https://doi.org/10.1177/0163278710380124

Sussman, S., Pokhrel, P., Sun, P., Rohrbach, L. A., & Spruijt-Metz, D. (2015). Prevalence and co-occurrence of addictive behaviours among former alternative high school youth: A longitudinal follow-up study. *Journal of Behavioral Addictions*, *4*(3), 189–194. https://doi.org/10.1556/2006.4.2015.027

Szabo, A., Amit, P., Griffiths, M. D., Kovácsik, R., & Demetrovics, Z. (2019). The psychometric evaluation of the revised exercise addiction inventory: Improved psychometric properties by changing item response rating. *Journal of Behavioral Addictions*, *8*(1), 157–161. https://doi.org/10.1556/2006.8.2019.06

Szerman, N., Martinez-Raga, J., Peris, L., Roncero, C., Basurte, I., Vega, P., Ruiz, P., & Casas, M. (2013). Rethinking dual disorders/pathology. *Addictive Disorders & Their Treatment*, *12*(1), 1–10. https://doi.org/10.1097/ADT.0b013e31826e7b6a

Talairach, J. (1988). Co-planar stereotaxic atlas of the human brain-3-dimensional proportional system. *An approach to cerebral imaging*. Thieme.

Tallon-Baudry, C. (2003). Oscillatory synchrony and human visual cognition. *Journal of Physiology-Paris*, *97*(2–3), 355–363. https://doi.org/10.1016/j.jphysparis.2003.09.009

Tallon-Baudry, C., Bertrand, O., Hénaff, M.-A., Isnard, J., & Fischer, C. (2005). Attention modulates gamma-band oscillations differently in the human lateral occipital cortex and fusiform gyrus. *Cerebral Cortex*, *15*(5), 654–662. https://doi.org/10.1093/cercor/bhh167

Tan, C., Šarlija, M., & Kasabov, N. (2020). Spiking neural networks: Background, recent development and the NeuCube architecture. *Neural Processing Letters*, *52*(2), 1675–1701. https://doi.org/10.1007/s11063-020-10322-8

Tang, J., Yu, Y., Du, Y., Ma, Y., Zhang, D., & Wang, J. (2014). Prevalence of Internet addiction and its association with stressful life events and psychological symptoms among adolescent Internet users. *Addictive Behaviours*, *39*(3), 744–747. https://doi.org/10.1016/j.addbeh.2013.12.010

Tavolacci, M. P., Ladner, J., Grigioni, S., Richard, L., Villet, H., & Dechelotte, P. (2013). Prevalence and association of perceived stress, substance use and behavioural addictions: A cross-sectional study among university students in France, 2009-2011. *BMC Public Health*. https://doi.org/10.1186/1471-2458-13-724

Tejeiro Salguero, R. A., & Bersabé Morán, R. M. (2002). Measuring problem video game playing in adolescents. *Addiction*. https://doi.org/10.1046/j.1360-0443.2002.00218.x

Tekin Erguzel, T., Tas, C., & Cebi, M. (2015). A wrapper-based approach for feature selection and classification of major depressive disorder–bipolar disorders. *Computers in Biology and Medicine*, *64*, 127–137. https://doi.org/10.1016/j.compbiomed.2015.06.021

Terry, A., Szabo, A., & Griffiths, M. (2004). The exercise addiction inventory: A new brief screening tool. *Addiction Research and Theory*, *12*(5), 489–499. https://doi.org/10.1080/16066350310001637363

Thatcher, R. W., North, D., & Biver, C. (2005). EEG and intelligence: Relations between EEG coherence, EEG phase delay and power. *Clinical Neurophysiology*, *116*(9), 2129–2141. https://doi.org/10.1016/j.clinph.2005.04.026

Tirapu-Ustarroz, J., Luna-Lario, P., Iglesias-Fernandez, M. D., & Hernaez-Goni, P. (2011). Cerebellar contribution to cognitive process: Current advances. *Revista de Neurologia*, *53*(5), 301–315. http://www.ncbi.nlm.nih.gov/pubmed/21796608

Triandis, H. C. (1996). The psychological measurement of cultural syndromes. *American Psychologist*, *51*(4), 407–415. https://doi.org/10.1037/0003-066X.51.4.407

Tsai, J., Huh, J., Idrisov, B., Galimov, A., Espada, J. P., Gonzálvez, M. T., & Sussman, S. (2016). Prevalence and co-occurrence of addictive behaviours among russian and spanish youth. *Journal of Drug Education*, *46*(1–2), 32–46. https://doi.org/10.1177/0047237917704635

Tsitsika, A., Janikian, M., Schoenmakers, T. M., Tzavela, E. C., Ólafsson, K., Wójcik, S., Macarie, G. F., Tzavara, C., Richardson, C., Lafsson, K. O. ´, Wó, S., Macarie, G. F., Tzavara, C., Richardson, C., Wojcik, S., Macarie, G. F., & Tzavara, C. (2014). internet addictive behaviour in adolescence: A cross-sectional study in seven european countries. *Cyberpsychology, Behaviour, and Social Networking*, *17*(8), 528–535. https://doi.org/10.1089/cyber.2013.0382

Tu, E., Kasabov, N., Othman, M., Li, Y., Worner, S., Yang, J., & Jia, Z. (2014). NeuCube(ST) for spatio-temporal data predictive modelling with a case study on ecological data. *2014 International Joint Conference on Neural Networks (IJCNN)*, 638–645. https://doi.org/10.1109/IJCNN.2014.6889717

Tullett-Prado, D., Stavropoulos, V., Mueller, K., Sharples, J., & Footitt, T. A. (2021). Internet gaming disorder profiles and their associations with social engagement behaviours. *Journal of Psychiatric Research*, *138*, 393–403. https://doi.org/10.1016/j.jpsychires.2021.04.037

Turel, O., & Bechara, A. (2019). Little video-gaming in adolescents can be protective, but too much is associated with increased substance use. *Substance Use & Misuse*, *54*(3), 384–395. https://doi.org/10.1080/10826084.2018.1496455

United Nations Publications. (2020). *World drug report 2020*. United Nations Publications.

https://wdr.unodc.org/wdr2020/index2020.html

Urbanoski, K. A., Castel, S., Rush, B. R., Bassani, D. G., & Wild, T. C. (2007). Use of mental health care services by Canadians with co-occurring substance dependence and mental disorders. *Psychiatric Services*. https://doi.org/10.1176/appi.ps.58.7.962

Usher-Smith, J. A., Sharp, S. J., & Griffin, S. J. (2016). The spectrum effect in tests for risk prediction, screening, and diagnosis. *BMJ*, i3139. https://doi.org/10.1136/bmj.i3139

van Rooij, A. J., Ferguson, C. J., Colder Carras, M., Kardefelt-Winther, D., Shi, J., Aarseth, E., Bean, A. M., Bergmark, K. H., Brus, A., Coulson, M., Deleuze, J., Dullur, P., Dunkels, E., Edman, J., Elson, M., Etchells, P. J., Fiskaali, A., Granic, I., Jansz, J., … Przybylski, A. K. (2018). A weak scientific basis for gaming disorder: Let us err on the side of caution. *Journal of Behavioral Addictions*, *7*(1), 1–9. https://doi.org/10.1556/2006.7.2018.19

van Rooij, A. J., Ferguson, C., Van de Mheen, D., & Schoenmakers, T. M. (2015). Problematic Internet use: Comparing video gaming and social media use. *Journal of Behavioral Addictions*, *4*, 1–62. https://doi.org/10.13140/RG.2.1.1643.7600

van Rooij, A. J., Kuss, D. J., Griffiths, M. D., Shorter, G. W., Schoenmakers, T. M., & van de Mheen, D. (2014). The (co-)occurrence of problematic video gaming, substance use, and psychosocial problems in adolescents. *Journal of Behavioral Addictions*, *3*(3), 157–165. https://doi.org/10.1556/JBA.3.2014.013

van Rooij, A. J., Schoenmakers, T. M., van den Eijnden, R. J., Vermulst, A. A., & van de Mheen, D. (2012). Video game addiction test: Validity and psychometric characteristics. *Cyberpsychology, Behaviour and Social Networking 5*(9), 507-511. https://doi.org/10.1089/cyber.2012.0007.

Verplanken, B., & Herabadi, A. (2001). Individual differences in impulse buying tendency: Feeling and no thinking. *European Journal of Personality*, *15*(S1), S71–S83. https://doi.org/10.1002/per.423

Vieira, S., Lopez Pinaya, W. H., & Mechelli, A. (2020). Introduction to machine learning. In *Machine learning* (pp. 1–20). Elsevier. https://doi.org/10.1016/B978-0-12-815739-8.00001-8

Vieira, S., Pinaya, W. H. L., & Mechelli, A. (2017). Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: Methods and applications. *Neuroscience & Biobehavioral Reviews*, *74*, 58–75. https://doi.org/10.1016/j.neubiorev.2017.01.002

Vollmer, C., Randler, C., Horzum, M. B., & Ayas, T. (2014). Computer game addiction in adolescents and its relationship to chronotype and personality. *SAGE Open*, *4*(1), 1-9. https://doi.org/10.1177/2158244013518054

von Collani, G., & Herzberg, P. Y. (2003). Eine revidierte Fassung der deutschsprachigen skala zum selbstwertgefühl von rosenberg. *Zeitschrift für differentielle und diagnostische psychologie, 24*(1), 3-7. https://doi.org/10.1024//0170-1789.24.1.3

von Stein, A., & Sarnthein, J. (2000). Different frequencies for different scales of cortical integration: from local gamma to long range alpha/theta synchronization. *International Journal of Psychophysiology*, *38*(3), 301–

313. https://doi.org/10.1016/S0167-8760(00)00172-0

Walther, B., Morgenstern, M., & Hanewinkel, R. (2012). Co-Occurrence of addictive behaviours: Personality factors related to substance use, gambling and computer gaming. *European Addiction Research*, *18*(4), 167–174. https://doi.org/10.1159/000335662

Walton, M. E., & Mars, R. B. (2007). Probing human and monkey anterior cingulate cortex in variable environments. *Cognitive, Affective, & Behavioral Neuroscience*, *7*(4), 413–422. https://doi.org/10.3758/CABN.7.4.413

Wang, C.-C., & Yang, H.-W. (2008). Passion for online shopping: the influence of personality and compulsive buying. *Social Behaviour and Personality: An International Journal*, *36*(5), 693–706. https://doi.org/10.2224/sbp.2008.36.5.693

Wang, G. Y., Kydd, R., & Russell, B. R. (2015). Resting EEG and ERPs findings in methadone-substituted opiate users: A review. *Acta Neurologica Belgica*, *115*(4), 539–546. https://doi.org/10.1007/s13760-015-0476-2

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

Wang, L., Wu, L., Wang, Y., Li, H., Liu, X., Du, X., & Dong, G. (2017). Altered brain activities associated with craving and cue reactivity in people with Internet gaming disorder: Evidence from the comparison with recreational Internet game users. *Frontiers in Psychology*, *8(1150)*. https://doi.org/10.3389/fpsyg.2017.01150

Wang, R., Li, M., Zhao, M., Yu, D., Hu, Y., Wiers, C. E., Wang, G.-J., Volkow, N. D., & Yuan, K. (2019). Internet gaming disorder: Deficits in functional and structural connectivity in the ventral tegmental area-Accumbens pathway. *Brain Imaging and Behaviour*, *13*(4), 1172–1181. https://doi.org/10.1007/s11682-018-9929-6

Wang, Y., Zhang, X., Huang, J., Zhu, M., Guan, Q., & Liu, C. (2013). Associations between EEG beta power abnormality and diagnosis in cognitive impairment post cerebral infarcts. *Journal of Molecular Neuroscience*, *49*(3), 632–638. https://doi.org/10.1007/s12031-012-9918-y

Wang, Z.-L., Potenza, M. N., Song, K.-R., Fang, X.-Y., Liu, L., Ma, S.-S., Xia, C.-C., Lan, J., Yao, Y.-W., & Zhang, J.-T. (2022). Neural classification of Internet gaming disorder and prediction of treatment response using a cue-reactivity fMRI task in young men. *Journal of Psychiatric Research*, *145*, 309–316. https://doi.org/10.1016/j.jpsychires.2020.11.014

Wang, Z. L., Dong, H. H., Du, X. X., Zhang, J.-T. T., & Dong, G.-H. H. (2020). Decreased effective connection from the parahippocampal gyrus to the prefrontal cortex in Internet gaming disorder: A MVPA and spDCM study. *Journal of Behavioral Addictions*, *9*(1), 105–115. https://doi.org/10.1556/2006.2020.00012

Wang, Z., Wu, L., Yuan, K., Hu, Y., Zheng, H., Du, X., & Dong, G. (2018). Cortical thickness and volume abnormalities in Internet gaming disorder: Evidence from comparison of recreational Internet game users. *European Journal of Neuroscience*, *48*(1), 1654–1666. https://doi.org/10.1111/ejn.13987

Wartberg, L., Kriston, L., Zieglmeier, M., Lincoln, T., & Kammerl, R. (2019). A longitudinal study on psychosocial causes and consequences of Internet gaming disorder in adolescence. *Psychological Medicine*, *49*(2), 287–294. https://doi.org/10.1017/S003329171800082X

Watson, D., & Hubbard, B. (1996). Adaptational style and dispositional structure: Coping in the context of the five-factor model. *Journal of Personality*, *64*(4), 737–774. https://doi.org/10.1111/j.1467-6494.1996.tb00943.x

Wei, J., Chen, T., Li, C., Liu, G., Qiu, J., & Wei, D. (2018). Eyes-open and eyes-closed resting states with opposite brain activity in sensorimotor and occipital regions: Multidimensional evidences from machine learning perspective. *Frontiers in Human Neuroscience*, *12(422)*. https://doi.org/10.3389/fnhum.2018.00422

Weible, A. P. (2013). Remembering to attend: The anterior cingulate cortex and remote memory. *Behavioural Brain Research*, *245*, 63–75. https://doi.org/10.1016/j.bbr.2013.02.010

Weller, B. E., Bowen, N. K., & Faubert, S. J. (2020). Latent class analysis: A guide to best practice. *Journal of Black Psychology*, *46*(4), 287–311. https://doi.org/10.1177/0095798420930932

WePC. (2021). *Video game industry statistics, trends and data in 2021*. WePC. https://www.wepc.com/news/video-game-statistics/

Winch, R. F., & Rosenberg, M. (2006). Society and the adolescent self-image. *Social Forces*, *44*(2), 255-256. https://doi.org/10.2307/2575639

Winkler, A., Dörsing, B., Rief, W., Shen, Y., & Glombiewski, J. A. (2013). Treatment of Internet addiction: A meta-analysis. *Clinical Psychology Review*, *33*(2), 317–329. https://doi.org/10.1016/j.cpr.2012.12.005

Winters, K. C., Stinchfield, R. D., & Fulkerson, J. (1993). Toward the development of an adolescent gambling problem severity scale. *Journal of Gambling Studies*, *9*(1), 63–84. https://doi.org/10.1007/BF01019925

Wölfling, K., Müller, K. W., & Beutel, M. (2011). Reliability and validity of the scale for the assessment of pathological computer-gaming (AICA-S). *Psychotherapie Psychosomatik Medizinische Psychologie*, *61*(5), 216-224. https://doi.org/10.1055/s-0030-1263145

Wölfling, K., Thalemann, R., & Grüsser-Sinopoli, S. (2008). Computerspielsucht: Ein psychopathologischer symptomkomplex im jugendalter. *Psychiatrische Praxis*, *35*(5), 226–232. https://doi.org/10.1055/s-2007-986238

Won, S.-D., & Han, C. (2018). Reliability and validity of the Korean version of the impaired control scale. *Psychiatry Investigation*, *15*(9), 852–860. https://doi.org/10.30773/pi.2018.05.04.1

World Health Organization. (2019). *ICD-11 for Mortality and Morbidity Statistics*. International Classification of Diseases-11. http://id.who.int/icd/entity/1448597234

Wysoski, S. G., Benuskova, L., & Kasabov, N. (2010). Evolving spiking neural networks for audiovisual information processing. *Neural Networks*, *23*(7), 819–835. https://doi.org/10.1016/j.neunet.2010.04.009

Yakovenko, I., & Hodgins, D. C. (2018). A scoping review of co-morbidity in individuals with disordered gambling. *International Gambling Studies*, *18*(1), 143–172. https://doi.org/10.1080/14459795.2017.1364400

Yao, Y.-W., Liu, L., Ma, S.-S., Shi, X.-H., Zhou, N., Zhang, J.-T., & Potenza, M. N. (2017). Functional and structural neural alterations in Internet gaming disorder: A systematic review and meta-analysis. *Neuroscience and Biobehavioral Reviews*, *83*, 313–324. https://doi.org/10.1016/j.neubiorev.2017.10.029

Yau, Y. H. C., Crowley, M. J., Mayes, L. C., & Potenza, M. N. (2012). Are Internet use and video-game-playing addictive behaviours? Biological, clinical and public health implications for youths and adults. *Minerva Psichiatrica*, *53*(3), 153–170. PMID: 2428843.

Yip, S. W., Gross, J. J., Chawla, M., Ma, S.-S., Shi, X.-H., Liu, L., Yao, Y.-W., Zhu, L., Worhunsky, P. D., & Zhang, J. (2018). Is neural processing of negative stimuli altered in addiction independent of drug effects? Findings from drug-naïve youth with Internet gaming disorder. *Neuropsychopharmacology*, *43*(6), 1364–1372. https://doi.org/10.1038/npp.2017.283

Yordanova, J., Kolev, V., Heinrich, H., Woerner, W., Banaschewski, T., & Rothenberger, A. (2002). Developmental event-related gamma oscillations: Effects of auditory attention. *European Journal of Neuroscience*, *16*(11), 2214–2224. https://doi.org/10.1046/j.1460-9568.2002.02286.x

Youh, J., Hong, J. S., Han, D. H., Chung, U. S., Min, K. J., Lee, Y. S., & Kim, S. M. (2017). Comparison of electroencephalography (EEG) coherence between major depressive disorder (MDD) without comorbidity and MDD comorbid with Internet gaming disorder. *Journal of Korean Medical Science*, *32*(7), 1160–1165. https://doi.org/10.3346/jkms.2017.32.7.1160

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

Yu, F., Sariyska, R., Lachmann, B., Wang, Q., Reuter, M., Weber, B., Trautner, P., Yao, S., Montag, C., & Becker, B. (2021). Convergent cross-sectional and longitudinal evidence for gaming-cue specific posterior parietal dysregulations in early stages of Internet gaming disorder. *Addiction Biology*, *26*(3). https://doi.org/10.1111/adb.12933

Yudko, E., Lozhkina, O., & Fouts, A. (2007). A comprehensive review of the psychometric properties of the drug abuse screening test. *Journal of Substance Abuse Treatment*, *32*(2), 189–198. https://doi.org/10.1016/j.jsat.2006.08.002

Yung, K., Eickhoff, E., Davis, D. L., Klam, W. P., & Doan, A. P. (2015). Internet addiction disorder and problematic use of Google Glass^{TM} in patient treated at a residential substance abuse treatment program. *Addictive Behaviours*, *41*, 58–60. https://doi.org/10.1016/j.addbeh.2014.09.024

Zhang, R., & Volkow, N. D. (2019). Brain default-mode network dysfunction in addiction. *NeuroImage*, *200*, 313–331. https://doi.org/10.1016/j.neuroimage.2019.06.036

Zhang, Y., Mei, S., Li, L., Chai, J., Li, J., & Du, H. (2015). The relationship between impulsivity and Internet addiction in Chinese college students: A moderated mediation analysis of meaning in life and self-esteem. *PLOS ONE*, *10*(7), e0131597. https://doi.org/10.1371/journal.pone.0131597

Zheng, H., Hu, Y., Wang, Z., Wang, M., Du, X., & Dong, G. (2019). Meta-analyses of the functional neural alterations in subjects with Internet gaming disorder: Similarities and differences across different paradigms. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *94*, 109656. https://doi.org/10.1016/j.pnpbp.2019.109656

Zhou, X., Zimmermann, K., Xin, F., Zhao, W., Derckx, R. T., Sassmannshausen, A., Scheele, D., Hurlemann, R., Weber, B., Kendrick, K. M., & Becker, B. (2019). Cue reactivity in the ventral striatum characterizes heavy cannabis use, whereas reactivity in the dorsal striatum mediates dependent use. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *4*(8), 751–762. https://doi.org/10.1016/j.bpsc.2019.04.006

Ziegler, M., Kemper, C. J., & Kruyen, P. (2014). Short scales – five misunderstandings and ways to overcome them. *Journal of Individual Differences*, *35*(4), 185–189. https://doi.org/10.1027/1614-0001/a000148

Zilverstand, A., Parvaz, M. A., & Goldstein, R. Z. (2017). Neuroimaging cognitive reappraisal in clinical populations to define neural targets for enhancing emotion regulation. A systematic review. *NeuroImage*, *151*, 105–116. https://doi.org/10.1016/j.neuroimage.2016.06.009

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *67*(2), 301–320. https://doi.org/10.1111/j.1467-9868.2005.00503.x

Zulkifli, N. F., Cob, Z. C., Latif, A. A., & Drus, S. M. (2020). A systematic review of machine learning in substance addiction. *2020 8th International Conference on Information Technology and Multimedia (ICIMU)*, 103–107. https://doi.org/10.1109/ICIMU49871.2020.9243581

Appendix I

Declaration of Collaborative Work

Literature Reviews

Burleigh, T. L., Griffiths, M. D., Sumich, A., Stavropoulos, V., & Kuss, D. J. (2019). A systematic review of the co-occurrence of gaming disorder and other potentially addictive behaviours. *Current Addiction Reports*, *6*(4), 383–401. https://doi.org/10.1007/s40429-019-00279-7

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 Behaviours*, *107*, 106429. https://doi.org/10.1016/j.addbeh.2020.106429

Burleigh, T. L., Griffiths, M. D., Sumich, A., Doborjeh, Z, & Kuss, D. J. (2022). Machine learning in gaming disorder: A systematic review. *Behavior & Information Technology, under review.*

Contribution of first author (TL Burleigh) to each of these literature reviews:

- Initiation of review
- Development of key ideas
- Literature collection
- Literature organisation
- Literature analysis
- Write-up
- Implementation of co-authors' feedback

Empirical Studies

Burleigh, T. L., Griffiths, M. D., Sumich, A., Wang, G., & Kuss, D. J. (2022). Coping and Co-occurrence of Gaming Disorder and Substance Use in Recovering Substance Users, *International Journal of Clinical Medicine, 11,* 7370. doi: 10.3390/jcm11247370

Burleigh, T. L., Griffiths, M. D., Sumich, A.,Wang, G., Stavropoulos, V., Kannis-Dymand, L., & Kuss, D. J. (2022). Co-Occurrence of Gaming Disorder and Other Potentially Addictive Behaviours Between Australia, New Zealand, and the United Kingdom, *International Journal of Environmental Research and Public Health, 19,* 16078. doi: 10.3390/ijerph192316078

Contribution of first author (TL Burleigh) to each of these Empirical Studies:

- Initiation of study
- Development of key ideas
- Literature analysis

- Data Collection
- Data Preparation and Analysis
- Write-up
- Implementation of co-authors' feedback