Problematic Internet Use: A Concern for Student Wellbeing and Academic Performance

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

Oonagh O'Brien

APRIL 20, 2022

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 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 A.

Dedication

This work is dedicated to my loving husband, Eoin and children, Finn, Roisin and Daire, as well as my wonderful extended family and friends. All of whom have encouraged and helped this doctoral research project in many different ways – thank you!

Acknowledgements

My supervisors Drs Daria Kuss, Alex Sumich and Eiman Kanjo were a wonderful source of feedback and support. I would like to express particular thanks to Daria, for her vision and diligence as well as her constant support and encouragement. It was a privilege to be guided by Daria. Dr. Alex Sumich acted as second in command and I appreciated very much his insight, as well as the time and attention he gave as a supervisor, well beyond what could reasonably be expected. Finally, thank you to Dr. Eiman Kanjo for her expertise which was always available when needed.

I would also like to thank Prof. Thomas Baguley for enlightening me on some of the more complicated aspects of statistical analysis. Thanks also to Steve MacFeeley for his guidance on the use of statistics.

Thanks to Kenneth Khaw at Ipinfo for giving me access to the IPinfo software which was an invaluable tool in the research.

Many thanks to my friends and colleagues in Munster Technology University (MTU), who stimulated and supported the research processes. In particular, I would like to thank Jonathon McCarthy and Conchubar O'Luasa for enabling the collection of data in MTU.

Thank you to everyone who has participated in this research, my colleagues who shared their expertise with me, and the students who were not reluctant to participate and share their time.

Last but not least, I'd like to thank Munster Technology University for funding this doctoral research project.

Peer-reviewed journal articles and Author Contribution

O'Brien, O., Sumich, A., Kanjo, E., & Kuss, D. J. (2022). WiFi at university: A better balance between education activity and distraction activity needed. *Computers and Education Open*, *3*, 100071. https://doi.org/10.11016/j. caeo2021.100071

Author Contribution :-

Oonagh O'Brien: Conceptualization, Methodology, Software, Data curation, Writing- Original draft preparation, Editing, Visualization, Investigation, Validation.

Alexander Sumich: Conceptualization, Methodology, Writing - Reviewing and Editing. Supervision

Eiman Kanjo: Conceptualization, Methodology, Writing- Reviewing and Editing.

Daria Kuss: Conceptualization, Methodology, Writing - Reviewing and Editing, Supervision.

O'Brien, O., Sumich, A., Baguley, T., & Kuss, D. J. (2022). A partial correlation network indicates links between wellbeing, loneliness, FOMO and problematic internet use in university students. *Behaviour &Amp; Information Technology*, 1–18. https://doi.org/10.1080/0144929x.2022.2142845

Author Contribution :-

Oonagh O'Brien: Conceptualization, Methodology, Software, Data curation, Writing- Original draft preparation, Editing, Visualization, Investigation, Validation.

Alexander Sumich: Conceptualization, Methodology, Writing - Reviewing and Editing. Supervision

Thom Baguley: Conceptualization, Methodology, Writing- Reviewing and Editing.

Daria Kuss: Conceptualization, Methodology, Writing - Reviewing and Editing, Supervision.

O'Brien, O., Sumich, A., Kanjo, E., & Kuss, D. J. (2023). Cyberslacking on University WiFi Highlights Strategies Required to Support Student Wellbeing and Academic Performance. *Manuscript submitted for publication*.

Author Contribution :-

Oonagh O'Brien: Conceptualization, Methodology, Software, Data curation, Writing- Original draft preparation, Editing, Visualization, Investigation, Validation.

Alexander Sumich: Conceptualization, Methodology, Writing - Reviewing and Editing. Supervision

Eiman Kanjo: Conceptualization, Methodology, Writing- Reviewing and Editing.

Daria Kuss: Conceptualization, Methodology, Writing - Reviewing and Editing, Supervision.

Conference Proceedings

O'Brien., O., Sumich, E. ., Kanjo, T., Kuss, D. J. (July, 2021). *Social Dilemma Explains Activity on a University WiFi*. [Paper presentation]. British Psychological Society's inaugural Cyberpsychology conference, 2021. https://www. delegate-reg. co. uk/cyber2021/programme

O'Brien, O., Sumich, A., Baguley, T., Kuss, D. J. (September, 2021). *Identifying influential symptoms and covariates in problematic internet use development and maintenance*. Affect, Personality & Embodied Brain Conference, 2021. https://apenetwork. files. wordpress.com/2021/09/ape2021-conference-programme. pdf

O'Brien., O., Sumich, E. ., Kanjo, T., Kuss, D. J. (2022). *Student problematic internet use understood using the I-PACE model, partial network correlation and variance partitioning*. 7th International Conference on Behavioral Addictions, 2022. http://icba. mat. org. hu/2022/

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

API	Application Programming Interface
BFAS	Bergen Facebook Addiction Scale
Birch	Balanced Iterative Reducing and Clustering using Hierarchies
BSMAS	Bergen Social Media Addiction Scale
CISCO	Commercial & Industrial Security Corporation
CIU	Compulsive Internet Use
CREC	NTU College of Business, Law and Social Sciences Research Ethics Committee
DBSCAN	Density-based Spatial Clustering of Applications with Noise
DSM-5	Diagnostic and Statistical Manual of Mental Disorders
Dst	Destination
EMA	Experience momentary assessment
ESM	Experience Sampling Method
FOMO	Fear of Missing Out
GB	Gradient Boosting
GPIUS	General Problematic Internet Use
HDBSCAN	Hierarchical Density-based Spatial Clustering of Applications with Noise
HSE	Health Service Executive
HTTP	HyperText Transfer Protocol
IA	Internet Addiction
IAB	Interactive Advertising Bureau
IAT	Internet Addiction Test
IGDS9-SF	Internet Gaming Disorder Scale – Short Form
IOS	iPhone Operating System
IP	Internet Protocol
I-PACE	Interaction Person Affect Cognition Execution (I-PACE) model
LR	Logistic Regression
MLP	Multilayer Perceptron
OECD	Organisation for Economic Cooperation and Development
OPTICS	Ordering Points to Identify the Clustering Structure
PC1	Principal Component 1
PC2	Principal Component 2
PCA	Principal Component Analysis
PPCS	Problematic Pornography Consumption Scale
PIU	Problematic Internet Use
PIUQ-SF-9	Problematic Internet Use Questionaire Short Form
POSI	Preference for Online Social Interaction

PSU	Problematic Smartphone Use
PWI	Personal Wellbeing Index
Q1	Quarter 1
Q2	Quarter 2
Q3	Quarter 3
Q4	Quarter 4
RDA	Redundancy Analysis Ordination
RF	Random Forest
SAS-SV	Smartphone Addiction Scale – Short Version
SNS	Social Network Sites
Src	Source
SSE	Sum of Squared Errors
SU	Smartphone Usage
UCLA	University of California and Los Angeles
US	User Session
VP	Variance Partitioning
WiFi	Wireless Network
XGBoost	eXtreme Gradient Boosting

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDICES

Abstract

Problematic Internet Use (PIU) has been linked to student loneliness, wellbeing and Fear of Missing Out (FOMO). Thus, there is a need to investigate the use of the internet and the impact of that use in universities. Reliance on self-assessment to identify PIU has generated concern in previous research, the need for measures that include assessment of actual behavior has been highlighted. This research used a method which is innovative in psychology, to gather and analyse objective data on internet activity in a university over an academic year. Student self-assessment data on PIU subtypes (general PIU, problematic smartphone use, problematic social media use, problematic internet gaming, and problematic pornography use), wellbeing, loneliness and FOMO were also gathered. The data were used to understand actual internet behavior, student assessment of that behavior and relationships with wellbeing, loneliness and FOMO.

The first and third study examined the Wifi digital traces of approximately 13,000 users at a university for an academic year. Principal component analysis identified patterns in the users' engagement with the internet. Machine learning identified clusters of users with the same pattern of activity and enabled prediction of education activity. In the second study, the self-assessment data from 834 university students explained how users of the university WiFi assessed their internet usage behavior, wellbeing, loneliness and FOMO. A partial correlation network and variance partitioning clarified relationships between PIU subtypes, wellbeing, loneliness and FOMO. The I-PACE model (Brand et al., 2019) was used to illuminate the findings in a model of behavioral addiction.

This research contributes to understanding PIU in students and links to loneliness, wellbeing and FOMO with: (i) objective measures of actual behavior; (ii) identification of patterns of internet behavior; (iii) prediction of activity on the internet using objective data; and (iv) use of partial correlation networks, variance partitioning and the I-PACE model to clarify the relationships between PIU subtypes and wellbeing, loneliness and FOMO.

Chapter 1. Student Problematic Internet Use, Well-being, Loneliness and FOMO: A Systematic Literature Review of Recent Findings, Interpreted Using the I-PACE model

1.1 Introduction

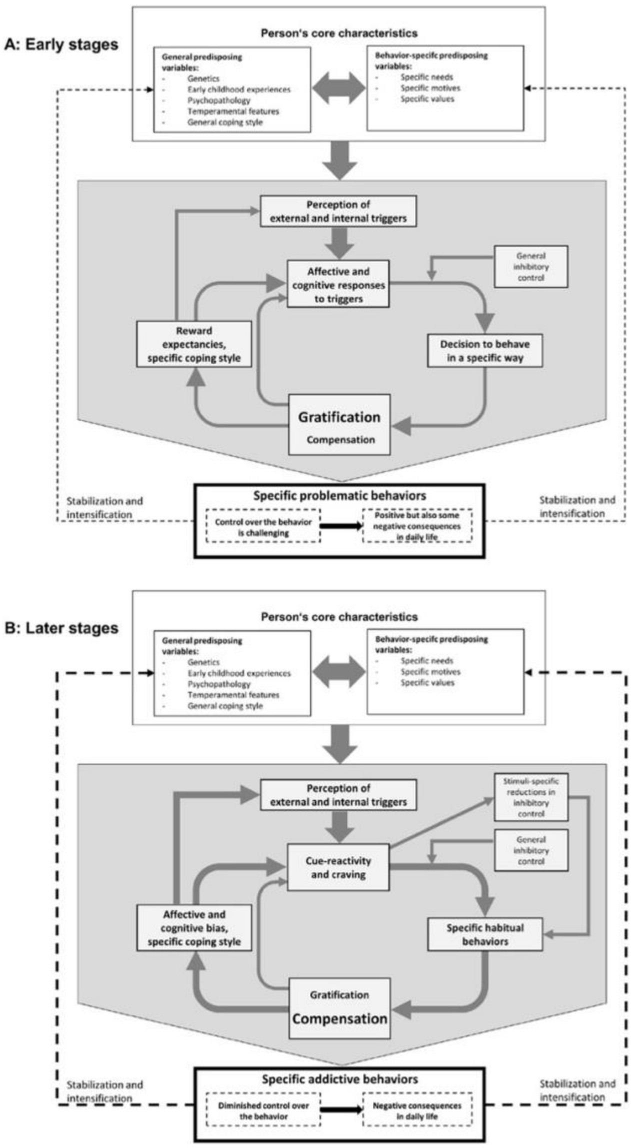
Although there is no agreed definition of problematic internet use (PIU) , in the current research it is understood as a behavioral pattern of internet use marked by preoccupation and unregulated and excessive use which leads to significant negative consequences not accounted for by any other disorder (Kuss & Pontes, 2019). Hence, PIU in the current research encompasses problematic behavior on the internet, when accessed from any medium, including a smartphone. Concern for the health and societal costs of PIU has resulted in recognition of the need for research to inform regulatory policies and clinical practices (Fineberg et al., 2018). Internet use has become central in education and in academic work and more so during the Covid-19 pandemic, as universities and colleges increase their dependency on online delivery (Qazi et al., 2020). As students have an increasing dependency on the internet (Qazi et al., 2020), they represent a particularly at-risk group for PIU. Hence there is a particular need to understand PIU and its potential impacts for students. College life can be difficult for students as they cope with managing their time, studies, health, finances and often new home environments (Murphy, 2017), PIU is an additional concern. Supports are needed for students to reduce the adverse impact of challenges to student wellbeing (Association for Higher Education and Disability, 2016). Understanding threats to student wellbeing have important implications for delivering the support that is required, PIU is one such threat. Wellbeing is demonstrated in multiple psychological dimensions including competence, emotional balance, positive engagement, optimism, resilience, positive emotion, positive relationships, self-esteem, and energy, wellbeing indicators include levels of stress, depression, anxiety and others (Ruggeri et al., 2020). Thus, the present review focuses on and analyses PIU and wellbeing research in college and university students.

Recent literature has highlighted the role of problematic internet use (PIU), and has found that together with loneliness and fear of missing out (FOMO), PIU is particularly prominent in students (Price & Smith, 2019; Shek & Yu, 2012) and may generally adversely affect student wellbeing (Casale & Fioravanti., 2011; Elhai et al., 2021; Elhai et al., 2018; Hebebci & Shelley, 2018; Reer et al., 2019; Stead & Bibby, 2017) and academic performance (Truzoli, 2019). FOMO is consistently linked to wellbeing and refers to worrying that others might have rewarding experiences which one is not part of, and a need to stay continually connected with others, often by using social media (Przybylski et al., 2013; Hebebci & Shelley, 2018). Social media usage has been linked with increased loneliness. However, this increase may be mediated by FOMO (Fumagalli et al., 2021). Lonely students may feel disconnected and thus be prone to FOMO. Indeed FOMO, loneliness and PIU have been related to and negatively correlated with wellbeing (Casale & Fioravanti, 2011; Hebebci & Shelley, 2018). PIU is consistently associated with wellbeing, loneliness and FOMO (Casale et al., 2018; Elhai et al., 2018, 2019; Elhai, Yang, Rozgonjuk, et al., 2020; Stead & Bibby, 2017). The European Parliamentary Research Service has recognised the harmful impacts of PIU in terms of health, wellbeing and normal functioning of the individual (Brey & Gauttier, 2019). Thus, given the concern for student wellbeing (Murphy, 2017), this research investigates the links between student FOMO, loneliness and wellbeing and PIU.

Whilst studies show that there is a relationship between PIU, FOMO, loneliness and wellbeing, it is difficult to coalesce the findings in order to explain the role of FOMO, loneliness and wellbeing in the development and maintenance of PIU. Davis's (2001) model identified PIU as a coping mechanism for other problems. This model was further developed by Caplan (2010) who suggested that PIU is a coping strategy for social anxiety and particularly exacerbated by poor self-control. In the Compensatory Internet Use Theory (CIUT), Kardefelt-Winther (2014) emphasised the importance of understanding motivations to use the internet. That is, PIU develops as a result of predisposing factors such as gender**,** loneliness or FOMO and choices to alleviate offline world stresses by using the internet. The Interaction Person Affect Cognition Execution (I-PACE) model extends existing models, explaining PIU as a result of predisposing factors, as well as moderating and mediating factors, such as cognitive affect and reactions to situational triggers, cognitive biases and coping strategies, which with reduced inhibitory control, instrumental conditioning and accessibility of the internet develop and maintain PIU see Figure 1 (Brand et al., 2019). The original I-PACE model (Brand et al., 2016) was extended to encompass behavioral addictions, other than internet use disorders, and highlighted the influence of the medium or environmental aspects of the behavioral addiction (Brand et al., 2019). Access to an addictive behavior online or otherwise, the reward options, the affordability, the accessibility and gratification, were identified as potential accelerators in the development of an addictive behavior in the updated model (Brand et al., 2019). In order to understand research findings and describe and characterise PIU, a comprehensive model is needed and the I-PACE model (2019) may be the most comprehensive model currently available (Moretta et al., 2022). Thus, the I-PACE (2019) model is used in the current review to provide a theoretical framework to interpret the findings of the research. The model is used to offer a potential explanation of the processes underlying the development and maintenance of PIU, the relationships between PIU, wellbeing, loneliness, FOMO and as an effective framework with which to consider research findings.

Figure 1

Interaction Person Affect Cognition Execution (I-PACE) ***M****odel. From "The Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors (Brand et al.,2019) : Update, generalization to addictive behaviors beyond internet-use disorders, and specification of the process character of addictive behaviors. " By M. Brand, E. Wegmann, R. Stark, A. Muller and K. Wolfgang, 2019 by Neuroscience and Biobehavioral Reviews,Permission to publish for non-commercial reasons under CC BY-NC-ND***.***



Studies on PIU report rates which vary from one to 13.9% in Europe (Andrie et al., 2019; Gómez et al., 2017; Macur et al., 2016; Foresight, 2019; Panel for the Future of Science and Technology, 2020), 8.9% in China and USA (Tang et al., 2018), 10.9% in the Middle East and a global rate of 6% (Cheng & Li, 2014). Rates vary depending on factors such as method of assessment, country, population age and activity examined (as well as PIU). Although, there is a vast array of psychometric tests used to measure PIU because of apparent lack of agreement on factors that identify PIU, often PIU is assessed using psychometric tests based on the symptoms of behavioral addiction (Griffiths, 2005; Young, 1998). In the current study, Griffiths' (2005) addiction components model will be used to assess the PIU measurement approach. This model identifies the symptoms of behavioral addiction as salience, mood modification, tolerance, withdrawal conflict and relapse. The use of many psychometric tests to measure PIU makes interpretation and comparison of research more difficult. Increased standardisation in PIU assessment as well as the use of a theoretical model to frame findings in an explanation of the process of development and maintenance of PIU would aid understanding and comparison of research findings and their context.

The aim of this review is to examine research findings relating to FOMO, loneliness, wellbeing and PIU in students to get a coherent understanding of the relationships using the I-PACE model. This research will also identify commonality in the factors to measure PIU in the research. This systematic review examines research findings relating to PIU, and the associations with FOMO, loneliness and wellbeing in university students and has the following research questions:

- Is there commonality in the addiction components or factors used to assess PIU?
- What are the current scientific findings on the relationships between loneliness, FOMO, wellbeing and PIU in university students?
- To what extent can findings in the relevant empirical research on the relationship between wellbeing, loneliness, FOMO and PIU be interpreted using the I-PACE model?

1.2 Methods

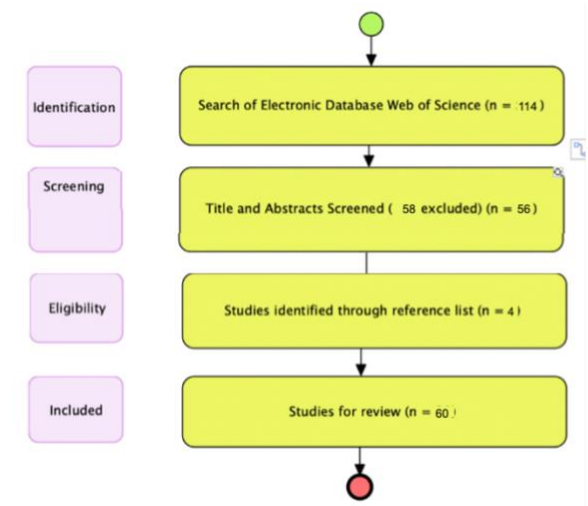
The reporting of this systematic review was guided by the standards of the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) Statement (Moher et al., 2009). To identify papers for review, an extensive search was performed using Web of Science databases. These databases were searched using the following search terms: ("Internet addict* "OR" internet disorder" OR "problematic internet us*" OR "Compuls* internet us*" OR "Pathological internet us*" OR "Excessive internet us*" OR "problematic social media us*" OR "Social media addict*" OR "Smartphone addict*" OR "Problematic smartphone us*" OR "problematic porn*" or "Internet dependency" or "Internet

Pathological" or "maladaptive internet" or "unhealthy internet" or "internet abuse" or "social network addiction" or "compulsive internet us*" or "internet use disorder") AND (smartphone or mobile or internet or "social media" or "online" or "iphone" or socialmedia) AND ("university student" or "college student" or undergrad* or under-grad*) AND (("Fear of missing out" OR FOMO or "fear of missing out" or "wellbeing" OR wellbeing or wellbeing or loneliness or "life satisfaction") OR ("I-PACE" or "iPACE" or "interaction person affect cognition execution" or "interaction-person-affect-cognition-execution")). References of collected articles were examined for additional studies. Studies were included if they were i) published in English, (ii) published in a peer-reviewed journal, (iii) data were empirical and quantitative, (iv) full text was available. Papers were excluded if (i) did not make reference to problematic internet usage and students and at least one of the following: I-PACE model, loneliness or FOMO or wellbeing; (ii) included less than 250 participants. The title and abstract of each study were screened for eligibility. Full texts of studies considered as potentially relevant were then retrieved and examined for eligibility. The search strategy is detailed in Figure 2 below.

The search results identified 114 articles when this was restricted to English articles, 97 remained. By examining the abstract and titles of the articles identified, 56 that were relevant to assessment of PIU using objective measures were identified. Full text of the articles were then assessed. Cross-checking the reference lists of (review) articles with our selection increased the total number of articles in our review by four (Esen et al., 2013; Kuss et al., 2013; Lopez-Fernandez et al., 2017; Odac & Kalkan, 2010), giving a total of 60 studies which were reviewed.

Figure 2.

Search Strategy.



1.3 Results

In order to examine research findings on indicators of PIU, an analysis of the factors/symptoms measured in the psychometric tests, which were used three times or more to measure PIU, was conducted see Table 1. A summary of the research papers reviewed, the analysis approach, the goal of the research and the research findings are presented in Table 2. Both the factors of PIU and the research findings are considered using the I-PACE model to determine if the model is useful in explaining the process of development and maintenance of PIU.

Table 1.

Factors Measured in Standard PIU Psychometric Tests

Psychometric Test	Social POSI	Withdrawal	Salience / Pre-occupation	Tolerance	Relapse	Compulsive Use	Negative Consequences / Conflict	Mood Modification / Escapism/Coping
Young IAT (Young, 1998)		4. Do you feel restless, moody, depressed or irritable when attempting to cut down or stop Internet use?	1. Do you feel preoccupied with the Internet (think about previous online activity or anticipate next on-line session)?	2. Do your feel the need to use the Internet with increasing amounts of time in order to achieve satisfaction? 5. Do you stay on-line longer than originally intended?	3. Have you repeatedly made unsuccessful efforts to control, cut back, or stop Internet use?		6. Have you jeopardised or risked the loss of significant relationship, job, educational or career opportunity because of the internet? 7. Have you lied to family members, therapist, or others to conceal the extent of involvement with the Internet?	8. Do you use the Internet as a way of escaping from problems or of relieving a dysphoric mood?
GPIUS-2 (Caplan, 2010)	1. I prefer online social interaction over face-to-face communication 6. Online social interaction is more comfortable for me than face-to-face interaction 11. I prefer communicating online rather than face to face	8. I would feel lost if I was unable to go online	3. When I haven't been online for some time, I become preoccupied with the thought of going online 13. I think obsessively about going online when I am offline			4. I have difficulty controlling the amount of time I spend online 9. I find it difficult to control my internet use 14. When offline, I have a hard time trying to resist the urge to go online	5. My internet use has made it difficult for me to manage my life. 10. I have missed social engagements or activities because of my Internet use. 15. My internet use has created problems for me in my life	2. I have used the internet to talk with others when I was feeling isolated 7. I have used the internet to make myself feel better when I was down 12. I have used the internet to make myself feel better when I was upset
SAS-SV (Kwon et al., 2013)		4. Won't be able to stand not having a smartphone. 5. Feel impatient and fretful when not holding my smartphone	6, Having my smartphone in my mind even when I am not using it. 2. Having hard time concentrating in class, while doing assignments, or while working due to smartphone use.	9. Using my smartphone for longer than I intended.		8. Constantly checking my smartphone so as not to miss conversations between other people on Twitter and Facebook 7. I will never give up using my smartphone even when my daily life is greatly affected by it.	1. Missed planned work due to smartphone use. 3. Feeling pain in the wrists or back of the neck because of using smartphone. 10. The people around me tell me I use my smartphone too much	

BFAS (Andreassen et al., 2012)		13. Become restless or troubled if you have been prohibited from using Facebook? 14. Become irritable if you have been prohibited from using Facebook 15. Felt bad if you, for different reasons, could not log on to Facebook for some time	1. Spend a lot of time thinking about Facebook or planned use of Facebook 2. Thought about how you could free more time to spend on Facebook 3. Thought alot about what has happened on Facebook recently	6. Felt that you had to use Facebook more and more to get the same pleasure from it 4. Spent more time on Facebook than initially intended 5. Felt an urge to use Facebook more and more	10. Experienced that others have told you to reduce your use of Facebook but not listened to them 11. Tried to cutdown the use of Facebook without success 12. Decided to use Facebook less frequently but not managed to do so		16. Used Facebook so much that it has had a negative impact on your job/studies? 17. Given less priority to hobbies, leisure activities, and exercise because of Facebook? 18. Ignored your partner, family members, or friends because of Facebook?	7. Used Facebook to forget about personal problems 8. Used Facebook to reduce feelings of guilt, anxiety, helplessness, and depression 9. Used Facebook in order to reduce restlessness

Table 2.

Summary of Research Papers Reviewed

Study	Aims	Sample, Location, Method	Instruments	Results
Adiele & Olatokun, 2014	Study on existence of Internet addiction (IA) among adolescents to determine if IA is distinct from offline behavioral addictions.	450 students (47.5% males and 52.5% females) Adolescent Africa Cross sectional Psychometric studies - quantitative	EPQR-S Lie Scale Short Form (Francis et al., 2006) Internet Addiction Test (Young, 1998) Gender question and question on time per week on internet, Reasons for Internet Use Hypersexual Behavioral Inventory (Reid et al., 2011) Problem Video Game Playing (Loton 2007)	Prevalence of IA 3.3%, ratio 3:1 male : female Socio-economic factors predictor for internet activity. IA usage 35+ hours/week problematic Negative consequences demonstrate problematic internet behavior. Offline addictions can motivate PIU
Arpaci, 2020	Study on gender and the relationship between problematic Internet use and nomophobia	490 students (31% male, 69% female) Age Mean 22.14(SD =3.88) Turkey Cross sectional Psychometric studies - quantitative	Online Cognition Scale (Davis & Besser, 2002) Nomophobia Questionnaire (NMP-Q) (Yildirim & Correia, 2015)	Gender differences in links between Nomophobia and PIU Loneliness / depression, distraction and reduced impulse control. Links significantly to Nomophobia in females only, links to loneliness/depression and distraction in men
Atroszko et al., 2018	Study on the relationship of different personality characteristics to Facebook addiction	1157 students (51.9% male, 472% female, 0.9% neither) Age Mean = 20.33 (SD =1.68) Poland Cross sectional Psychometric studies - quantitative	BFAS (Andreassen et al., 2012) Polish version of TIPI (Gosling et al., 2003). Polish adaptation (Atroszko, 2015) of Short loneliness Scale (Hughes et al., 2004) Polish adaptation of Perceived Stress Scale (Cohen et al., 1983) Non-standard or single item on Self-efficacy, Narcissism, Self-esteem, General health, sleep quality, and quality of life, Social anxiety	Facebook addiction linked to increased social anxiety, narcissism, extraversion, loneliness, and lower general self-belief. Facebook linked to reduced wellbeing (impact on general health, sleep quality, and stress)
Bakioğlu, 2020	Study on loneliness and the links to internet addiction and social self-efficacy	325 undergraduates female: 57.8%; male, 422% age between 17 and 30 years (*M*= 20.54, *SD* = 1.99) Turkey Cross sectional	Internet Addiction Test-Short Form (Young, 1998) The Social Efficacy and Social Outcome Expectation Scale (Wright et al., 2013) The UCLA loneliness Scale. (Russell et al., 1996)	Internet addiction has an indirect link to social self-efficacy, the link is mediated by loneliness.
Caplan, 2002	Study to develop a theory-based measure of PIU. Use of the measure to understand the links between thoughts on the internet and behavior, with other wellbeing indicators such as, depression, self-esteem, loneliness, and shyness.	386 undergraduates (70% females and 30% males) Age 18 to 57 years old (M=20, SD=222 years) Delaware, USA Cross sectional Psychometric studies - quantitative	Generalised Problematic Internet Use Scale (GPIUS) (Caplan, 2002) Beck Depression Inventory-II (Beck et al., 1996) Rosenberg Self Esteem Scale (Petersen, 1965) UCLA loneliness Scale (Russell et al., 1996) Social Reticence Scale (Jones et al., 1986)	GPIUS valid reliable scale. All GPIUS subscales significantly correlated with depression, loneliness, shyness, and self-esteem, perceived social benefits. Highest correlations with compulsivity, negative outcomes. Preference for online interaction, generalized PIU. Loneliness explains a significant amount of variance in negative consequences of PIU, and may be more influential than psychological wellbing in predicting outcomes.

Casale et al., 2018	Investigate the links between and social media problematic use, considering fear of negative evaluation and perception of low self-presentational skills as well as the mediating role of positive thoughts on social media use.	N = 579 undergraduates (54.6% female, 45.4% male) Age Mean = 22.39 (SD =2.82) years Italy Cross sectional Psychometric studies - quantitative	Brief Fear of Negative Evaluation || (Carleton et al., 2007) Social Control Sub scale (Galeazzi et al., 2002) Fear of Missing Out Scale (Przybylski et al., 2013) Bergen's Social Media Addiction Scale (Monacis et al., 2017a) Self-report to assess meta-cognitions developed – 5 questions	FOMO directly and indirectly associated with SNS problematic use. FOMO predicts metacognitions about SNS usefulness to manage FOMO In males positive metacognition fully mediated link between fear of negative evaluation and FOMO Lower presentational skills females both direct and indirect effect on problematic SNS use. Positive meta-cognitions on behavior in SNS was a means of controlling FOMO
Casale & Fioravanti ., 2015	Investigation of the association between psychological wellbeing and problematic internet use.	N=495 undergraduates (58.8% female, 412% male) Age 18 to 26 years old, (M= 20.88 *SD* = 1.98 years). Italy Cross sectional Psychometric studies - quantitative	Questions on time spent online for various activities email etc. Italian version of Generalised Problematic Internet Usage 2 (GPIUS2) (Caplan, 2010) Psychological wellbeing scales (Sirigatti et al., 2009)	Levels of independence, control of environment, and positive Relationships are negatively linked to internet use to regulate emotions, compulsive use of the internet, and the negative consequences that can result. Low psychological wellbeing is linked with problematic use of the Internet.
Casale et al., 2014	Study on whether low social support and fear of negative evaluations in face to face encounters mediate the links between perfectionism and problematic internet use.	N =465 undergraduates (51.6% female, 48.4% male) Age Mean = 21.91 (SD =223) years Italy Cross-sectional Psychometric studies	Italian version of GPIUS2 (Caplan, 2010) Italian version of Multi-dimensional perfectionism scale (Ghisi et al., 2010) Italian version of Brief Fear of Negative Evaluation (Leary, 1983)	Male PIU and socially prescribed perfectionism (SPP) were fully mediated by fear of negative evaluation and perception of low social support, same results for female negative evaluation, social support was not a significant mediator. PIU may be in part a defensive response to SPP
Ceyhan, 2011	Investigation of links between university students' problematic internet use and communication skills and internet use purposes.	411 university students 52.3% female, 47.7% male Age not available Turkey Cross-sectional Psychometric studies - quantitative	The problematic internet use scale (PIUS) (Ceyhan et al., 2007) The communication skills assessment scale (Korkut, 1996) Demographic information on themselves and internet behavior	Students perceived communication skills not linked to their internet use PIU significantly higher for those who use internet for entertainment purposes and to establish social relationships than those who use it to obtain information.
Chang & Lin., 2019	Longitudinal study of the co-occurrence of different gaming motives, gamer profiles, gamer characteristics, gamer problematic Internet use, gamer depression, and other wellbeing indicators at five different times.	387 students (28% female, 72% male) Age Mean = 19.43 (SD = 0.67) years Taiwan Longitudinal – group of students every 6 months for 2 years – 5 assessment time points Psychometric studies - quantitative	Online gaming motive scales of advancement, escapism and socializing adapted from (Yee, 2006b) Problematic internet use (Liao et al., 2018) Beck Depression inventory (Beck et al., 1996) Academic performance, Stress, Gaming time question(s)	4 types of gamers – high, medium, low and healthy engagement. High engagement gamers risky for, higher depression, higher PIU at all 4 measuring times. Major difference between high engagement and healthy engagement gamers in level of escapism motives and consequent risk of negative consequences. Escapism may be a risk factor for depression, PIU and other wellbeing indicators in college gamers.
Chang, S. et al., 2018	Examination of the longitudinal mediation effects of gaming motives between online gaming and problematic Internet use (PIU). Three gaming motivations were studied - escapism, advancement, and socializing.	389 students (28% female, 72% male) Age Mean = 19.43 (SD = 0.67) years Taiwan Longitudinal – group of students every year 2012,2013,2014 – 3 assessment time points Psychometric studies - quantitative	Four questions on game involvement Online Gaming Motivation Scale Chinese Version (Yee, 2006a) Problematic internet use(Chen et al., 2017)	Escapism and advancement positively correlated with PIU, while socialising failed to predict PIU. Direct effect of gaming on PIU weak, in contradiction of other cross-sectional studies Motive of escapism was correlated with more time spent gaming. Over use of emotion focused coping strategy may heighten risk of PIU

Coduto et al., 2020	Examination of the relationship between anxiety, the problematic use of dating applications, and links with loneliness.	269 participants 62.1% female 38.9% male Age Mean 20.85 (SD = 2.45) years USA Cross-sectional Psychometric studies - quantitative	Social Phobia and Anxiety Index scale (de Vente et al., 2014) Dating applications 3 questions adapted from Caplan 2003 UCLA loneliness Scale (Russell et al., 1996)	Lonely most likely to experience negative outcomes. Awareness of compulsive use and potential negative outcomes can help avoid such use
Dang et al., 2019	Study using the I-PACE model to consider if emotional Intelligence predicts Internet Gaming Disorder, directly or indirectly	282 undergraduate students 60.6 % female,39.4% male Age Mean 20.47 years China Cross-sectional and longitudinal – 2 assessment time points over one year Psychometric studies - quantitative	IGD tendency was measured by nine diagnostic criteria listed in the fifth edition of the *and Statistical Manual of Mental Disorders* Chinese version of the 16-item Wong and Law's Emotional Intelligence Scale (WLEIS) Coping Flexibility Scale (CFS) DASS-21 (Lovibond & Lovibond, 1995) Demographic Variables	Emotional intelligence linked indirectly and negatively with problematic gaming in cross-sectional and longitudinal data. Depression mediated the links between: (i) emotional intelligence and problematic gaming and (ii) coping and problematic gaming. Findings offer support for the I-PACE model. Problematic gaming may be addressed by addressing depressive symptoms in school-based workshops which focus on increasing emotional intelligence and coping options.
Demirtepe-Saygılı & Metin-Orta., 2020	Study on the underlying mechanisms in the links between intentional use of the Internet for personal purposes during class hours, and possible negative consequences of misuse of the Internet on health and wellbeing, and the role of coping strategies.	282 undergraduate students 35% male, 65% female Age between 17 and 34, mean 21.41 years (SD 221) Ankara, Turkey Cross-sectional Psychometric studies - quantitative	Cyberloafing Scale (Akbulut et al., 2016) Ways of Coping Inventory (Folkman & Lazarus, 1980) Brief Symptom Inventory (Derogatis, 1992)	Positive relationship between cyberloafing and psychological symptoms, higher level of emotion focused coping relates to higher levels of cyberloafing
Elhai, Yang, McKay, et al., 2020	Investigation of COVID-19 anxiety and depression symptoms associated with problematic smartphone use severity in Chinese adults	908 Chinese adults 82.8% female,17.8% male Age Mean 40.37 (SD = 927) years Chinese city Tianjin Cross-sectional Psychometric studies – quantitative Participants from WeChat	DASS-21(Lovibond & Lovibond,1995) Generalized Anxiety Disorder Scale (GAD-7) (Spitzer et al., 2006) Smartphone Addiction Scale-Short Version (SAS-SV) (Kwon et al., 2013) Questions on COVID-19 News Exposure and threat of death	COVID-19 anxiety linked with PSU, depression and anxiety. Survey responses suggested 12% had at least moderate depression, and 24% had moderate anxiety., COVID- 19 anxiety no longer predicted PSU severity, when links to general anxiety and depression controlled.
Elhai, Yang, Dempsey, et al., 2020	Study on the links between rumination and negative smartphone use expectancies to understand links with greater levels of problematic smartphone use.	286 undergraduate students 62.9% female,37.8% male Age Mean 19. .72 (SD = 2.6) years American Cross-sectional Psychometric studies - quantitative	DASS-21 (Lovibond & Lovibond, 1995) Ruminative Thought Style Questionnaire (RTSQ) (Brinker & Dozois., 2009) Smartphone Addiction Scale-Short Version (SAS-SV) (Kwon et al., 2013) Smartphone Use Expectancies Scale	Two subgroups of participants, with mild and severe PSU were indentifiable by strength of withdrawal symptoms. Thoughts about smartphone use as a coping strategy for distress were linked with symptoms of PSU. Findings highlight the importance of response variables, such as internet-related cognitive bias and coping, in the I-PACE model (Brand et al., 2019), as more important than background psychological variables in influencing PIU and PSU.
Elhai, Gallinari, et al., 2020	Investigation of links between depression, anxiety and FOMO with social, non-social and problematic smartphone use	316 undergraduate students 68% female,32% male Age Mean 1921 (SD = 1.74) years American Cross-sectional Psychometric studies - quantitative	DASS-21 (Lovibond & Lovibond, 1995) The smartphone addiction scale (Kwon et al., 2013) Fear of Missing Out Scale (Przybylski et al., 2013) Process and Social Smarphone Use (Van Deursen et al., 2015)	Non-social smartphone use which included entertainment use was examined with social smartphone use, was linked to increases in problematic smartphone use. FOMO mediated relations between depression and non-social smartphone use. FOMO mediated links between depression and anxiety and PSU severity. Non-social use of a smartphone use was potentially a coping mechanism for anxiety.

Elhai et al., 2019	Analyse of the fear of missing out (FOMO) as a possible mediator in the links between both depression and anxiety and problematic smartphone use (PSU).	1034 undergraduate students 65.3% female,34.7% male Age Mean 19.34 (SD = 1.61) years China Cross-sectional Psychometric studies - quantitative	Smartphone Usage Frequency Scale (Elhai et al., 2016) The smartphone addiction scale (Kwon et al., 2013) DASS-21 (Lovibond & Lovibund, 1995) Fear of Missing Out Scale (Przybylski et al., 2013)	FOMO links with frequency of smartphone use and the level of PSU. FOMO mediated links between anxiety and smartphone use and PSU. FOMO did not explain links between depression and PSU.
Elhai et al., 2018	Examination of "fear of missing out" (FOMO) and its link with psychopathology and technology use measures.	296 Undergraduates 76.7% female, 23.3% male Age Mean 19.44 (SD = 2.16) years Mid-West USA Cross-sectional Psychometric studies - quantitative	Smartphone Usage Frequency Scale (Elhai et al., 2016) The smartphone addiction scale: (Kwon et al., 2013) Fear of Missing Out Scale (Przybylski et al., 2013) DASS-21 (Lovibond & Lovibond, 1995) Process and Social Use Scale (Van Deursen et al., 2015) Ruminative Thought Style Questionnaire (RTSQ) (Brinker & Dozois, 2009) Boredom proneness scale short form (BPS-S) (Struk et al., 2017)	FOMO linked to age, sex, race, and relationship status with small effect. FOMO related to negative consequences, frequency of social use and severity of PSU. Negative affects mediated the link between FOMO and PSU, only rumination mediated relations between FOMO and smartphone use frequency. FOMO mediated links between negative affective and PSU. Negative affect may be significant in explaining how FOMO links to PSU.
Elhai, Yang, Rozgonjuk , et al., 2020	Investigation of using machine learning to model PSU severity: The significant role of fear of missing out	1097 undergraduates, 81.9% female, 18.1% male Age mean 19.38 (SD = 1.18) years China Cross-sectional	Smartphone Addiction Scale-Short Version (SAS-SV) (Kwon et al., 2013) DASS-21 (Lovibond & Lovibund, 1995) Fear of Missing Out Scale (Przybylski et al., 2013) Ruminative Responses Scale (RRS) (Nolen-Hoeksema et al., 2008)	Depression or anxiety severity high contributors to PSU FOMO, rumination, more influential in PSU.
Esen et al., 2013	Examination of the relationship between university students internet use and loneliness and self-efficacy	507 students, 45% female, 55% male Age not available Turkey Cross-sectional Psychometric studies - quantitative	Social Self-efficacy Scale (Smith & Betz, 2000) UCLA loneliness scale (Russell et al., 1996) Internet Addiction Scale (Young, 1998)	Significant links between IA and loneliness but not social self-efficacy Higher score in internet use linked with higher levels of loneliness
Fioravanti et al., 2020	Investigation of measurement of active and passive Facebook use, and its link to Facebook addiction.	533 students, 49.5% female, 50.5% male Mean Age 22.73 SD 2,77 Italy Cross-sectional Psychometric studies - quantitative	Demographics GPIUS-2 (Caplan, 2010) BFAS (Andreassen et al., 2012) Active and Passive use of Facebook Scale (self-developed)	Measurement of active and Passive use of Facebook is useful.
Gentina & Rowe, 2020	Examination of the association between youth materialism and smart phone dependency via social oriented smartphone use.	463 students 58% female 42% male Age Mean = 16.8 years French Cross-sectional Psychometric studies - quantitative	Youth Materialism Scale (Goldberg et al., 2003) The mobile phone Involvement Questionnaire (Walsh et al., 2010) Semi-structured interviews	Female materialism is linked with problematic smartphone dependency via social-oriented smartphone use, this link is not significant for boys. Youth materialism is positively linked to problematic smartphone dependency via process-oriented smartphone use for both males and females, however the relationship is stronger for boys than for girls.
Hao et al., 2020	Examination of the association between problematic mobile phone use and altruism.	512 students 442% female 55.8% male Age Mean = 2123 (SD = 2.47) years Lebanon Cross-sectional Psychometric studies - quantitative	Mobile phone addiction index (Leung, 2008) The college students altruism Questionnaire (li,2008) The Toponto Alexthymia Scale (Bagby et al., 2020) Interpersonal Reactivity Index Scale (Davis, 1983)	Problematic Mobile Phone use was negatively linked with altruism via alexithymia, cognitive empathy and affective empathy, both directly and indirectly.

Hawi & Samaha, 2019	Investigation of similarities and differences in links between technology addictions and personality, in particular, self-esteem, and self-construal.	512 students 442% female 55.8% male Age Mean = 2123 (SD = 2.47) years Lebanon Cross-sectional Psychometric studies - quantitative	Basic demographic information as well as items on social media and internet frequency of use. Internet Addiction Test (Young, 1998) Social media addiction questionnaire (Hawi & Samaha, 2017) Rosenberg Self Esteem Scale (Petersen, 1965) Satisfaction with life scale (Diener & Diener, 1995) Ten Item Personality Inventory (Gosling et al., 2003) Self-Construal Scale (Singelis, 1994)	Agreeableness, conscientiousness, openness to experiences, emotional stability, self-esteem, how often social media checked, and internet use linked to internet addiction (IA) and social media addiction (SMA). Age, life satisfaction and self-conceptualisation did not predict either IA or SMA Real self and extraversion predicted IA ; gender, posting updates, number of friends, and independent self-conceptualisation predicted SMA
Hebebci & Shelley, 2018	Investigation of the relationship between problematic Internet use sub-scales and loneliness.	392 undergraduates (57% female, 43% male) Age Mean = 22 years Turkey Cross-sectional Psychometric studies - quantitative	PIUS (Ceyhan et al., 2007) UCLA loneliness scale (Russell et al., 1996)	Social benefit/social comfort directly linked to overuse of the internet and negative consequences, linked to loneliness indirectly. Negative consequences predicts loneliness and overuse of the internet. Note increase in internet use linked to decreased loneliness.
Huang, 2010	Investigation of stability in Internet addiction over time, identify the link between prior academic self-perception on individual-level, mean-level stability, and ipsative stability of internet addiction.	351 freshman students over 4 assessment points. (53.6% female 44.4% male) Age not available Taiwan Longitudinal – 5 assessment time points from freshman year to end of junior year (3 years) Psychometric studies - quantitative	Chen Internet Addiction Scale (CIAS) (Chen et al., 2003) Dimensions of self-concept (Michael & Smith, 1976)	Stability in internet addiction over time. Internet addiction measured by Chen Internet Addiction Scale was structurally invariant over time. Academic self-concept had no effect on internet addiction.
Kabasakal ., 2015	Investigation in to PIU in university students and links to gender, grades, satisfaction with the university department, parent's education, smoking, alcohol use, gambling, parents relationship, duration of Internet use, and internet use for academic purposes. Examination of family functioning and life satisfaction as predictors of PIU in university students.	663 students (66% female, 44% male) Age between 17 and 23 years (M = 20.33 and SD = 1.42) Turkey Cross-sectional Psychometric studies - quantitative	PIUS (Ceyhan et al., 2007) Family Evaluation Scale (Epstein et al., 1978) Satisfaction with life scale (Diener & Diener, 1995) Demographic questions and questions on behaviors	PIU differs with gender. Smoking habits, alcohol use and gambling significant linked to PIU. Inverse relationship between PIU negative consequences and academic performance. PIU has a significant link with family functioning. Significant inverse link between PIU and life satisfaction. Time spent on internet is an indicator of PIU
Kittinger et al., 2012	Determine how the use of Facebook relates to PIU.	281 students (72% female, 28% male) Age 20.17 (SD = 1.44) years USA Cross-sectional Psychometric studies - quantitative	Self-report items for demographic and face book use Internet Addiction Scale (Young, 1998)	Facebook use better predictor of PIU than time online. Combination gender, age, loneliness, social anxiety, ADHD and alcohol use are risks for developing and maintaining PIU
Koç & Turan, 2020	Investigate links between self-esteem and subjective wellbeing and social network site use and smartphone addiction using Social Cognitive Theory	734 students (38.6% female, 61.4% male) Age not provided Turkey Cross-sectional Psychometric studies - quantitative	Demographic information Rosenberg Self-Esteem Scale (Petersen, 1965) Smartphone Dependance Questionnaire & Negahban, 2013) SNS Intensity Scale (Salehan& Negahban, 2013)	Young people tend to use SNSs to increase their social network, an extrinsic outcome, rather than subjective wellbeing, an intrinsic outcome. High score on SNS intensity scale linked with high levels of smartphone use, which may be linked to a decrease in subjective wellbeing. Low self-esteem linked to smartphone addiction.

Kuss et al., 2013	Study of prevalence IA and clarify links between personality traits and specific Internet uses in risk for IA.	2257 students (one third male, two thirds female) Age mean = 22.67 years , SD = 6.34 years, with a range from 18 to 64 years English Cross-sectional Psychometric studies - quantitative	Assessment for Computer and Internet Addiction-Screener (AICA-S) (Wolfgang et al.,2010) NEO five factor inventory (Costa & McCrae., 1992)	Internet activities, personality traits, may predispose to internet addiction, 32% rated as addicted to the internet. Personality traits and online activities explained 21.5% of the variance in addiction levels. Online shopping and neuroticism linked with a decrease in IA, online gaming and openness to experience increased IA. Frequent online shopping and social online activities, high neuroticism and low agreeableness increase IA
Li et al., 2020	Examination of Chinese Trait-State Fear of Missing Out Scale (T-SFoMOS-C) investigating its reliability and validity and measurement invariance in university students.	2017 students (one third male, two thirds female) Age with a range from 17 to 25 years Chinese Cross-sectional Psychometric studies - quantitative	Trait-State Fear of Missing Out Scale (Wegmann et al., 2017) Social Network Site Intensity Scale (Salehan & Negahban, 2013) International-Positive and Negative Affect Schedule – Short Form (I-PANAS-SF) (Thompson, 2007)	The Chinese version of the T-SFoMOS-C is relatively reliable and valid among different groups, and is a useful measure to use in Chinese university students.
Li et al., 2018	Study of the links between stressful life events and WeChat addiction on life satisfaction, as well as the mediating role of WeChat addiction on stressful life events and life satisfaction,	463 undergraduate students (53% female, 47% male) Age 17 to 23 years (M = 19.12, SD = 0.98) China Cross-sectional Psychometric studies - quantitative	The adolescent self-rating Life Events Checklist (ASLEC) (Liu et al., 1997) WeChat addiction scale developed by authors The satisfaction with life scale (SWLS) (Diener & Diener, 1995)	Suppressing effect of WeChat addiction on the negative impact of stressful life events on life satisfaction.
Lin et al., 2018	Study of Integration Hypothesis, healthier patterns of internet usage may be developed with harmony between people's online and offline 15ersona. An integration of online/offline personna is proposed.	626 undergraduates (58.5% female, 41.5% male) Age = 20.1 (*SD* = 1.4) China Cross-sectional Psychometric studies - quantitative	Online and offline integration scale (OOIS) – author developed Internet use decisional balance Questionnaire (IDBQ) Author developed Internet Addiction Test (IAT) (Young, 1998) The satisfaction with life scale (SWLS) (Diener & Diener, 1985) UCLA loneliness scale (Russell et al., 1996) Chinese Big Five Personality Inventory	Participants with higher level of online/offline integration have higher satisfaction with life, are more extrovert, have more positive view of the internet, less loneliness, lower Internet addiction. An integrated online and offline personna mediates the link between extraversion and psychological outcomes
Liu & Ma 2018b,	Investigation to examine the roles of FOMO and PSU in the links between receiving social support and Facebook addiction in a Chinese setting.	465 undergraduates (69% female, 31% male) Age between 16 and 24(M = 18.83, *SD* = 1.08) China Cross-sectional Psychometric studies - quantitative	Chinese adaptation of Facebook Measure of Social Support (McCloskey et al., 2015) Fear of Missing Out Scale (Przybylski et al., 2013) SAS-SV (Kwon et al., 2013) Chinese Social Media Addiction Scale (Liu & Ma, 2018a)	FOMO and PSU linked via online social networking sites and addiction to the sites, both in series and in parallel.
Lopez-Fernandez et al., 2017	Examination of patterns of mobile phones dependence in 10 European countries and determine how socio-demographics, geographic differences, mobile phone usage patterns, and associated activities predicted dependence	2775 young adults from European universities (72.8% female, 272% male) Age 18-29 years, Mean = 22.53, SD = 2.84 Finland and UK; Spain and Italy; Hungary and Poland; France, Belgium, Germany, and Switzerland Cross-sectional Psychometric studies - quantitative	PMPUQ-SV (Billieux et al., 2008) Socio Demographics	Northern and Southern Europeans most intense users of mobile phones; less in Eastern Europe. Percentage of highly dependent mobile phone users higher in Belgium, UK, and France. Risk factors for smartphone PIU were daily use, gender, social networking, playing video games, shopping and TV viewing, chatting, messaging, and downloading activities.

Lu et al., 2015	Examination of the risk factors of Problematic Internet Use (PIU) Identify a model of PIU to explore the links between cognitive distortion, depression, motivation, loneliness, stressful life events and PIU.	1493 undergraduate students 43.9% female, 56.1% mal Age = 21.18 (SD = 1.73) years Malaysia Cross-sectional Psychometric studies - quantitative	Internet Addiction Test (Young, 1998) Inventory of Cognitive Distortion (unpublished doctorate dissertation (Yurica, 2002) Leung's motivation of internet use scale(Leung, 2009) UCLA loneliness scale (Russell et al., 1996) DASS-21 (Lovibond & Lovibond, 1995) Stressful life events scale for university students adapted from student stress survey and Chinese college stress scale	Cognitive distortion was a mediator of PIU and partially mediated the link between motivation and stressful life events to PIU, fully mediated the effect of depression to PIU; while, depression was also a mediator which partially and fully mediated the effect from stressful life events and loneliness respectively to cognitive distortion.
Marciano et al., 2021	Longitudinal study examining the links between Smartphone Use (SU) and PSU during adolescence, if personality traits are considered as predisposing factors.	855 adolescents students 53.7% female, 46.3% mal Age = 11.36 (SD = 0.55) years Swiss Longtitudinal (annually over 4 years) Psychometric studies - quantitative	SAS-SV (Kwon et al., 2013) Personality Traits 24 items from the "Personality Inventory for DSM-5, Brief Form (PID-5-BF)	In a person, SU significantly increased PSU at all four time points, but not *vice versa*.
Moberg & Anestis, 2015	Investigation of the influence of online interactions and behaviors on Joiner's (2005) interpersonal-psychological theory of suicide. Study if suicidal desire develops in response to feelings of not belonging and of being a burden.	305 undergraduates (83.6% female, 16.4% male). Age ranged from 18 to 45 (*M* = 20.61; *SD* = 3.82) USA Cross-sectional Psychometric studies - quantitative	GPIUS- 2 (Caplan, 2010) Internet Use Questionnaire developed by researchers in the study DASS-21(Lovibond & Lovibond, 1995)	A general tendency to have negative interactions on social networking sites could link to suicidal desire because of feelings of not belonging and these effects maybe significant above and beyond depression symptoms. Social networking has a strong association with thwarted belongingness.
Morahan-Martin & Schumacher, 2000	Assessment of a high risk population for PIU, to assess level of PIU and how the internet is used and the links with PIU	277 undergraduate (45.85% female, 54.15% male) Age 20.72 (SD=2.35) years. USA Cross-sectional Psychometric studies - quantitative	Questions on Demographic characteristic, Internet Experience, Pathological Use scale, Internet sites used, Reasons for internet use, Internet Behavior and attitudes scale UCLA loneliness scale (Russell et al., 1996)	Level of PIU reported varied from 27.2% no symptoms, 64.7% one to three symptoms to 8.1% four or more symptoms. Problematic users were more often males and using online games and technologically sophisticated sites, no difference in chat use. Problematic users higher on the UCLA loneliness Scale, and were socially disinhibited online.
Odac & Kalkan, 2010	Investigation of PIU and patterns of internet use in university students and examine links between PIU, loneliness and dating anxiety.	493 students 62% female 38% male Mean Age 17.71 (SD = 0.45) Turkey Cross-sectional Psychometric studies - quantitative	Online Cognition Scale Keser-Ozcan et al., 2005 UCLA loneliness scale (Russell et al., 1996) Dating Anxiety scale-adolescent form (Kalkan, 2008)	Links between PIU and loneliness , communication anxiety , unpopularity anxiety , physiological symptoms, dating anxiety sub-scales were identified. PIU significantly higher if online 5h+/day. Levels of PIU were significantly higher in males.
Odaci & Çelik, 2013	Study of links between internet dependence and coping with stress and self-efficacy and whether internet dependence vary depending on sex roles, gender, and duration of Internet use.	623 students 72.9% female 27.1% male Mean Age 19.11 (SD = 0.91) Turkey Cross-sectional Psychometric studies - quantitative	Demographic Information IAT (Young, 1998) Coping with Stress Scale (Lazarus & Folkman, 1984) General Self-Effiacy Scale (Sherer et al., 1982) Bern Sex Role Inventory (Bem, 1974)	Negative links identified between internet dependence and seeking social support. Negative links between internet dependence and self-efficacy. Students' IA scores varied depending on gender.
Ozdemir et al., 2018	Examination of prevalence of nomophobia in university students and any links with nomophobia, self-esteem, loneliness and self- happiness, considering if gender or year of study influence.	729 univeristy students (70.6% female, 29.4% male) Age not available Turkey/Pakistan Cross sectional Psychometric studies - quantitative	Nomophobia Scale (NMP-Q) (Yildirim & Correia, 2015) UCLA loneliness Scale (Russell et al., 1996) Rosenberg Self Esteem Scale (Petersen, 1965) Self-Happiness Scale (Lyubomirsky & Lepper, 1999)	Links between gender and self-esteem, gender and nomophobia were found. Differences identified between Turkish and Pakistani students' scores on nomophobia, loneliness and self-happiness, no difference on self- esteem.

Özdemir et al., 2014	Examination of the direct and indirect links between depression, loneliness, low self-control, and Internet addiction	648 under- graduate students (34% female, 66% male) Age 22.46 years (SD = 2.45) Turkey Cross sectional Psychometric studies - quantitative	Internet Addiction Test (Young, 1998) Self-Control (Grasmick et al., 1993) Depression (Derogatis, 1993) UCLA loneliness scale (Russell et al., 1996)	Of depression and loneliness, only loneliness was related to Internet addiction through low self-control.
Peng et al., 2020	Assessment of whether teacher autonomy support, self-esteem and life satisfaction impact on adolescent Smartphone Use Disorder. (SUD)	1912 high school students (63.18% female, 36.82% male) Mean Age 14.66 years (SD = 1.38) Chinese Cross sectional Psychometric studies - quantitative	Learning Climate Questionnaire (LCQ) Autonomy Support subscale (Williams & Deci, 1996) Rosenberg Self Esteem Scale (Petersen, 1965) Mobile Phone Addiction Index (MPAI) (Leung, 2008)	Self-esteem mediated the link between teacher support and adolescent PSU. Links between this support and PSU was moderated by life satisfaction: when the effect of life satisfaction was high, there was an inverse link with PSU, when life satisfaction was low, teacher autonomy support was positively linked with adolescent PSU.
Primi et al., 2021	Investigatation of the psychometric properties of the Italian version of the BFAS among adolescents and young adults.	1134 under- graduate students (50% female, 50% male) Age Range 14-33 years (M = 20.7 SD = 3.5) Italy Cross sectional Psychometric studies - quantitative	GPIUS-2 (Caplan, 2010) IAT (Young, 1998) UCLA (Russell, 1996) Rosenberg Self-esteem Scale (Petersen, 1965) BFAS (Andreassen et al., 2012)	BFAS scores were positively linked with PIU and problematic Social Network use, scores were negatively linked with self-esteem, and positively linked with loneliness. The BFAS scale is stable measure for both genders. BFAS is a valuable and useful scale for measuring levels of problematic Facebook use in Italian adolescents and young adults.
Romero-Rodríguez et al., 2020	Investigation of the link between smartphone addiction and Instagram use, on the self-esteem of physical education students.	385 under- graduate students (61.8% female, 382% male) Age Range 18 and 35 years (M = 22.17 SD = 4.89) Spain Cross sectional Psychometric studies - quantitative	SAS-SV (Kwon et al., 2013) Social Media Intensity Scale (SMIS) (Ellison et al., 2007) Rosenberg Self-esteem Scale (Petersen, 1965)	Gender and age were factors that influenced PSU. A link between smartphone addiction and level of Instagram use was significant. Smartphone addiction was related to students' self-esteem. Level of Instagram use did not affect self-esteem. .
Servidio, 2021	Investigation of the links between PSU and maximization theory and if fear of missing out (FOMO) and self- esteem could mediate this relationship.	under- graduate students (7.5% female, 24.5% male) Age Range 19 and 85 years (M = 23.46 SD = 3.56) Italy Cross sectional Psychometric studies - quantitative	FOMO scale (Przybylski et al., 2013) SAS-SV (Kwon et al., 2013) Rosenberg Self-esteem Scale (Petersen, 1965) Maximization Scale (Schwartz et al., 2002)	PSU, maximization, and FOMO were linked; maximization and self-esteem were inversely linked. FOMO and self-esteem mediated the relationship between PSU and maximization thus it may be that those who maximize have increased FOMO, especially when fear missing out on "better" social experiences and exhibit low self-esteem. Thus, higher FOMO and low self-esteem may be a driver of PSU.
Shane-Simpson et al., 2016	Investigation of the factors of compulsive internet use (CIU), such as offline social difficulties and links to autism spectrum disorder (ASD), thus determining whether individuals cope with offline stresses with online interactions.	Study 1 : 597 under- graduates (53% female, 47% male) Study 2 matched a sample of students with ASD (n = 33) to neurotypical students (n = 33) Age Study 1 18 to 41 years (M = 20; SD = 3.48). Age study 2 With ASD 18 to 37 (M=20.84, SD=3.91) Without ASD 18 to 35 (M = 20. 72, SD = 3.64); USA Cross sectional Psychometric studies - quantitative	Demographic and friending behavior questions Facebook connection strategies scale (Ellison et al., 2011) Social Responsiveness Scale(Constantino, 2013) Compulsive Internet Use Scale (Meerkerk et al., 2009) Rosenberg Self Esteem Scale (Petersen, 1965)	A link between CIU and autistic traits was explained by restricted interests and repetitive behaviors (RIRB); a link between RIRB and information-seeking behaviors was identified. Non-social personality characteristics explain CIU more than individuals' attempts to compensate for offline social challenges. No significant differences in CIU scores for participants.

Stead & Bibby, 2017	Investigation of Personality, FOMO and PIU and links to subjective wellbeing	495 participants (69% female, 31% male) Age 22.46 years (SD = 2.45) UK Cross sectional Psychometric studies - quantitative	Ten-Item Personality Inventory (TIPI) (Gosling et al., 2003) Fear of Missing Out Scale (Przybylski et al., 2013) Modified questionnaire on social media use Life satisfaction questions (Przybylski et al., 2013)	Subjective wellbeing, not predicted by age or sex. Conscientiousness, extraversion, emotional stability and agreeableness were positively related to subjective wellbeing. FOMO and PIU were significantly and negatively linked to overall subjective wellbeing. FOMO and PIU were negatively linked with emotional wellbeing and personal relationships wellbeing but not physical wellbeing. Personality was linked with subjective wellbeing however both FOMO and PIU negatively affect subjective wellbeing more than personality.
Tian et al., 2019	Examination of links between shyness and generalized PIU to understand how shyness influences through the mediating effect of interpersonal relationships, loneliness, and maladaptive thoughts. Gender difference was considered.	1621 participants (6725% female, 32.75% male) Age 21.68 years (SD = 2.01) China Cross sectional Psychometric studies - quantitative	A revision of the Cheek and Buss shyness scale (Cheek & Buss, 1981) Chinese version of the Interpersonal Relationship Scale (Fang et al., 2007) The Chinese version of UCLA (Russell et al., 1996) The Chinese version of the maladaptive cognitions scale (Li et al., 2010) The Chinese version of the IAT (Young, 1998)	Shyness linked with general PIU from maladaptive thoughts; Shyness linked with general PIU via loneliness which was linked with maladaptive cognitions; Shyness could possibly reduce general PIU via interpersonal relationships, loneliness, maladaptive thoughts; Levels of shyness and general PIU were similar males and females, the strength of links between them were stronger for males.
Wang, 2019	Analysis of links between free-time management, leisure boredom, and internet addiction (IA).	475 Taiwanese undergraduate students (54.9% female, 45.1% male) Mean Age = 19.71 (*SD* = 1.52) years Taiwan Cross-sectional Psychometric studies - quantitative	Free time management scale (Wang et al., 2011) Boredom during leisure time scale (Weybright et al., 2015) Chen Internet Addiction Scale (Chen et al., 2003)	Free-time management reduces boredom during leisure time, and boredom during free-time is a risk for IA. Boredom in free-time is a mediator between free-time management and IA. Free-time management significantly affects boredom in leisure time and boredom in leisure time significantly affects IA.
Wohn & Larose, 2014	Investigation of relationships between loneliness, Facebook use, and college adjustment in first-year students.	1639 students survey 1, 1616 survey 2, 391 completed both (70.1% female, 29.9% male) Age Mean 17.75 (SD=.741) years. USA Longitudinal 2 surveys – 2 assessment time points – start and end of one semester Psychometric studies - quantitative	UCLA loneliness scale (Russell et al., 1996) Student adjustment to college scale (Baker & Siryk, 1984) Compulsive SNS drawn from (Caplan, 2010) (Meerkerk et al., 2009) and others	Compulsive use of Facebook had a stronger link with academic motivation than regular use of Facebook, neither were directly linked with academic performance. Too much time spent on Facebook was weakly but directly linked with poorer academic performance. loneliness was a stronger mark of college adjustment than Facebook usage
Yang, Yu, Liu et al., 2019	Study of a health education intervention and its impact on health behaviors and mental health in Chinese college students	532 Chinese undergraduate students (52.1% female, 47.9% male) Mean age19.49 (SD:0.90) years China Longitudinal – 2 assessment time points – before and after 7 week health education class intervention Psychometric studies - quantitative	Health behaviors and mental health were assessed using a questionnaire twice a week over 7 weeks, questions covered, knowledge, attitude, and practice of health behaviors.	Participants in the 7 week health intervention showed favourable changes on health behaviors vs control group with no intervention. Participants in the intervention reported significantly increased level of high physical activity and regular breakfast, reductions in screen time and lower risk of IA. The effects of the intervention on wellbeing and self-efficacy were insignificant.

Yang,Asbury & Griffiths , 2019	A Study of PSU in Undergraduate Students	265 students (69% female, 31% male) Age 22.46 years (SD = 2.45) British Cross sectional Qualitative study- analysis of responses to 5 open ended questions	Participant were asked about attitudes towards smartphone use, reasons for using smartphones, and what they thought were the consequences of smartphone use. Responses were assessed using framework analysis.	Indicators of PSU are uncontrolled frequent checking, using late at night, use in class for distraction. Explanations for PSU were might miss messages, boredom in class, poor self-regulation, and reasons like boring lectures. Smartphone use had positive and negative relationships with life satisfaction, social relationships, physical health, and study. Students identified a need for better self-regulation to manage PSU. Smartphone use benefit as well as cause harm in university students. PSU can reflect mental wellbeing issues, poor self-regulation, and social problems.
Ye & Lin, 2015)	Study of the impact of online communications on wellbeing measuring locus of control, loneliness, subjective wellbeing, and POSI.	260 Chinese undergraduate students (67.5% female, 32.5% male) Mean Age = 20.1 (*SD* = 12) years China Cross-sectional Psychometric studies - quantitative	Demographic information, reference for online social interaction (POSI) was measured with four items from Caplan (2010) (Caplan, 2010). Locus of control (Rotter, 1966) Campbell Index of wellbeing. (Campbell, 1976) UCLA loneliness scale (Russell et al., 1996)	Locus of control positively linked to loneliness and preference for online social interaction (POSI), but negatively linked to Subjective wellbeing; Loneliness (positively) and Subjective wellbeing (negatively) were related to POSI; Loneliness and Subjective wellbeing had a full mediating effect between locus of control and POSI. Lonely, unhappy, and externally controlled students are more likely to engage in online social interaction. Addressing students' locus of control, loneliness, and happiness may reduce PIU.
Zhang et al., 2021	Study using the I-PACE model (Brand et al., 2019) to explain how parental phubbing might accelerate adolescent mobile phone addiction through social anxiety and core self-evaluations (CSE).	471 Chinese undergraduate students (60% female, 40% male) Mean Age = 13.46 (*SD* = 1.11) years China Cross-sectional Psychometric studies - quantitative	Social Anxiety Scale for Children (SASC; La Greca & Stone, 1988) Core Self-evaluations Scale (CSES) (Du et al., 2012) Mobile Phone Addiction Scale (MPAS; Hong et al., 2012) 9-item Partner Phubbing Scale (Roberts & David, 2016)	Parental phubbing is related to adolescent mobile phone addiction, directly through social anxiety, core self-evaluation (CSE), and through the serial mediating role of social anxiety and CSE.
Zhang & Wu, 2020	Examination of the effects of smartphone addiction on sleep, in particular the impact of self-regulation and bedtime procrastination	431 Chinese undergraduate students (66% female, 34% male) 18 to 26 years (M = 19.36, SD = 1.06) China Cross-sectional Psychometric studies - quantitative	Pittsburgh Sleep Quality Index Smartphone Addiction Inventory Short Form (Lin et al., 2017) Bedtime Procastination Scale (Kroese et al., 2014) Self-regulation Questionnaire (Neal & Carey, 2005)	One third of participants reported poor sleep. Smartphone addiction and bedtime procrastination had a significant positive link on sleep quality, self-regulation had a significant negative link, with poor sleep. The indirect effects of smartphone addiction, through self-regulation and bedtime procrastination, on poor sleep quality were statistically significant. Both bedtime procrastination and poor self-regulation can be linked to smartphone addiction and poor sleep quality.
Zheng et al., 2020	Study using the I-PACE model (Brand et al.,2019) and social comparison theory, analysis of the role of upward social comparison and state anxiety in the relationships between passive social media use and online compulsive buying among female students.	799 Chinese undergraduate students (67% female, 33% male) Mean age = 20.71, SD = 22 China Cross-sectional Psychometric studies - quantitative	Passive Facebook Use (Liu et al., 2017) Chinese version of IOWA-Netherlands Comparison Orientation Measure (Gibbons & Buunk, 1999) Chinese short version of DASS-21 (Lovibond & Lovibond, 1995) Chinese version of Onlines Compulsive Buying Scale (Dittmar et al., 2007)	Passive social media use was linked to online compulsive buying; if online shopping was controlled for, passive upward social comparison and anxiety mediated the link, This link was mediated by upward social comparison and state anxiety, also a sequential mediating effect of upward social comparison and state anxiety was found.
Zhong et al., 2021	Study of the factors that influence cyberbullying in university students	947 Chinese college students (67% female, 33% male) Mean age = 19.86, SD = 1.63 China Cross-sectional Psychometric studies - quantitative	The Big Five Personality Test (Howard et al., 1996) Life satisfaction scale (Diener et al., 1985) A digital citizenship questionnaire including Young's (1996) IAT A cyberbullying questionnaire (Topcu & Erdur-Baker, 2012)	University students' digital citizenship scores have a significant negative correlation with cyberbullying but not with being cyberbullied

1.3.1 PIU

PIU is often conceptualized as behavior and thoughts associated with internet use, which an individual is struggling to control and which results in marked distress in daily life (Caplan, 2002; Young, 1996). Activities related to general internet use, social media use, gaming, smartphone use, and other subtypes of internet use, while distinct, can all lead to compulsive behavior and cognitions associated with the internet, and have been linked with loneliness, wellbeing and FOMO (Casale et al., 2018; Chang & lin, 2019; Elhai, Yang, Rozgonjuk, et al., 2020; Hebebci & Shelley, 2018). The psychometric tests measuring PIU identified in the research, included tests focused on general internet use, smartphone usage, gaming and social media which are considered internet behaviors encompassed by PIU in this research.

There were more than 13 different psychometric tests used to assess levels of general PIU, there were 10 different psychometric tests to measure problematic smartphone use, there were eight different psychometric tests used to measure problematic social media use and two different psychometric tests used to measure gaming, 18 of the papers used non-standard or self-developed questionnaires to measure aspects of PIU (Adiele & Olatokun, 2014; Casale & Fioravanti, 2015; Ceyhan, 2011; Chang et al., 2018; Chang & Lin, 2019; Coduto et al., 2020; Dang et al., 2019; Fioravanti & Casale, 2020; Hawi & Samaha, 2019; Kittinger et al., 2012; B. Li et al., 2018; Moberg & Anestis, 2015; Morahan-Martin & Schumacher, 2000; Shane-Simpson et al., 2016; Stead & Bibby, 2017; Yang et al., 2019; Ye & Lin, 2015; Zhong et al., 2021) in the 60 research papers reviewed. Young's (1998) Internet Addiction Test (IAT) was used 11 times (Adiele & Olatokun, 2014; Bakioğlu, 2020; Esen et al., 2013; Hawi & Samaha, 2019; Kittinger et al., 2012; Lin et al., 2018; Lu & Yeo, 2015; Odaci & Çelik, 2013; Özdemir et al., 2014; Primi et al., 2021; Tian et al., 2019). The next most frequently used test was the Smartphone Addiction Scale Short Version (SAS-SV) (Kwon et al., 2013) which was used 10 times (Elhai et al., 2018, 2019; Elhai, Gallinari, et al., 2020; Elhai, Yang, Dempsey, et al., 2020; Elhai, Yang, McKay, et al., 2020; Elhai, Yang, Rozgonjuk, et al., 2020; Liu & Ma, 2018b; Marciano et al., 2021; Romero-Rodríguez et al., 2020; Servidio, 2021), followed by the Generalised Problematic Internet Use Scale 2 (GPIUS2) (Caplan, 2010) which was used five times (Casale et al., 2014, 2015; Fioravanti & Casale, 2020; Moberg & Anestis, 2015; Primi et al., 2021), the Bergen Facebook Addiction Scale (BFAS) (Andreassen et al., 2012) was used three times (Atroszko et al., 2018; Fioravanti & Casale, 2020; Primi et al., 2021). There were six psychometric tests used twice see Table 3. While there were 26 different psychometric tests that measured some aspect of PIU used once see Table 4.

Table 3.

Psychometric Tests Used Twice

Paper	Test
Arpaci, 2020; Ozdemir et al., 2018	The Nomophobia questionnaire (Yildirim et al., 2015)
Chang et al., 2018; Chang & Lin, 2019	Online gaming motive scales of advancement, escapism and socializing (Yee, 2006b)
Chang et al., 2018; Chang & Lin, 2019	Problematic internet use(Liao et al., 2018)
Elhai et al., 2018, 2019	Smartphone Usage Frequency Scale (Elhai et al., 2016)
Hebebci & Shelley, 2018; Kabasakal., 2015	The Problematic Internet Use Scale (PIUS) (Ceyhan et al., 2007)
Huang, 2010; Wang, 2019	The Chen Internet Addiction Scale (CIAS) (Chen et al., 2003)

Table 4.

Psychometric Tests Used Once

Paper	Psychometric Test
Arpaci, 2020	Online Cognition Scale (Davis & Besser, 2002)
Casale et al., 2018	Bergen's Social Media Addiction Scale (Monacis et al., 2017b)
Chang et al., 2018	Online Gaming Motivation Scale Chinese Version (Yee, 2006a)
Demirtepe-Saygılı & Metin-Orta., 2020	Cyberloafing Scale (Akbulut et al., 2016)
Elhai, Yang, Dempsey, et al., 2020	Smartphone Use Expectancies Scale
Elhai, Gallinari, et al., 2020	Process and Social Smarphone Use (Van Deursen et al., 2015)
Gentina & Rowe, 2020	The mobile phone Involvement Questionnaire (Walsh et al., 2010)
Hao et al., 2020	Mobile phone addiction index (Leung, 2008)
Hawi & Samaha, 2019	Social media addiction questionnaire (Hawi & Samaha17a)
Koç & Turan, 2020	The Smartphone Dependance Questionnaire (Salehan & Negahban, 2013)
Kuss et al., 2013	The Assessment for Computer and Internet Addiction-Screener (AICA-S) (Wolfgang et al., 2010)
Li et al., 2020	The Social Network Site Intensity Scale (Salehan & Negahban, 2013)
Lin et al., 2018	Internet use decisional balance Questionnaire (IDBQ)
Liu & Ma., 2018b	Chinese version of Facebook Measure of Social Support (McCloskey et al., 2015)
Liu & Ma., 2018b	Chinese Social Media Addiction Scale (Liu & Ma, 2018a)
Lopez-Fernandez, 2017	PMPUQ-SV (Billieux et al., 2008)
Odac & Kalkan, 2010	Online Cognition Scale (Keser-Ozcan and Buzlu, 2005)
Peng et al., 2020	Mobile Phone Addiction Index (MPAI) (Leung, 2008)
Romero-Rodríguez et al., 2020	Social Media Intensity Scale (SMIS) (Ellison et al., 2007)
Shane-Simpson et al., 2016	Compulsive Internet Use Scale (Meerkerk et al., 2009)
Shane-Simpson et al., 2016	Facebook connection strategies scale (Ellison et al., 2011)
Wang, 2019	Chen Internet Addiction Scale (Chen et al., 2003)
Zhang et al., 2021	Mobile Phone Addiction Scale (MPAS; Hong et al., 2012)
Zhang & Wu, 2020	Smartphone Addiction Inventory Short Form (Lin et al., 2017)
Zheng et al., 2020	Passive Facebook Use (Liu et al., 2017)
Zhong et al., 2021	A cyberbullying questionnaire (Topcu & Erdur-Baker 2012)

The psychometric tests used three times or more to measure PIU were analysed in depth. The analysis identified the factors measured in the psychometric tests, using the symptoms/factors of behavioral addictions identified in Griffiths (Griffiths, 2005) components model see Table 1. In the components model, symptoms of behavioral addiction are salience, mood modification, tolerance, withdrawal., conflict and relapse (Griffiths, 2005). By judging questions or statements in each of the psychometric instruments, the extent to which they measured the factors was determined. The factors Preference for Online Social Interaction (POSI) and compulsive use were also considered as potential factors of PIU, these factors were identified by Caplan (2010). The factors withdrawal., salience/pre-occupation and negative consequences were measured in all of the psychometric tests examined, see Table 1. Withdrawal was measured using questions to determine if not being able to go online or access a smartphone generated feelings of being lost, being troubled, feeling bad, impatient, fretful or uneasy. Questions such as ‘Do you feel restless, moody, depressed or irritable when attempting to cut down or stop internet use?’ (Young, 1996). Salience/Pre-occupation with internet use was measured by questions or rating statements like ‘I think obsessively about going online when I am offline’ (Caplan, 2010). Negative Consequences or Conflict created by overuse of the internet was measured by ranking level of agreement with questions or statements like ‘I missed planned work due to smartphone use’ (Kwon et al., 2013). Use or overuse of the internet for Mood Modification/Escapism/Coping was also generally agreed on as a factor to be measured to assess PIU except in the SAS-SV (Kwon et al., 2013). It was measured using questions or statements like ‘I have used the internet to make myself feel better when I was down. ’ (Caplan, 2010). Tolerance was also identified as a factor in three of the four tests, however was not a factor in the GPIUS2 (Caplan, 2010). Tolerance was measured using statements or questions like ‘Felt that you had to use Facebook more and more to get the same pleasure from it’ (Andreassen et al., 2012).

There was no agreement on Compulsive Use or Relapse as factors of PIU. Compulsive use was not a factor in the IAT (Young, 1998) or BFAS (Andreassen et al., 2012). Compulsive Use was measured with responses to statements like ‘I find it difficult to control my Internet Use. ’ or ‘'When offline, I have a hard time trying to resist the urge to go online’ (Caplan, 2010). Relapse was included as a factor in the IAT (Young, 1998) and BFAS (Andreassen et al., 2012) which did not include compulsive use as a Factor. The SAS-SV (Kwon et al., 2013) and GPIUS-2 (Caplan, 2010) did not include relapse as a factor but did include compulsive use. Relapse was measured in the IAT using questions like ‘Have you repeatedly made unsuccessful efforts to control, cut-back or stop internet use? Or ‘Tried to cutdown the use of Facebook without success’ (Young, 1998). It may be that there is a similar construct being measured in relapse and compulsive use. Relapse in PIU is a recurrence of use of the internet problematically after a period of abstinence or control presumably driven by an urge to do so (Jiang et al., 2013), while compulsive use is PIU that is driven by an urge that compels (Griffiths, 2005).

Preference for online social interaction (POSI) was only measured in the GPIUS2, there was no consensus on this factor in the four most used psychometric tests. POSI was measured using statements like 'I prefer online social interaction over face-to-face communication'. The GPIUS-2 measured POSI using questions to identify whether online communication is preferred to face to face or more comfortable than face to face or just generally preferred.

1.3.2 PIU and its relationship with loneliness, FOMO and wellbeing in students

In the papers reviewed in this research the participants were college students except three studies, one in China, one in France and on in Switzerland where the students were in school. The mean age of participants across the research papers was 20.5 years with a standard deviation of 22 years. Approximately 60.5% of the total participants across all included studies were female. Of the papers reviewed, 17 had Chinese participants, 10 Turkish, 10 American, six Italian, four Taiwanese, two Lebanese, one British, one English and one from Turkey / Pakistan, and one each from Africa, Poland, Europe, Spain, France and Malaysia see Table 2.

The measurement of loneliness was standardised across the research papers using the UCLA loneliness Scale (Russell et al., 1996). The 20-item scale which measures subjective feelings of loneliness as well as feelings of isolation and disconnectedness from others was used in 15 of the 16 research papers which measured loneliness. The findings in the research examined was correlational so it was not possible to determine whether loneliness was the cause or effect of PIU. Loneliness correlated with PIU and negative outcomes from internet use (Bakioğlu, 2020; Esen et al., 2013; Primi et al., 2021; Tian et al., 2019) as such, loneliness is a risk factor for increasing severity of PIU and loneliness is a potential effect of increasing severity of PIU, see Table 2.

Measurement of FOMO was standardised in the research examined. Przybylski's and colleagues' (2013) 10-item psychometric test was used eight of the nine papers that measured FOMO (Przybylski et al., 2013). Findings in the research examined were correlational so it was not possible to identify whether FOMO was a cause and/or effect of PIU. The correlations suggest that FOMO is a risk factor for PIU and increased FOMO may be an effect of PIU (Elhai, Yang, Dempsey, et al., 2020; Hebebci & Shelley, 2018; Servidio, 2021; Z. Yang et al., 2019; see Table 2).

Wellbeing is a combination of psychological wellbeing, social wellbeing, and physical wellbeing (Pressman et al., 2020). In the research examined multiple psychological health and social health variables were measured and findings consistently show that reduced scores in wellbeing indicators correlated with increased scores in PIU measures (Atroszko et al., 2018; Casale & Fioravanti, 2015; Chang & Lin, 2019; Kabasakal., 2015; Moberg & Anestis, 2015; Odac & Kalkan, 2010; Ye & Lin, 2015).

Wellbeing was measured in the research using 34 different psychometric tests. Of these tests, only the Satisfaction with Life Scale (Hawi & Samaha, 2019; Kabasakal., 2015; B. Li et al., 2018; Lin et al., 2018), DASS-21 (Lovibond & Lovibond, 1995), Beck Depression Inventory (Caplan, 2002; Chang & Lin, 2019; Elhai et al., 2018, 2019; Lu & Yeo, 2015; Moberg & Anestis, 2015), Rosenberg Stress Scale (Hawi & Samaha, 2019; Ozdemir et al., 2018; Shane-Simpson et al., 2016) were used more than once see Table 2. None of the studies determined if increasing severity of PIU was a cause or effect or both for reduced wellbeing see Table 2. The correlations however suggested that reduced wellbeing is a risk factor for increasing severity of PIU and/or reduced wellbeing may be an effect of increasing severity of PIU.

The psychological health and social health variables examined in the research in relation to wellbeing can be classified into three broad categories: general wellbeing; depression and stress and self-esteem, shyness and social anxiety see Table 2.

To measure general wellbeing the Satisfaction with Life Scale (Diener et al., 1985) was used five times, Self-happiness Scale (Lyubomirsky & Lepper, 1999), Campbell Wellbeing Index (Campbell, 1976) and Psychological Wellbeing Scale were all used once, see Table 2. General wellbeing variables examined included cognitive distortion, self-concept, self-efficacy, self-control, locus of control, dispositional rumination, perfectionism, adjustment to college and boredom proneness (Atroszko et al., 2018; Caplan, 2002; Casale et al., 2014, Casale & Fioravanti, 2015; Esen et al., 2013; Hawi & Samaha, 2019; Huang, 2010; Kabasakal., 2015; Li et al., 2018; Lin et al., 2018; Lu & Yeo, 2015; Ozdemir et al., 2018; Wang, 2019; Wohn & Larose, 2014; Ye & Lin, 2015; Zhong et al., 2021).

To measure depression and stress, the Beck Depression Inventory was used twice and the Depression Anxiety and Stress Scale – 21 (DASS-21) was used 10 times, the Depression Scale (Derogatis, 1993) and the Perceived Stress Scale (Cohen et al., 1983) were also used, see Table 2. Wellbeing indicators depression and stress were measured and examined in 14 research articles (Atroszko et al., 2018; Busch & McCarthy, 2021; Caplan, 2002; Dang et al., 2019; Elhai et al., 2018, 2019; Elhai, Gallinari, et al., 2020; Elhai, Yang, Dempsey, et al., 2020; Elhai, Yang, McKay, et al., 2020; Elhai, Yang, Rozgonjuk, et al., 2020; Kabasakal., 2015; Lu & Yeo, 2015; Odac & Kalkan, 2010; Özdemir et al., 2014).

To measure self-esteem, shyness and social anxiety, the Rosenberg Self-esteem Scale (Rosenberg, 1965) was used seven times (Caplan, 2002; Hawi & Samaha, 2019; Koç & Turan, 2020; Ozdemir et al., 2018; Primi et al., 2021; Servidio, 2021; Shane-Simpson et al., 2016), the Social Efficacy and Social Outcome Expectation Scale (Wright et al., 2013) used once (Bakioğlu, 2020), Social Control Subscale (Galeazzi et al., 2002) used once (Casale et al., 2018), Social Reticence Scale (Jones et al., 1986) used once (Caplan, 2002), Social Phobia and Anxiety Index Scale (de Vente et al., 2014) used once (Coduto et al., 2020), Social Self-efficacy Scale (Smith & Betz, 2000), Dimensions of Self-concept (Michael & Smith, 1976), Dating Anxiety Scale Adolescent Form (Kalkan, 2008), A Brief Measure for Assessing Generalized Anxiety Disorder (GAD-7) (Spitzer et al., 2006), Social Anxiety Scale for Children (La Greca & Stone, 1993), Cheek and Buss Shyness Scale (Cheek & Buss, 1981) and Social Responsiveness Scale (Constantino, 2013) were also used, see Table 2. The variables examined in the research reflecting the self-esteem, shyness or social anxiety aspect of wellbeing included self-concept, self-esteem, social control, social responsiveness, communication skills, dating anxiety shyness and fear of negative evaluation (Atroszko et al., 2018; Bakioğlu, 2020; Caplan, 2002; Casale & Fioravanti., 2015, 2018; Ceyhan, 2011; Coduto et al., 2020; Elhai et al., 2018; Elhai, Yang, McKay, et al., 2020; Esen et al., 2013; Hawi & Samaha, 2019; Huang, 2010; Koç & Turan, 2020; Lu & Yeo, 2015; Odac & Kalkan, 2010; Odaci & Çelik, 2013; Özdemir et al., 2014; Peng et al., 2020; Primi et al., 2021; Romero-Rodríguez et al., 2020; Servidio, 2021; Shane-Simpson et al., 2016; Tian et al., 2019; Ye & Lin, 2015).

1.3.3 Wellbeing, Loneliness, FOMO and PIU Findings Framed Using the I-PACE model.

Four of the research papers examined used the I-PACE model to frame their findings (Dang et al., 2019; Elhai, Yang, Dempsey, et al., 2020; Zhang et al., 2021; Zheng et al., 2020). Each of these studies found support for the I-PACE model. A person's core character may predispose to PIU and combined with affective and cognitive factors may relate to increasing severity of PIU. Potential moderating and mediating variables for PIU identified were emotional intelligence, depression and coping flexibility (Dang et al., 2019). Mediating variables in the association between PIU sub-types (passive use of social networks and online shopping) were anxiety and upward social comparison. Anxiety and upward social comparison may trigger cognitive responses and affective reaction when passively using social network sites or online shopping, as such are risks for increasing severity of PIU (Zheng et al., 2020). Equally, the correlational association may indicate that increasing severity of PIU could trigger responses and reaction that may affect anxiety and upward social comparison. Perceived parental phubbing subjectively experienced was found to be directly associated with problematic smartphone use (Zhang et al., 2021). Parental phubbing may create social anxiety or impact core self-evaluation which mediates the association with PIU or vice versa. Correlations between PIU and parental phubbing may be explained as an affective and cognitive response to the phubbing, the anxiety and the core self-evaluation resulting in a decision to use the internet as a coping strategy alternatively the use of the internet may influence the mediating anxiety and core self-evaluation (Zhang et al., 2021). Previous research has suggested that while predisposing variables are risks for development and maintenance of PIU as described in the I-PACE model, dysfunctional coping or the response variables should be the focus for managing PIU (Elhai, Yang, Dempsey, et al., 2020).

When the findings in the research examined were interpreted using the I-PACE model, it appears that biological factors as well as psychological factors could be interpreted as predisposing to PIU. Gender was the main predisposing biological factor found to be associated with PIU, 11 of the studies found significant correlations between gender and PIU. Some found being male was a risk for PIU (Tian et al., 2019). Others found being female was a risk for social media addiction (Atroszko et al., 2018; Hawi & Samaha, 2019; Kittinger et al., 2012; Lopez-Fernandez et al., 2017). Gender predicted differences in response to FOMO (Casale et al., 2018) and gender-related social connectedness differences characterised FOMO (Elhai et al., 2018).

The findings in the research examined and the I-PACE model suggest that PIU is associated with psychological predisposing factors such as a person's core characteristics, personality, social cognitions and psychopathology Figure 1. The potential predisposing social cognitions and psychological factors for PIU examined in the research for which links were found to PIU were numerous. They included loneliness (Atroszko et al., 2018; Bakioğlu, 2020; Caplan, 2002; Coduto et al., 2020; Esen et al., 2013; Hebebci & Shelley, 2018; Kittinger et al., 2012; Lin et al., 2018; Lu & Yeo, 2015; Morahan-Martin & Schumacher, 2000; Odac & Kalkan, 2010; Ozdemir et al., 2018; Özdemir et al., 2014; Primi et al., 2021; Tian et al., 2019; Wohn & Larose, 2014; Ye & Lin, 2015), FOMO (Casale et al., 2018; Elhai et al., 2018, 2019; Elhai, Gallinari, et al., 2020; Elhai, Yang, Rozgonjuk, et al., 2020; Li et al., 2020; Liu & Ma, 2018b; Servidio, 2021; Stead & Bibby, 2017), life satisfaction (Kabasakal., 2015; Li et al., 2018; Peng et al., 2020; Yang et al., 2019; Ye & Lin, 2015), wellbeing (Atroszko et al., 2018; Casale & Fioravanti, 2015; Koç & Turan, 2020; Ye & Lin, 2015), social anxiety or shyness (Atroszko et al., 2018; Caplan, 2010; Casale et al., 2014; Chang et al., 2018; Coduto et al., 2020; Elhai et al., 2019; Elhai, Gallinari, et al., 2020; Elhai, Yang, Dempsey, et al., 2020; Kittinger et al., 2012; Tian et al., 2019; Yang et al., 2019; Zhang & Wu, 2020), anxiety (Elhai et al., 2019; Elhai, Gallinari, et al., 2020; Elhai, Yang, Dempsey, et al., 2020; Elhai, Yang, McKay, et al., 2020; Odac & Kalkan, 2010; Zheng et al., 2020), depression (Caplan, 2002; Casale et al., 2014; Chang & Lin, 2019; Dang et al., 2019; Elhai et al., 2019; Elhai, Gallinari, et al., 2020; Elhai, Yang, Dempsey, et al., 2020; Elhai, Yang, McKay, et al., 2020; Lu & Yeo, 2015) , stress (Atroszko et al., 2018; Li et al., 2018; Lu & Yeo, 2015; Odaci & Çelik, 2013), personality (Adiele & Olatokun, 2014; Atroszko et al., 2018; Kuss et al., 2013; Lin et al., 2018; Marciano et al., 2021), extraversion (Atroszko et al., 2018; Hawi & Samaha, 2019; Lin et al., 2018; Stead & Bibby, 2017), ruminative thought style (Elhai et al., 2018; Elhai, Yang, Dempsey, et al., 2020; Elhai, Yang, Rozgonjuk, et al., 2020), openness to experiences (Hawi & Samaha, 2017; Kuss et al., 2013), self-esteem (Caplan, 2002; Casale et al., 2014; Hawi & Samaha, 2017; Hawi & Samaha, 2019; Koç & Turan, 2020; Peng et al., 2020; Primi et al., 2021; Romero-Rodríguez et al., 2020; Servidio, 2021), self-efficacy (Atroszko et al., 2018; Bakioğlu, 2020; Odaci & Çelik, 2013). Other factors that were also examined and found to correlate with PIU were alcohol use (Kabasakal., 2015; Kittinger et al., 2012), emotional intelligence (Dang et al., 2019), emotional stability (Casale et al., 2014; Hawi & Samaha, 2019; Stead & Bibby, 2017), fear of negative evaluation (Casale et al., 2014, 2018), extraversion (Hawi & Samaha, 2017; X. Lin et al., 2018), ADHD (Kittinger et al., 2012), low agreeableness (Kuss et al., 2013; Stead & Bibby, 2017) being socially disinhibited (Morahan-Martin & Schumacher, 2000). narcissism (Atroszko et al., 2018), alexithymia (Hao et al., 2020), cognitive empathy (Hao et al., 2020), affective empathy (Hao et al., 2020), agreeableness (Hawi & Samaha, 2019), neuroticism (Kuss et al., 2013), low social support (Casale et al., 2014), levels of autonomy, environmental mastery, and positive relations with others (Casale& Fioravanti, 2015), real-self (Hawi & Samaha, 2017), conscientiousness (Hawi & Samaha, 2017), cognitive distortion (Lu & Yeo, 2015) and psychoticism (Marciano et al., 2021).

The research identified a number of variables with associations with PIU which may affect or be affected by PIU. FOMO could be considered as a cognitive effect in the I-PACE model, a reaction to pre-disposing social anxiety or depression which influences the decision to use the internet (Casale et al., 2018) or vice versa. FOMO may mediate the relationship between potentially predisposing factors anxiety and depression and PIU or vice versa (Coduto et al., 2020; Elhai et al., 2019; Elhai, Gallinari, et al., 2020). FOMO may also be a moderator of PIU or vice versa (Elhai, Yang, Dempsey, et al., 2020). A situational trigger such as an image on social media may create FOMO as a cognitive affective response. Cognitive affective responses and coping mechanisms such as checking social media in response to FOMO may lead to decisions to behave in specific ways which may influence the development of PIU (Brand et al., 2019). Research suggested these responses could be more important than predisposing factors in influencing PIU development and maintenance (Elhai, Yang, Dempsey, et al., 2020). If social media is used to avoid FOMO, the gratification or compensation received may reinforce the use of social media, potentially leading to FOMO, creating a possible behavioral cycle, a process identified as instrumental conditioning in the I-PACE model. Using the internet as a coping strategy to avoid offline stresses is a potential mediator between predisposing factors and PIU. As all of the findings in the studies examined were correlational the direction of the relationships between variables were not established and therefore the relationship between variables examined and PIU may be cause or effect.

PIU was explained in the research as a maladaptive coping strategy (mediator or moderator in I-PACE) for life’s problems and a means to regulate mood (Atroszko et al., 2018; Casale et al., 2014,2018;

Casale & Fioravanti, 2015; Ceyhan, 2011; Chang et al., 2018; Dang et al., 2019; Demirtepe-Saygılı & Metin-Orta., 2020; Elhai, Yang, Rozgonjuk, et al., 2020; Kuss et al., 2013; Li et al., 2018; Yang et al., 2019). In longitudinal studies (Chang et al., 2018; Chang & Lin, 2019), PIU was consistently correlated with heavy use of the internet for gaming when a choice to use the game was motivated by a desire to avoid real-life stresses, a potentially maladaptive coping strategy, suggesting it was not the intensity of the game usage, but the motivation to avoid offline stresses which correlated with PIU (Chang et al., 2018; Chang & Lin, 2019). This coping strategy could be explained as moderating the association between predisposing factors and PIU.

This review of existing research found that internet use expectancies or comfort expectancies about internet use was found consistently to correlate with PIU (Caplan, 2002; Casale et al., 2018; Elhai, Yang, Dempsey, et al., 2020; Elhai, Yang, Rozgonjuk, et al., 2020; Hebebci & Shelley, 2018; Lu & Yeo, 2015; Tian et al., 2019). The reviewed findings provide empirical evidence to support the proposal that a decision to use certain applications on the internet may be affected by cognitive biases (Casale et al., 2018; Elhai, Yang, Rozgonjuk, et al., 2020; Tian et al., 2019). For example, research has found that FOMO is linked to cognitive bias or thoughts about effectiveness of social media use to manage FOMO (Casale et al., 2018; Elhai et al., 2018). And positive thoughts about internet usefulness to mitigate FOMO mediate the relationship between FOMO and PIU (Casale et al., 2018; Elhai et al., 2018). Hence FOMO may also be conceptualized as a moderator between predisposing factors and the development and maintenance of PIU using the I-PACE model. FOMO may create a cognitive bias that contributes to PIU or PIU creates a cognitive bias that contributes to FOMO (Elhai et al., 2018).

In the research examined, withdrawal, salience / pre-occupation, tolerance, relapse / compulsive use, negative consequences / conflict and mood, modification/escapism/coping and POSI were factors used for measuring PIU in the psychometric tests. The symptoms of PIU measured in the psychometric tests include pre-occupation, mood modification or escapism and withdrawal see Table 1, moderating (cognitive and attentional biases and coping strategy) and mediating (cognitive and affective reactions to situational triggers) variables in the I-PACE model (Brand et al., 2019). The criteria assessed in the psychometric tools include tolerance and compulsive use or relapse see Table1, all of which relate to instrumental conditioning. In combination with reduced inhibitory control, instrumental conditioning may support the development of PIU according to the I-PACE model (Brand et al., 2016). The research examined also suggests that poor self-regulation is a contributor to PIU (Casale & Fioravanti, 2015; Yang et al., 2019), a factor identified in the I-PACE model as reduced inhibitory control.

1.4 Discussion

The current systematic review investigated the scientific findings on the relationships between student loneliness, FOMO, wellbeing and PIU and interpreted the findings using the theoretical framework of the I-PACE model (Brand et al., 2019).

The research examined used a number of validated psychometric tests to measure PIU as well as novel self-developed scales or questions. The present chapter synthesises the findings through examination of PIU measurement/conceptualisation using Griffiths components model. Previous research has found the psychometric tests of PIU have been developed using a combination of the DSM-IV criteria for pathological gambling and/or substance dependence (American Psychiatric Association, 2013), the cognitive-behavioral model of GPIU (Davis, 2001) and Griffith's components model (2005). The components of behavioral addiction identified by Griffith are consistent factors in the psychometric tests used (Moretta et al., 2022). The detailed examination of the factors measured by the questions/statements in the psychometric tests most frequently used in Table 1 is summarised in Table 5. The summary presented in table 5 highlights the consistent measurement of the factors, negative consequences, withdrawal and salience/pre-occupation, with some consistency in mood modification/escaping/coping. Compulsion or alternatively relapse was also a factor in the tests.

Table 5

Concentration of Agreement on Factors to Measure PIU

Psychometric Test	Withdrawal	Salience / Pre-occupation	Tolerance	Relapse / Compulsive Use	Negative Consequences / Conflict	Mood Mod / Escapism / Coping
Young IAT(Young, 1998)	X	X	X	X	X	X
GPIUS-2 (Caplan, 2010)	X	X		X	X	X
SAS-SV (Kwon et al., 2013)	X	X	X	X	X	
BFAS (Andreassen et al., 2012)	X	X	X	X	X	X

The psychometric tests analysed all measured factors relating to a behavioral addiction as defined by Griffith's components model see Table 5. The level of agreement suggests standardisation of psychometric tests to measure PIU is feasible. Such standardisation would be beneficial as it would enable more effective comparison of PIU in research findings. Agreement on the factors to assess/measure PIU in a 'gold standard' psychometric test would improve future comparison of research outputs and increase reliability of comparisons across studies. A 'gold standard' test using the best elements of existing tests could offer benefits when interpreting and comparing research outputs beyond any potential benefits of using a large variety of bespoke tests to measure PIU.

The present systematic literature review identified that when findings are integrated using the I-PACE model, loneliness, FOMO and reduced wellbeing may be recognised as predisposing psychological factors which prompt or encourage individuals to use the internet to avoid offline stressors. Moderators and mediators of PIU in the I-PACE model are cognitive biases or coping strategies, experience on the internet and conceptions about the internet which influence the decision to use the internet. Loneliness, FOMO and reduced wellbeing may be considered as moderators or mediators of PIU in the I-PACE model. For example, images of others' activities on social media may create an affective reaction of loneliness or FOMO or unhappiness and generate or strengthen a decision to use social media to alleviate anxiety (Casale & Fioravanti, 2011; Ceyhan, 2011; Elhai et al., 2018; Hebebci & Shelley, 2018).

The internet can be used as a coping mechanism to divert from distress. Internet use which compensates or gratifies can reinforce thoughts about the internet as an effective coping mechanism. Gratification as explained in the I-PACE model may reinforce cognitive biases about internet use as an effective strategy for coping with offline stresses. As supported by the investigated studies, the I-PACE model explains how behaviors on the internet which are reinforced by gratification and compensation received on the internet, may motivate to spend more time online (Brand et al., 2016; Young & Brand, 2017). Using the internet as a coping strategy to manage loneliness or FOMO can be effective; managing loneliness by making new social connections online, and managing FOMO by checking what others are doing. However, the negative consequences of overuse of the internet to manage loneliness appears to increase loneliness and lonelier people appear to have more negative consequences, potentially as a result of neglect of offline relationships (Ceyhan, 2011; Wohn & Larose, 2014). Research has also found that using the internet to cope with FOMO may increase anxiety (Casale & Fioravanti, 2011; Elhai et al., 2018; Hebebci & Shelley, 2018).

In the I-PACE model, inhibitory control is reduced as problematic internet use develops with instrumental conditioning (Young & Brand, 2017), research findings in this review appear to support this. Previous research has explained PIU as reflecting poor self-regulation (Yang et al., 2019). Research findings show that compulsivity was linked to PIU when reacting to situational triggers (Caplan, 2002) and that loneliness was related to internet addiction through low self-control (Yang et al., 2019).

Research also suggests that individuals who are not psychosocially healthy may struggle regulating their Internet use (Kim et al., 2009).

1.5 Future Research and Limitations

In this research the definition of PIU includes all behavior on the internet regardless of the activity from which it stems. There were over 35 standard psychometric tests that met this definition. A gold standard suite of tests developed based on the best elements of the tests already most frequently used would be of great benefit if used in future research. Two of the most frequently used tests measured, general internet use (IAT and GPIUS2). While another frequently used test focused on problematic smartphone use specifically (SAS-SV). A fourth measured problematic social media use (BFAS) see Table 1. Future research would benefit from a standardised definition of PIU and standardised psychometric tests to measure PIU. It may be necessary to have specific tests to measure specific behaviors on the internet rather than a single test measuring all behaviors on the internet however there is still scope for standardisation. The variety of instruments for measuring PIU make the current research findings more difficult to compare and understand.

The I-PACE model allowed for a comprehensive understanding of the variables assessed in the research. The I-PACE model can frame research findings in the process of development and maintenance of PIU. Future research could benefit from considering findings within a theoretical framework, such as the I-PACE model.

Future research could also evaluate the effect of addressing moderating and mediating variables, such as cognitive affect and coping strategy, as identified in the I-PACE model to understand if they are an effective focus for reducing PIU.

This systematic review was limited to research findings that related to students, all but three of the studies related to university or college students, a systematic review which considered a more general population would further test the effectiveness of the I-PACE model to explain PIU development and maintenance.

1.6 Summary and Conclusions

The reviewed studies show FOMO, reduced wellbeing and loneliness were found to have consistent correlations with increasing severity of PIU (Atroszko et al., 2018; Casale & Fioravanti, 2015; Chang & Lin, 2019; Elhai et al., 2019; Elhai, Gallinari, et al., 2020; Esen et al., 2013; Hawi & Samaha, 2019;

Kabasakal., 2015; Moberg & Anestis, 2015; Odac & Kalkan, 2010; Stead & Bibby, 2017; Ye & Lin, 2015). The research did not establish cause and effect, and the correlations indicate that FOMO, reduced wellbeing and loneliness may be risks for developing and/or maintaining PIU. Alternatively, PIU maybe a cause of loneliness, FOMO and reduced wellbeing (Caplan, 2002; Coduto et al., 2020; Hebebci & Shelley, 2018). Regardless of whether loneliness and reduced wellbeing is a cause or effect of PIU, the consistent correlations found in the reviewed research suggest addressing PIU is worth considering as a means to reduce loneliness and improve wellbeing in university student populations.

The results of the present review have important implications for improving student mental health and wellbeing. There are several ways identified in the research that healthy internet behaviors may be developed by managing moderating and mediating variables identified in the I-PACE model. Moderating and mediating variables in the I-PACE model such as coping strategy, cognitive biases about internet usefulness and cognitive affect and reaction to situational triggers may be important in identifying and managing PIU and developing healthy internet use behaviors (Elhai, Yang, Dempsey, et al., 2020). The effects of FOMO on PIU may be controlled by managing cognitive bias (Elhai, Yang, Dempsey, et al., 2020). Managing thoughts about social networking sites' usefulness may reduce anxiety, negative effect and PIU (Casale et al., 2018). PIU may also be reduced by developing emotional intelligence and coping strategies for real-life stresses so that using the internet for distraction is not the default strategy (Dang et al., 2019; Elhai, Yang, Rozgonjuk, et al., 2020). PIU may also be addressed by tackling the real-life stresses for which using the internet may be a coping strategy (Caplan, 2002; Esen et al., 2013; Hawi e & Samaha, 2019; Odac & Kalkan, 2010). Managing thoughts about usefulness of social networking sites and awareness of triggers for compulsive internet use may be effective in managing PIU (Casale et al., 2018; Coduto et al., 2020). Recognising cognitive affect and reaction to situational triggers and reduced inhibitory control, awareness of compulsive use and potential negative outcomes may help avoid PIU (Coduto et al., 2020). Reduction of PIU could focus on improved self-regulation or increased inhibitory control (Caplan, 2002; Esen et al., 2013; Hawi & Samaha, 2019; Odac & Kalkan, 2010; Yang et al., 2019).

In this chapter a systematic review of existing research findings relating to FOMO, loneliness, wellbeing and PIU in students were examined. The I-PACE model (Brand et al., 2019) was used to frame the findings in order to obtain a coherent understanding of the findings. Griffiths (2005) components model was used to understand the commonality in the factors to measure PIU. A reliance on self-assessment to assess PIU was evident, in the next chapter research which used objective measures to assess PIU and internet behavior is examined.

Chapter 2. Systematic Literature Review of Research Using Objective Data to Understand Internet Behavior and Problematic Internet Use

2.1 Introduction

The Internet has many positive uses, giving access to information, entertainment, and enabling communication. However, some individuals use the internet problematically. Thus, there is growing public concern about the health and societal costs of PIU (Fineberg et al., 2018). Consequently, research is needed to refine the conceptualisation of PIU and further understand its impact (Fineberg et al., 2018).

Some researchers suggest that measurements of PIU like other behavioral addiction measurements in psychology, have an over-reliance on self-assessment. For example, Griffoen et al. (2020) found 93.6% of social media studies relied on self-assessment. While Dolinski (2018) observed that only about 6% of personality and social psychology studies include behavioral measurement. Self-reports have been used very effectively, in psychological research. Self-assessment tools can be convenient, inexpensive, easy to use, quick to administer, give direct testimony and can be standardised and validated (McDonald, 2008). However, there are concerns about the limitations of research which relies exclusively on self-report (Ryding & Kuss, 2020). Thus, development and evaluation of objective methods for measuring actual internet behavior are needed. The present review aims to identify and assess objective measures of internet behavior and smartphone use used in research and their contribution to research on PIU.

While there is no agreed definition of PIU, for the purpose of this review it is understood as internet use that is excessive or poorly controlled that leads to difficulties or distress (Weinstein & Lejoyeux, 2010). To assess PIU, it is necessary to measure or identify the consequences of internet overuse that lead to impairment or distress (Weinstein & Lejoyeux, 2010). Assessment of negative consequences requires an element of self-assessment. However, complementing self-assessment with more objective measures could offer support for findings from self-assessment. Objective measures in this review are understood as robust assessments, which use reliable processes to establish measurement correctness, processes which are transparent and impersonal (Munroe & Hardie, 2019). Digital traces of internet activity are impersonal and transparent records of internet behaviors, records which are not influenced by prejudice, judgment or delusion (Daston et al., 2007) and as such are objective measures.

Digital traces of internet activity can generate big data, huge volumes, of a variety of data, at speed(velocity). Big data generated from digital traces can enable identification of the larger behavioral patterns in internet use, by identifying the details of actual usage and discovering meaningful patterns in the data (Fischer et al., 2020). The discovery of meaningful patterns in big data could enable understanding and prediction of internet behavior. Although there is potential to understand internet use with digital traces, there are challenges in storage, processing and analysis of the data (Yaquob et al., 2016). Obtaining meaningful information from a big data set requires methodological and interdisciplinary skills, technical proficiencies to contend with the data as well as subject matter expertise to interpret the significance of the data in a specific functional domain (Espinosa et al., 2019). Nevertheless, by combining understanding of internet behavior from data generated from digital traces, with data collected from surveys or psychological scales, researchers may link action sequences to traits. Thus, test whether observed behavior and self-report data align with each other and theory on internet behavior (Fischer et al., 2020).

Collection of data without active data entry by a participant is called unobtrusive, passive monitoring and enables continuous data collection over longer periods of time (Asselbergs et al., 2016; Bentley et al., 2019). Unobtrusive passive monitoring describes collection of data from digital traces of internet accesses on a network (Asselbergs et al., 2016; Fischer et al., 2020). Already, unobtrusive passive measurement of activity on the internet is frequently used for analysing behavior for security and network management purposes (Maier et al., 2009; Trevisan et al., 2020). Digital trace data can be gathered consistently and frequently, with great fidelity and complexity, at a fraction of the effort and cost required to gather similar data using methods such as observation, surveys or interviews. Moreover, the exactness and realism of digital traces ensures that generalisability across a population is maximised (Chang et al., 2014). Research is needed to further understand the potential benefits and harms of digital technologies (Melo et al., 2020). Passive monitoring of digital traces is one way data for this research could be collected. Reviews evaluating passive monitoring have identified that real-time measurement can enable assessment of variables more precisely and in a less intrusive manner than self-report measures (Bentley et al., 2019; Cornet & Holden, 2018).

A smartphone app installed on a research participants phone can be used to collect objective data on smartphone or internet use, however this method of gathering data is more obtrusive. An app must be installed on a participant’s smartphone, the app uses smartphone resources such as battery, processing power and storage. This resource usage may affect the participant's experience on the phone. The monitoring app may also interact with the participant by requesting permission to access resources or by looking for other responses. Some apps do Experience Sampling Method (ESM) or Experience momentary assessment (EMA) which regularly prompts the user for responses to surveys. ESM/EMA are characterized by (a) gathering survey data in the real-world environments; (b) an assessment of a participant's current or recent state or behavior that is delivered in the natural environment; (c) assessments may be generated when an event occurs or a particular time or may be random; and (d) may be repeated (Stone & Shiffman, 1994). Using ESM/EMA to gather psychometric or survey data can offer improvements on a random-measurement approach. ESM/EMA can deliver near real time self-assessment in the natural environment. Hence, retrospective and heuristic biases that may distort recollections of experiences and behavior in psychometric tests can be reduced or minimised however the method still depends on the participant's accurate and unbiased recall (Trull et al., 2014; Bentley et al., 2019). EMA or ESM compliance rates have been found to reduce significantly in two weeks of data collection (Shiffman et al., 2008), suggesting that when using ESM/EMA, the response burden may negatively affect the response rates and measurements over time (Asselbergs et al., 2016). ESM/EMA participants can be confused by and make mistakes in following monitoring schemes or stop participating because of frustration or burden (Bertz et al., 2018). Thus, ESM/EMA as a means of data collection has advantages and disadvantages both of which should be considered when considering EMA/ESM as a research method.

In a less obtrusive method than smartphone apps, objective data sets on internet use can be gathered from interactions on Facebook, data which can be accessed using the Facebook graph API, The Graph API is a primary way to access data in the Facebook platform. It is a HTTP-based Application Programming Interface (API) that applications can use to programmatically query data from Facebook. Using the API large volumes of Facebook data from Facebook users, spanning a lengthy duration can be accessed (Facebook, 2022). Electronic permission must be given by a participant to access their Facebook data. Once permission is given, a data set on Facebook usage for the participant can be downloaded using the API.

The present review aims to identify and assess objective measures that have been used in the research examined, to assess PIU. The usage patterns that objective data can highlight may deliver more comprehensive information on behavioral patterns on the internet. Therefore, the present paper aims to (i) identify objective measures used in research to assess PIU, and (ii) summarise the characteristics, strengths and limitations of objective measures for assessing PIU.

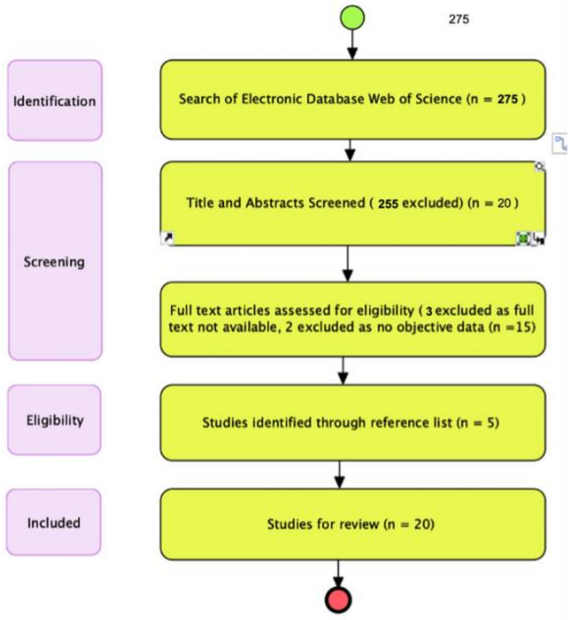
2.2 Methods

The reporting of this systematic review was guided by the standards of the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) Statement (Moher et al., 2009). To identify papers for review, an extensive search was performed using Web of Science databases. These databases were searched using the following search terms: ("objective measur*" or "actual measur*" or "objective data" or "actual data" or "passive measur* or “usage behavio*”) AND (smartphone or mobile or internet or "social media” or “online” or “iphone” or socialmedia) AND (addict* OR compuls* OR excess* OR problem* OR disord* OR “academic performance”). To focus on current approaches of collecting objective data research was limited to research published in the last five years. References of identified articles were examined for additional studies. Studies were included if they were i) published in English, (ii) published in a peer-reviewed journal, (iii) full text was available (iiii) Published between December 2016 and April 2021. Papers were excluded if (i) no objective measures of internet use (ii) did not make reference to problematic internet usage The title and abstract of each study were screened for potential for inclusion. Full texts of potentially relevant studies were then retrieved and examined for eligibility. The search strategy is detailed in Figure 2 below.

The search results identified 275 English articles published between 1/01/2016 and 16/10/2021. By examining the abstract and titles of the articles identified, 20 that were relevant to assessment of PIU using objective measures were identified. Full text of the articles were then assessed. The full text of three articles were not available (Paik & Kim, 2019; Nagamori et al.,2019; Masood et al., 2020). Two articles were excluded as they did not review objective data (Kirchner & Shiffman, 2016; Kaye et al., 2020). Cross-checking the reference lists of (review) articles with our selection increased the total number of articles in our review by five, giving a total of 20 studies which were reviewed. See Figure 3 for a schematic overview of the search process.

Figure 3.

Search Strategy



2.3 Results

An analysis of the different methodologies used to gather objective measurements of internet use and the methodologies used to investigate internet behavior was done. In the empirical research examined, there were three methodologies used to collect objective data. The methodologies identified were accessing historical records on Facebook-usage using the Facebook data API, passive monitoring of smartphone behavior using smartphone apps, and passive unobtrusive monitoring of network usage with digital traces.

2.3.1 Facebook API

Facebook offers an API for data access, where data from a verified user's Facebook account can be made available for download. Objective data were gathered using the Facebook API with electronic permission from research participants. The permissions granted were used to request programmatically, data from Facebook, on users' likes and/or status updates, over a period of time. Of the two studies which accessed Facebook data, one study gathered data on 1094 participants over 12 months (Marengo et al., 2020) and the other gathered data on 5,208 participants over 3 years (Shakya & Christakis, 2016). The objective data gathered related to a large number of participants, spanned a long period of time, was accurate, specific and easily interpreted. However the data was limited to Facebook likes and status updates, there was a programming effort required to interface with the Facebook API, only a limited set of users' Facebook data was accessed (likes and status updates) and there was a reluctance from participants to give permission to access their Facebook data. A summary of the empirical research papers reviewed which used Facebook data and the research findings are presented in Table 6.

2.3.2 Smartphone Application

A smartphone application which was developed to collect data on smartphone activity was deployed on participants smartphones in 10 studies (Dissing et al., 2019; Kanjo et al., 2017; Kita & Luria, 2018; Kim et al., 2019; Sela et al., 2020; Lee et al., 2020; Marengo et al., 2021; Robayo-Pinzon et al., 2021; Wang et al., 2014; Zhou et al., 2016). The number of participants and duration of the studies varied greatly from 50 participants for five weeks (Kanjo et al., 2017), 85 participants for 14 days (Sela et al., 2020), 221 participants for four months (Kita & Luria, 2018), 124 participants for one week (Marengo et al., 2021), 187 for seven days (Lee et al., 2020), 535 participants for three months (Dissing et al., 2019), 84 participants for 14 weeks (Kim et al., 2019) and 48 participants for 10 weeks (Wang et al., 2014). Development of a smartphone app if not already available and deployment of the smartphone app on a participants smartphone, enabled collection of objective data on the phone usage. In some instances researchers developed or redeveloped the app and in others the researchers re-used an app previously developed. Development of an app gives great control over the data that is collected however requires considerable effort. As the app must be deployed on a research participant's phone, there is a need to support the participant to ensure there was no difficulties with the app. All of the apps used for gathering objective data in the research, except for one (Zhou et al., 2016) could only be deployed on an android phone so potential participants who used an iOs phone or Apple phone could not participate. In one study research participants who used an iPhone were given an Android phone to use for the research (Dissing et al., 2020). If a participant was given a second phone in the research, it raises questions on what they did with their usual phone, one could surmise it was also used but the data on the usage was not collected. Of the 10 studies which used smartphone apps for monitoring, six of the studies developed or reconfigured the apps that were to be used for monitoring (Dissing et al., 2020; Kanjo et al., 2017; Kim et al., 2019; Lee et al., 2020; Wang et al., 2014; Zhou et al., 2016), three studies used previously developed monitoring applications (Kita & Luria, 2018; Marengo et al., 2021; Robayo-Pinzon et al., 2021) and one study (Sela et al., 2020) did not give any information on the app that was used. A smartphone app installed for research, uses phone battery, storage and processing power and this use may become an issue for the participant. Smartphone apps can be developed to do EMA while gathering objective data on smartphone usage. This capability is an advantage however the collection of data using EMA may become a burden on the participant and encourage the participant to remove the app or disengage with the research. The participant was aware of the app collecting data on their phone, in some cases explicit permission was required to collect notifications (Kanjo et al., 2017), in others, the app initiated EMA. Awareness of the presence of the app may have influenced behavior. A summary of the empirical research papers reviewed which used Smartphone apps to gather objective data and the research findings are presented in Table 7.

2.3.3 Digital Traces

Digital traces of transactions on a computer network were gathered as objective data in five studies. In the studies which used digital traces, traces of WiFi activity of users on a network, were collected. The studies collected and analysed, records of all user activity on the WiFi network (Zhou et al., 2016; Xu et al., 2019; Kotz & Essien, 2005; Camacho et al., 2020; Kesheng et al., 2020). In the studies which used WiFi digital traces, there were 700 participants with data collection spanning 14 weeks (Zhou et al., 2016), 4000 users for 80 days (Xu et al., 2019), 2000 users for 11 weeks (Kotz & Essien, 2005), 40,000 users over seven years (Camacho et al., 2020), and 3245 participants over four years (Kesheng et al., 2020). The number of participants and the duration of the research varied however the length of the studies and the number of participants was greater than all of the studies that used smartphone apps to collect objective data. In the studies, digital traces were used to understand student physical movements on the college campus (Camacho et al., 2020; Kotz & Essien, 2005) or frequency of connection to the internet (Xu et al., 2019) or times online and volume of traffic (Kesheng et al., 2020) as well as WiFi activity in a classroom environment (Zhou et al., 2016). Using digital traces on a WiFi network enables collection of objective data on all user internet activity on the WiFi. However, collection and processing of digital traces require management of the huge volumes of data that were generated, as well as cleaning and processing of the data. Two studies which collected digital traces, also used objective data from student records and these studies were able to consider an individual student's WiFi usage in conjunction with the information on that student's record (Kesheng et al., 2020; Xu et al., 2019). A summary of the empirical research papers reviewed that used digital traces and the research findings are presented in Table 8.

Table 6.

Overview of Quantitative Research Papers Reviewed which Used Facebook API to Collect Objective Data

Authors	Participants	Psychometric Tests	Aims	Objective measure and Methodology	Findings
Marengo, 2020	1094 Facebook users recruited online, 72% females, aged 18–35. Duration : 1 year	Italian Bergen Social Media Addiction Scale (Monacis et al., 2016) Revised version of Ten Item Personality Inventory (Chiorri et al., 2015)	Testing the mediating role of online activity using objective data on the the interplay between neuroticism, extraversion, and social media addiction in young adult Facebook users:	The Facebook API was used to request data on participants posts for the 12 months prior, self-assessed data on personality characteristics was also collected from the same participants Data was analysed using Multiple linear Regression	Neuroticism is related to social media addiction. . Neuroticism and Extraversion linked with higher use of Facebook. Link between extraverts positive likes, and resultant increase in usage.
Shakya & Christakis, 2016	5,208 subjects nationally representative Gallup Panel Social Network Study. Duration : 3 years Subset of participants in each year gave permission for access to facebook data.	Non-standard measures of health and wellbeing; real world social network measures; facebook measures and control variables.	Determine if Facebook Use is associated with Compromised Well-Being: A Longitudinal Study	The Facebook API was used to request data on participants likes and status updates for previous 3 years , this data was combined with data from the same participants data from the Gallup Panel Social Network survey, Data analysed using linear Regression and multiple linear regression	Facebook use negatively linked with wellbeing and future diminished wellbeing, a standard-deviation increase in “likes clicked”, “links clicked”, or “status updates” was related to a decrease of 5%–8% of a standard deviation in self-reported mental health. The negative links between Facebook use and mental health were comparable to or greater than the positive impact of offline interactions.

Table 7.

Overview of Quantitative Research Papers Reviewed which Used a Smartphone App to Collect Objective Data

Authors	Participants	Psychometric Test	Aims	App Used / Objective measure of behavior	Findings
Dissing et al., 2019	Copenhagen Network Study, 535 first-year students (mean age 21.3, 77% male) Duration 3 months	The data was derived from the Copenhagen Network Study (Stopczynski et al., 2014)	To examine high perceived stress and social interaction among students, based on objective measures of face-to-face and smartphone interactions	Participants received android phone with customised tracking app installed after completing self-reported on perceived stress, they were subsequently followed for three months with continuous Bluetooth recordings of face-to-face interactions and smartphone interactions (calls and texts) measuring the network size, frequency, and duration of interactions. Logistic regression used for data analysis	High perceived stress individuals were more likely to have a bigger call and text network and have more calls and texts compared to individuals with low perceived stress. Stressed students have more smartphone interaction perhaps in seeking social support or it may be that more smartphone interaction is stressful.
Kanjo et al., 2017	34 users randomly selected from email to Nottingham Trent and University of Kent email lists	Positive and Negative Affect Schedule (PANAS) (Watson et al., 1988)	To Determine if interaction with Smart Phone Notifications are Affective Sensors to indicate mood/emotion	Smartphone app NotiMind installed on participants phones. Explicit permission for, notification access required for Notimind Instruction manual to support participants, email address for help Smartphone app monitored notifications over a five-week period and requested EMA response to PANAS 3 times a day Supervised Machine learning on notification features which were strongly correlated to PANAS scores (label)	Large numbers of smartphone notifications were linked to an increase in negative affect. There is potential to predict experience of positive, neutral or negative affective states based on interactions with notifications.
Kim et al., 2019	84 students Duration 14 weeks	we collected self-reports about the perceived difficulty levels every week and organizational efficiency of lectures in each month. SAS (Smartphone Addiction Scale) score (Kwon et al., 2013).	Understanding smartphone usage in college classrooms:	Researcher developed Smartphone app for smartphone usage and sensor data collection installed on participants smartpnone, and a web-based portal for survey data collection. Android only. EMA three times per week on class evaluation – once per month course evaluation, As well as psychometric tests at end of period Web portal for ema survey data collection.	Students used their phones for over 25% of the class duration. Phone usage was evident throughout the class, and phone distractions happened every 3 or 4 minutes and lasted for over a minute. Students under estimated their in class usage of smartphones. Predictors of in-class usage were daily usage, class size, and lecture organization. Phone usage patterns were negatively linked with student grades.

Kita & Luria, 2018	221 young drivers (64.7% male) aged 17–22 years	International Personality Item Pool scale ("International Personality Item Pool," 2006) Smartphone Addiction Scale questionnaire (Kwonet al., 2013)	Identify the role of smartphone addiction on the relationship between personality and young drivers' smartphone use while driving	App installed on smartphone which measures the number of times drivers touch their smartphones. The app was developed previously (Albert & Lotan, 2018) and configured for use in this research. Participants paid to participate (55USD) Data analysed using multiple linear regression	Participants interacted with their smartphones on average 1.71 times per minute while driving. Smartphone use while driving was negatively linked to openness to experience and also with extraversion and neuroticism, there was a mediating effect of smartphone addiction on the link between neuroticism and smartphone use while driving.
Lee et al., 2020	A total of 187 participants were recruited in Hong Kong, (mean age 19.4, 71.7% female) between 2017 and 2018. Duration – 7 days Participants paid for participation	Non standard questionnaire on smartphone usage habits	Validation of Self-Reported Smartphone Usage Against Objectively-Measured Smartphone Usage	A smartphone usage tracking app was installed on all participants' smartphone. Android only app developed by researchers which tracked opening and closing of apps on the phone. Spearman correlations and mean differences used for data analyses	Differences between self-report and actual usage of apps except for on gaming apps
Marengo et al., 2021	124 adult smartphone users (females , 62.9%; age: mean 23.84 years, SD 829 years) recruited at German university campus. Paid for participation. Duration – 1 week	Smartphone addiction scale German version (Kwon et al., 2013)	Exploring the Associations Between Self-reported Tendencies Toward Smartphone Use Disorder and Objective Recordings of Smartphone, Instant Messaging, and Social Networking	Installed smartphone app (Insights, 2022) app on participants smartphone. Guided installation in lab. Android only app. Smartphone and social network usage monitoring app over 1 week. Participants also filled in a self-report measure for assessing the multiple components of tendencies toward Smartphone Usage Disorder (SmUD) Response to Smartphone addiction scale – one month from start of study Data analysed using Pearson correlations and Multiple linear regression.	Frequency of smartphone use and use of messaging apps had links with at least 1 element of smartphone usage disorder. The cyberspace-oriented factor exhibited the strongest relationships. Actual smartphone usage was indirectly linked to problematic use by the frequency of the use of image-based social networking apps.
Robayo-Pinzon et al., 2021	20 students from, a private university in Colombia (thirteen women, average age = 212 years, range = 19–26). Duration – 4 weeks	Spanish version of the Smartphone Addiction Inventory (SPAI) (Simó-Sanz et al., 2018)	Does excessive use of smartphones and apps make us more impulsive? An approach from behavioral economics	StayFree® app (available for Android operating systems on the Google Play Store platform) was installed to gather an objective measurement of the usage time of smartphones. A computer-based intertemporal choice task in lab environment. Data analysis using logistic regression	Time spent on smartphones and apps did not predict a consumer's impulsive choice, a correlation exists between usage time of smartphones and WhatsApp and Facebook apps and users' dependence level on the device. Dependence on a smartphone had a positive link with the selection of an impulsive choice.

Sela et al., 2020	85 participants (aged 12–16, 59% male), 85 parent participants one for each adolescent (aged 33-52, 43% male) Duration – 14 days	Family Environment Scale (FES) (Moos & Moos, 1994) Beck Depression Inventory (BDI) (Beck, 1967) FOMO scale (Przybylski et al., 2013) Generalized Problematic Internet Use Scale 2 (GPIUS 2) (Caplan, 2010).	Family environment and problematic internet use among adolescents: The mediating roles of depression and Fear of Missing Out	Smartphone App installed on participants' smartphones. Informationg gathered on average time on online activity per day; average time on online activity during the day (8AM - 22PM); average time on online activity at night (22PM - 8AM); average time per day on: online games, social network sites, YouTube, shopping sites, gambling sites, pornography sites, and other content. No information on smartphone app except it created a log data of time online. Data analysed with Pearson correlations, hierarchical linear regression, structural equation modeling	Results suggest that low family expressiveness and PIU and time spent online are mediated by depression and FOMO. .
Wang et al., 2014	48 students Duration - 10 week	Patient Health Questionnaire (PHQ-9) (Kroenke et al., 2001) Perceived Stress Scale level (PSS)(Cohen et al., 1983) Flourishing Scale UCLA Loneliness Scale	Assess Mental Health, Academic Performance and Behavioral Trends of College Students Using Smartphones	StudentLife Smartphone App installed on participants' smartphones. Students are trained on how to use the app and respond to EMA. Students do not need to interact with the background sensing or upload functions. They are shown how to respond to the Mobile EMA system. 3-13 EMA questions per day dependent on schedule for student.	Links identified between mental health and educational outcomes and the sensor data gathered from the smartphone .
Zhou et al., 2016	700 students 9 weeks	NONE	EDUM: classroom education measurements via large-scale WiFi networks	TUNet researcher developed Android and iOS mobile app and TUNow Android only, WiFi traces oand details of 700 mobile participants smartphone activity was tracked on university WLAN to understand if students attended lectures, were on time and used their phone during a lecture.	Attendance and punctuality suggest Wednesday is the most hard-working day. Class attendance and lateness are highest early in the day, and drop as the day progresses. As students number of years in college increases attendance reduces and punctuality decreases. More night activity for 2nd and 4th year students than 1st and 3rd year. On average students with higher GPA attend classess more and are not punctual compared to lower GPA students. Students are more distracted as the day progresses. Device usage is highest at the beginning of a lecture, reduces, then increases again.

Table 8.

Overview of Quantitative Research Papers Reviewed which Used Digital Traces to Collect Objective Data

Authors	Participant Information	Psychometric Tests	Aims	App Used / Objective measure of behavior	Findings
Camacho, et al., 2020	Digital trace of 40,000 authenticated users, and 600,000 distinct WiFi stations - 7TB of raw data Duration 7 years	NONE	Longitudinal analysis of a campus WiFi network	WiFi trace of network processed into connection sessions	The number of user sessions has increased 10-fold but more consistent in last 5 years. The number of active sessions shows a daily, weekly and yearly patterns. Average of 25 daily sessions per user and 12 daily sessions per device, although distribution of sessions is uneven. Mobile sessions have doubled possibly as a result of the emergence of smartphones, and laptops in 2004 had no network activity when closed.
Kesheng et al., 2020	3245 student 23.843 million Internet access data in four years.	NONE	Data Mining and Feature Analysis of College Students' Campus Network Behavior	Online date, offline date, online time, offline time, inbound traffic, outbound traffic, total traffic of campus network usage data Analysis using Clustering and PCA	Four groups of students with different characteristics of Internet access, 350 students of the total with large network usage. Academic and other aspects of performance of these students are affected. In class usage of smartphone negatively correlated with grades
Kotz & Essien, 2005	1706 campus users Duration 11 weeks	NONE	Analysis of a Campus-Wide Wireless Network	A trace of WiFi network activity in a university	Traffic predominantly from residents, connections from laptops, a lot of web traffic, network backup and file sharing.
Xu et al., 2019	4000 college students. One semester	NONE	Prediction of academic performance associated with internet usage behaviors using machine learning algorithms	A set of features, including online duration, Internet traffic volume, and connection frequency, from the real Internet usage data of Machine learning algorithms used to predict academic performance from these features. Data from student records which could be linked to WiFi activity.	Internet connection frequency variables positively linked with academic performance, Internet traffic volume variables negatively related to academic performance. As the number of features increase, prediction accuracy is generally improved in the methods. The results show that Internet usage data are capable of differentiating and predicting student's academic performance.

Zhou et al., 2016	700 students 9 weeks	NONE	EDUM: classroom education measurements via large-scale WiFi networks	TUNet researcher developed Android and iOS mobile app and TUNow Android only, WiFi traces and details of participants smartphone activity was tracked on university WLAN to understand if students attended lectures, were on time and used their phone during a lecture.	Attendance and punctuality suggest Wednesday is the most hard-working day. Class attendance and lateness are highest early in the day, and drop as the day progresses. As students number of years in college increases attendance reduces and punctuality decreases. More night activity for 2^{nd} and 4^{th} year students than 1st and 3rd year. On average students with higher GPA attend classess more and are not punctual compared to lower GPA students. Students are more distracted as the day progresses. Device usage is highest at the beginning of a lecture, reduces, then increases again.

Four systematic reviews of research that used objective measures to identify PIU were also examined in this review. Ryding & Kuss (2020) concluded from their examination of research on objective measures used to assess problematic smartphone use, that psychometric tests cannot capture comprehensively unconscious smartphone behaviors or some dynamic and naturally occurring behaviors associated with smartphone use. Research has also found that objective data can enable identification of usage patterns which are ecologically valid in a short time frame (Ryding & Kuss, 2020). Parry et al. (2020) in their systematic review of research that measured digital media use from logged data and self-reported methods found that self-reports of time on the internet rarely accurately reflected logged digital media use. Logged digital media use were records of activities categorised as either ‘phone’, ‘gaming’, ‘social media’, ‘computer’, or ‘Internet’ use. The choice of categorisation in Parry et al. ’s (2020) research was based on the source of the logged data. In instances in which overlap needed to be considered (e. g., social media on a phone), the most specific medium known was used as the categorisation (Parry et al., 2020). Kaye et al. (2020) reviewed research that measured screen-time and found that there are conceptual difficulties with assessing screen time. Dienlin and Johannes (2020) in their review of research on the impact of digital technology on adolescents’ wellbeing found that in research with large-scale samples, objective measures of digital technology use, and experience sampling of wellbeing are lacking. Dienlin and Johannes (2020) suggest research was needed to address the limitations of research based exclusively on self-report data. While Facebook API or a smartphone app or digital traces generate data that are objective measures however these data do not reflect the users’ assessment of their behavior, hence are not sufficient alone to assess PIU.

There were 10 empirical research papers examined see Table 6 and Table 7 which used psychometric tests and surveys. Psychometric tests were used to assess level of problematic social media use and social networking (Marengo et al., 2020; Shakya & Christakis, 2016), FOMO and generalised problematic internet use (Sela et al., 2020), smartphone problematic use (Kita & Luria, 2018; Kim et al., 2019; Marengo et al., 2021; Lee et al., 2020). Psychometric tests were also used in the research to understand, extraversion, neuroticism and/or personality (Kita & Luria, 2018; Marengo et al., 2020), family environment, depression, (Sela et al., 2020), perceived stress (Dissing et al., 2019) and impulsive choice (Robayo-Pinzon et al., 2021) and feelings and emotions (Kanjo et al., 2017).

Subjective data were collected in eight of the studies using surveys (Dissing et al., 2019; Kita & Luria, 2018; Lee et al., 2020; Marengo et al., 2020, 2021; Robayo-Pinzon et al., 2021; Sela et al., 2020; Shakya & Christakis, 2016) and three studies used EMA (Kanjo et al., 2017; Kim et al., 2019; Wang et al., 2014). Of the three studies which used EMA, the type and frequency of EMA requests varied. One used EMA to collect psychometric data on feelings and emotions, three times per day (Kanjo et al., 2017). EMA was used in another study, where the number of questions varied from three to 13 questions per day. The variance depended on the student schedule for example if the student has assignment deadlines, multiple stress EMA were scheduled. In another study a photographic affect meter was used to capture student’s mood, pop up questions were asked to measure depression, perceived stress, flourishing (i. e., self-perceived success) and loneliness (Wang et al., 2014). Using EMA in other research, participants were asked four questions, 3 times each week, on how they assessed their experience in a class (Kim et al., 2019). Each week the students were asked to rank each course’s difficulty, interest, and workload on a 5-point Likert scale and if there was a quiz or exam on a binary scale. Each student ranked the course each month based on the university's three-item course evaluation questionnaire using a 5-point Likert scale, this evaluation related to organization of a class, instructor's delivery effectiveness, and the class's helpfulness for learning (Kim et al., 2019). A third study which used EMA requested the participant to respond to a psychometric test on feelings and emotions, three times each day (Kanjo et al., 2017).

2.4 Discussion

The present review aimed to identify and assess objective measures that have been used in the research examined to assess PIU. Three different methods for collecting objective data were identified and evaluated. The methods were using Facebook API, using a smartphone app and using digital network traces. The characteristics of each method were examined, and the advantages and disadvantages of each method were assessed. Although each of the methods had different characteristics, strengths and limitations, using Facebook API, using a smartphone app and using digital network traces to gather data on internet use were all reliable processes for establishing an accurate measure of interactions on the internet. Each method had a process that was transparent and impersonal (Munroe & Hardie, 2019), thus, each gathered objective data. Using digital traces, using Facebook API, using a smartphone app and using digital network traces to gather data on internet use enabled an objective picture of actual behavior on the internet or on a smartphone to be developed.

Network digital traces of internet behavior offer potential to identify larger behavioral patterns in internet use by enabling collection of huge volumes of data with exact details of actual usage (Fischer et al., 2020). However, research which used digital traces that were examined in this study focused on measurements of users behavior, such as traffic volume and connection frequency (Kesheng et al., 2020, Xu et al., 2019), movement on campus (Camacho et al., 2020), number of internet accesses, file sharing and the type of device (Kotz & Essien, 2005). Collection of digital traces could enable identification of a full suite of behaviors that a user engages in on the internet and could assess unconscious behaviors, or naturally occurring changes in behaviors (Bentley et al., 2019; Ellis, Kaye, et al., 2018) and thus could address some of the concerns that have been highlighted on limitations on the range of behaviors examined when measuring PIU using self-assessment only. However, this was not done comprehensively in the research which used digital traces that were examined in this study. The studies which used smartphone apps and the Facebook API also focused on measuring a limited set of user behavior, Facebook likes, Facebook status updates, how often a phone was used or time spent on calls, messaging or texts or the number of notifications received on the phone see Table 6 and Table 7. So while gathering objective data may offer potential to develop a very detailed picture of internet behavior using objective data, the potential was not exploited fully in any of the research examined.

If PIU is to be understood as internet use that is excessive or poorly controlled and leads to impairment or distress (Weinstein & Lejoyeux, 2010), self-assessment is necessary to understand adverse consequences of problematic internet behavior. There was no assessment of the impact of internet behavior in the studies that used digital traces (see Table 8). Without assessment of the impact of internet use these studies could not assess PIU. However, two of the studies found correlations between internet behavior and academic performance, as indicated by student results (Kesheng et al., 2020; Xu et al., 2019). All of the Facebook studies (see Table 6) and eight of the 10 Smartphone studies (see Table 7) measured the impact of internet use using psychometric tests and thus were able to make inferences on PIU, rather than just report patterns of internet behavior. Three of the Smartphone studies (Kanjo et al., 2017; Kim et al., 2019; Wang et al., 2014) used EMA. The use of EMA ensured that the self-assessment by the participants was performed in a natural environment with limited retrospective and heuristic biases, which may distort recollections of experiences (Trull et al., 2014; Bentley et al., 2019). However, the self-report EMA or ESM still predominantly relied on explicit respondent input and the three studies reported that the compliance rates eroded as the study progressed. Kanjo et al. (2017) found some participants stopped responding to the questionnaires after a few days and some did not respond at all. Similar participant attrition has been reported in previous research (Bertz et al., 2018; Shiffman et al., 2008). The research examined, which quantified users' experience with technology, as well as quantifying a subset of actual internet behaviors, addressed concerns on inaccuracy of exclusively using self-report to measure technology use behaviors which are intertwined with daily life (Ellis, 2019). Findings from research which includes objective measures on internet use may be more robust to criticism.

When considering the different methods to collect objective data on PIU each method should be considered on its merits in order to identify the most appropriate method for a study. Digital traces enabled collection of the most comprehensive set of user data, with the highest number of participants for the longest time period, addressing concern on limited size of data sets to measure behavior (Ellis, 2019). However, digital traces were not able to explain a user's assessment of their internet behavior and/or the consequences of the behavior and managing and interpreting the large volume of data generated by digital traces was complex. A smartphone application used to monitor internet use on a phone, offers great control of the data generated and potential for direct interaction with the participant, however a smartphone application may require development effort, participation could be restricted by the operating system of the phone, participant support may be required for the app, awareness by the participant of the installed app could impact behavior and a potential negative impact of the app on the phone's resources could encourage participants to disengage. Using the Facebook API offers access to huge volumes of data however Facebook is a single social media application so the data gathered is on Facebook use and does not give an overview of general use. Interfacing with the Facebook API requires programming effort and there is a reluctance by participants to give direct access to their Facebook data. Each methodology assessed captured objective data on internet or smartphone behavior however none of the methodologies collected all behavior, the Facebook API is limited to data on Facebook, the smartphone app is limited to specific data on a single device and the digital traces of WiFi behavior do not encompass all of a user's internet behavior, other user behavior accessing the internet, for example using a telecom provider, is not captured.

2.5 Conclusion

Objective data are not susceptible to self-serving bias and systematic patterns of misreporting of internet use as can potentially happen in psychometric assessment (Busch & McCarthy, 2021; Ryding & Kuss, 2020). Thus, more reliable research conclusions could result from assessment of actual behavior and complementing evidence from self-reports. Objective data sets may offer a more comprehensive view of internet or smartphone behavior, potentially gathering a more comprehensive set of data from a greater number of participants for a longer duration. Digital traces as an objective measure of internet use can offer a complete picture of actual internet activity only if evaluated in depth which is complex and requires expertise in big data management and data mining. Smartphone apps offer great control over the data that is collected and potential to capture a comprehensive data set however this method has disadvantages relating to cost of development, support and impact on the user. Facebook offers potential to collect large datasets but from a single social media application and requires explicit permission from users and some development effort. Objective data can be used to identify patterns of internet behavior that relate to PIU identified in psychometric tests. The choice of the method to gather objective data on internet use in a study should be determined by the aims of the study and the advantages and disadvantages of each approach. Internet use or smartphone usage patterns deduced from objective data are unbiased and verifiable and hence are more robust to criticism. Research can use objective data to complement data generated from self-assessment. Having reviewed research which uses objective data to understand internet behavior in this chapter and research on student PIU, FOMO, wellbeing and loneliness in the previous chapter, the next chapter evaluates the research approach to research methodologies and methods used in the empirical studies in this thesis.

Chapter 3. Methods and Methodology

3.1 Introduction

The research methodologies and methods used in this thesis are evaluated in this chapter. Firstly by outlining the philosophical and conceptual framework that informed the research and then identifying how ontological and epistemological issues were addressed in the specific methodological strategies used. The goal of this research was to further understand problematic internet use by developing objective methods to approximate use of the internet and its impact on wellbeing. Positivist and interpretivist ontologies were considered for the research. Positivist research relies on empirical or scientific evidence, while interpretivist relies on subjective knowledge (Armstrong, 2013). This research measures in quantitative terms internet behavior and wellbeing factors thus a positivist ontological approach was taken, quantitative methods were used to measure the reality of actual internet use and participants' psychological factors (Tuli, 2011). A positivist epistemological framework explains how confidence in findings in this research was rationally constrained by the evidence (Steup, 2021). The framework is used to explain how findings can be justified, using the evidence from the research (Pring, 2012). There are different scientific methods within the positivist approach, deductive research draws on existing theory to create hypotheses which can be tested, inductive reasoning moves from particular observations to create more generalizable theory to explain what is and abductive reasoning suggests what may be (Behfar & Okhuysen, 2018; Pierce, 1903/1997, Shani et al., 2020). Hypothesis to be tested in this research were developed based on existing theory in a deductive technique. Thus, this research can be described as quantitative deductive, testing a hypothesis developed from existing theory and using measured data, to conclusively either prove or otherwise the hypotheses (Greenhalgh & Taylor, 1997).

1.1.1 Epistemological approach

The epistemology approach explains the assumptions made in the research about what constitutes valid knowledge and how it is obtained (Richards, 2003), thus defining what constitutes evidence in the research and the constraints of the research.

Some research suggests a nuanced epistemological approach is required to manage big data innovations and exploit their potential in a social science research project (Kitchin, 2014). An empiricist view of big data suggests knowledge is based on experience thus analytical tools that identify patterns in the data will enable the data to speak free of theory and enable insightful knowledge on complex phenomena (Kitchin, 2014). Empiricists expect the analysis of big data, will enable prediction of future behavior based on the pattern of previous behavior. There are weaknesses in the empiricist approach as big data cannot capture a complete picture of a domain. Analysis of data is always influenced by the analyser and there is difficulty interpreting meaning from analysis without domain specific knowledge. It is one thing to identify patterns in the data, however, it requires contextual knowledge and theory to explain them. Data provides a limited understanding of human life and needs to be interpreted (Kitchin, 2014). A hypothesis was identified, information was gathered and quantified, then analysis was performed with statistical methods to test the hypothesis in the three quantitative studies. This chapter provides a detailed account of the specific research methods employed, questionnaire content, passive monitoring and data analysis techniques. To ensure data were valid and interpreted correctly an interdisciplinary team worked on the study, with input from computer scientists with expertise in big data and analytics and input from psychologists with expertise in interpretation of human behavior. More data do not necessarily generate more knowledge (Babbage et al., 1864) thus, interdisciplinary collaboration in the interpretation was more likely to yield productive results.

The focus of this chapter is to explain the methodologies used to gather data which would quantify the reality of actual internet use and the methodologies used to assess the research participants' report of their internet use, wellbeing, loneliness and FOMO. There were two methods of gathering data in the research design, unobtrusive passive measurement of behavior on the university Wi-Fi and survey of the university student body. Data on users' actual behavior on the university Wi-Fi in were gathered using unobtrusive passive monitoring. Data on student's self-assessment of their internet behavior and its impact were obtained via a questionnaire survey method. Results were considered within the I-PACE framework (Brand et al., 2019).

This research aims to further understand behavioral patterns on the internet, problematic internet use and the effect of PIU on student wellbeing, loneliness and FOMO. The research questions and research objectives from each of the three quantitative studies are detailed in the studies in chapters five, six and seven however they are summarised below.

3.1.1 Study 1

- To what extent do the patterns of actual behavior identified on a university Wi-Fi over an academic year suggest it is used for education?
- To what extent do users of a university Wi-Fi spend their time on distraction or educational activities?

3.1.2 Study 2

- *Hypothesis 1:* The relationships between the PIU subtypes, wellbeing, loneliness and FOMO differ for males and females.
- *Hypothesis 2:* Men in comparison to women have a higher level of generalised PIU.
- *Hypothesis 3:* Women in comparison to men have a higher level of problematic smartphone usage and problematic social media usage.
- *Hypothesis 4:* Decreased student wellbeing is explained by the interaction between loneliness and general PIU.
- *Hypothesis 5*: Student loneliness is explained by the interaction between general PIU, problematic smartphone use, and problematic social media use.
- *Hypothesis 6:* Student FOMO is explained by the interaction between general PIU and problematic smartphone use.

3.1.3 Study 3

- Are there groups of users whose behavior pattern of internet usage on a university WiFi distinguishes them from each other?
- To what extent does the pattern of user WiFi behavior enable prediction of education-related WiFi-activity at university?

3.2 Methodologies

The methodology is the plan or strategy lying behind the choice of methods to achieve the desired outcomes (Crotty, 1998) and answer the research questions. The methodologies chosen in this research reflect the perspective of the researchers (Hathcoat et al., 2018). The ontological approach in the studies developed from the lead researcher's 10 years of experience as a computer science lecturer and 10 years of experience as a telecommunications engineer and the supervision team's psychologists' experience in psychological research and computer scientist's research in computer science research as well as the supervision team's previous experience in interdisciplinary research. The research team recognised that there was potential to greater understand student internet behavior and the impact of the behavior on their wellbeing from digital traces of internet activity on a university network and responses to psychometric tests from the same student body. The ontological approach is realist, as both the digital traces and the research participants' assessment of the consequences of their internet use and wellbeing, loneliness and FOMO are seen to exist without the researchers' interpretation (Hood, 2013). An interdisciplinary team worked on the research studies, a team which included computer scientists with expertise in big data and analytics and psychologists with expertise in research and theory on problematic internet use and interpreting human behavior.

3.2.1 Study 1

In the first study the research team used digital traces from a university WiFi, gathered over an academic year, to identify patterns in the usage of the WiFi. Monitoring digital traces of internet behavior on a network has potential to provide objective knowledge of internet behavior. The digital traces enabled identification of the larger behavioral patterns in internet use by observing the details of actual usage (Fischer et al, 2020). The discovery of meaningful patterns in big data can enable understanding of behavior. Unobtrusive passive objective monitoring, used in this study, is the collection of data, without active data entry by the participant, allowing for continuous data collection over longer periods of time (Asselbergs et al., 2016; Bentley et al., 2019). Digital traces as objective data can be gathered consistently and frequently with great accuracy at a fraction of the effort and cost of other data collection methods such as surveys. Moreover, the exactness of and realism of data generated by digital traces ensures that generalisability across the population is maximised (Chang et al., 2014). Extracting meaningful information from the large data set required interdisciplinary skills, technical skills to manage the data as well as expertise in cyberpsychology to interpret the meaning of internet behavior (Espinosa et al., 2019; Yaquob et al., 2016). Objective passive monitoring can enable assessment of variables more precisely and in a less intrusive manner then self-report measures (Bentley et al., 2019; Cornet & Holden, 2018). Although there was little psychological research which used network digital traces to investigate internet behavior, techniques used with digital traces in network management were used in this research and hypothesis on behavior were guided by existing research findings on student internet use. Data from digital traces cannot enable assessment of how the internet users felt about their internet behavior or how they assessed its impact. This weakness in the first study was addressed in the second study, where users of the same network, where the digital traces were gathered, assessed their internet use and wellbeing in an electronic survey conducted in the academic year the digital data was gathered.

Study 1 used big data gathered from digital traces on a university to test hypothesis on internet behavior in a deductive method. The data gathered could be described as big data as it had the required characteristics of high volume, velocity, and variety. The study, by combining behavioral data with data from surveys or psychological scales, enabled the researchers to link action sequences to traits. Analysis was done to understand internet behavior and further investigation determined if the observed behavior aligned with the self-report data. Both behavioral data and self-report data were used to test the hypothesis (Fischer et al, 2020).

Previous research analysing actual user behavior on the internet have been constrained by the number of participants (<200) or depended on an application on the phone (Jayarajah et al., 2015; Wang et al., 2014). Or used psychometric assessment, which measures experiences with internet use as opposed to assessing actual behavior (Ellis et al., 2019). Spatial-temporal research into internet use is needed to understand how the the potential benefits and harms of internet use are balanced in education (Melo et al., 2020). This study used digital traces to enable analysis of the full suite of user activities of all users of a university WiFi network over time.

3.2.2 Study 2

In the second study, data was gathered from an electronic survey which included psychometric tests to evaluate self-assessment of internet use and wellbeing. The survey data was used to understand how students assessed their internet behavior and its impact on their wellbeing. While self-reports do not suffice for a determination of diagnosis, the results from psychometric tests can be a useful indicator of the construct being measured (Nunnally, 2021). The Digital traces gathered in the first and third study identified patterns of internet behavior, however self-assessment data was needed to understand the impact of that behavior. The second study provided this information with data gathered from the users of the network, on how they assessed their internet use and wellbeing.

The second study using psychometric tests and other self-assessment data used a deductive method in the research. From the results of the students' self-assessment of the sub-types of PIU (problematic internet use, problematic smartphone use, problematic social media use, problematic gaming, and problematic pornography consumption) and wellbeing, loneliness and FOMO, a partial correlation network was created to understand the relationships between the subtypes of PIU in developing and maintaining PIU and its relationship to wellbeing, FOMO and loneliness. The results were examined, in a deductive process, to see if the findings supported the theory in the hypothesis.

In the second study, the power of data analytics in a partial correlation network, was used to gain understanding of the relationships between the subtypes of PIU, general problematic internet use, problematic smartphone use, problematic social media use, problematic internet gaming, and problematic internet pornography consumption and wellbeing, FOMO and loneliness. A partial correlation network highlighted the unique bivariate relationships between the PIU subtypes and the correlates, after partialling out all other effects in the network. To further understand the shared contribution of the PIU subtypes and correlates on a dependent variable, the relationships in the partial correlation network were analysed using variation partitioning (VP). In particular the relationships between PIU subtypes and correlates with wellbeing, loneliness and FOMO were considered. The findings were interpreted using the I-PACE model in a deductive process to determine if the model was supported (Brand et al., 2019).

3.2.3 Study 3

In the third empirical study, the research team used the digital traces gathered from a university WiFi over an academic year, in the first study (O'Brien et al., 2022). All of the benefits and challenges of gathering and using objective data to assess internet behavior described for Study 1, are relevant for this study also. Using objective data from digital signatures, enables data to be gathered consistently and accurately on the full suite of user internet behavior at low cost however the big data can be difficult to process, manage and interpret.

Study 3, like study 1 used big data gathered from digital traces on a university to test hypothesis on internet behavior in a deductive method. The data gathered in study 1 which was used in this study had characteristics of high volume, velocity, and variety and as such could be described as big data. Using big data generated from digital traces in this study had advantages, as it was not constrained by a limited number of participants (<200) nor did it depend on a tracking application on the phone (Jayarajah et al., 2015; Wang et al., 2014). The data for this study was objective data and could be used to assess actual behavior, other research using psychometric assessment quantifies experiences with internet technology (Ellis et al., 2019). This spatial-temporal research into internet behavior used supervised and unsupervised machine learning to identify patterns in the internet behavior and to understand the characteristics of internet behavior.

3.3 Research Methods

In this section, brief descriptions of each study will be presented as well as a detailed description of the methods used in each study to gather data, process and analyse data. Where the study was published in a peer-reviewed journal, the details of the method will be included in the chapter for the empirical study as published and a summary of the method is included here.

3.3.1 Study 1

This study is an analysis of internet activities on Munster Technology University Wi-Fi in 2018/2019 with data from more than two and a half million user sessions over an academic year. A User Session describes each user's activity when logged on to the WiFi. It is a one-dimensional vector with nine numeric values representing the number of flows in each classification (O'Brien et al., 2022). The classifications are advertising, streaming, education, gaming, search, shopping, social media and other. Principal Component Analysis (PCA) was performed to identify the most important dimensions of the users' behavior.

In study 1 details of the actual internet behavior of users on the university WiFi was gathered using the method for gathering digital traces explained in detail in chapter 4 section 2. The data gathered was analysed using principal component analysis (PCA). PCA reduced the dimesions of the data and identified the variables/factors of importance in the data (Jolliffe, 2002). The appropriateness of applying PCA was verified by reviewing the correlations of the features in the dataset using a Bartlett's test of sphericity, this ensured that the correlation matrix was not the identity matrix. The p-value calculated was <0.1, thus PCA was appropriate.

Data were scaled using standardisation, prior to PCA to ensure the high-variance variables would not dominate the first few principal components (Jolliffe, 1990). The standardised data had a mean of 0 and range between 1 and –1 and was calculated using the formula

$$z = (x - \mu) / \sigma$$

Outliers were removed after standardisation. Data in a user session were considered to be an outlier if the number of flows in a classification was more than three standard deviations (σ) from the mean (μ). The number of user sessions removed as outliers for the year was 128,422; PCA does not require the data in the features to have a normal distribution (Jolliffe & Cadima, 2016). Therefore, although the data were skewed after standardising and after outliers were removed, the data were not normalised. PCA analysis was implemented using SciKit-learn (a popular Python data analytics library). PCA Analysis was performed on the data for each of the nine months of the academic year as well as the combined data for the nine months.

The method for this study is detailed in 4.2.

3.3.2 Study 2

University students are a group that may be particularly prone to problematic internet use (PIU). In study 2 an effective sample of 834 university students, with an average age of 22 years and 45% male, responded to a survey which was emailed to approximately 12,000 students enrolled in a university. The email contained information about the study as well as a link to an online questionnaire. The questionnaire which included demographic questions, general questions on internet use and scales measuring general problematic internet use, problematic smartphone use, problematic social media use, problematic gaming, problematic pornography consumption, wellbeing, loneliness and FOMO.

The psychometric tests to measure PIU subtypes used in the survey were the Smartphone Addiction Scale – Short Version (SAS-SV) (Kwon, Kim, et al., 2013), the Problematic internet use questionnaire short form, PIUQ-SF-9 (Koronczai et al., 2011), the Bergen Social Media Addiction Scale (BSMAS), adapted from the Bergen Facebook Addiction Scale, the nine-item Internet Gaming Disorder Scale–Short-Form (IGDS9-SF) (Pontes & Griffiths, 2015), the Problematic Pornography Consumption Scale (PPCS-18), (Bőthe et al., 2018). The psychometric tests used to measure mental health were the Personal Wellbeing Index (PWI) (The International Well Being Group, 2013) , the UCLA Loneliness Scale (Version 3) (Russell et al., 1980) and the FOMO scale developed by Przybylski et al. (2013).

General statistics were calculated to identify the percentage of male and female student responses to the psychometric tests which indicated PIU or low wellbeing or loneliness. The calculations were done using the psychometric test scores and the standard cut-off points in use for each psychometric test. Details of the mean and standard deviations in the scores for males and females were also calculated. The survey data was identified as non-parametric using Shapiro Wilk tests, thus Mann-Whitney tests were used to identify differences in responses in males and females for each psychometric test.

All of the analyses on the data in the study was done using R and the bootnet library (R Core Team, 2020). A partial correlation network was used to gain insight into relationships between the variables measured in the study (Bhushan et al., 2019; Epskamp & Fried, 2018). The created network represented the strength of relationships between the variables, and was useful to explore whether the relationships were in line with theory. The interaction between the many variables in the network were likely not to have been examined in this manner before thus the analysis was expected to clarify the interactions (Bhushan et al., 2019). Nodes in the partial correlation network represented the psychometric tests and the edges represented a statistical relationship that is estimated using partial correlation techniques. To investigate the importance of individual variables, the centrality measures node strength, closeness and betweenness were calculated (Barrat et al., 2004; Boccaletti et al., 2006; Opsahl et al., 2010).

To further understand the shared contribution of the PIU subtypes and correlates on a dependent variable, the relationships in the partial correlation network were analysed using variation partitioning. In particular the relationships between PIU subtypes and correlates with wellbeing, loneliness and FOMO were considered. Variance partitioning was introduced by Borcard (1992) and is often used in ecological analysis and modelling (e. g., Bienhold et al., 2012, Dray et al., 2012). However variance partitioning is not often used in psychology research. The method attempts to "partition" or resolve the explanatory power of the independent variables identified in matrices in relation to the same response or dependent variables defined in another matrix. When predictors are correlated, as in this research, the common effects can indicate the extent and pattern of the predictors' shared variance in predicting variance in the criterion (Nimon & Oswald, 2013). R and the vegan library was used for variation partitioning analysis (Oksanen et al., 2020).

The method for this study is detailed in 5.2.

3.3.3 Study 3

Machine learning was used to analyse data on user internet activities collected on a university Wi-Fi over an academic year, cleaned and prepared in a previous study (O'Brien et al., 2022). The Wi-Fi is used by 12,000 students and 1,000 staff in the university to access the internet from mobile devices, such as phones and laptops, when users are on a university campus. Data for 2,563,206 user sessions were gathered on the university network between September 2018 and May 2019. As stated previously a user session describes each user's activity when logged on to the WiFi. It is a one-dimensional vector with nine numeric values representing the number of flows in each classification (O'Brien et al., 2022). The features of each user session are described in Table 9 (O'Brien et al., 2022).

Table 9.

Descriptions of Features in Each User Session (O'Brien et al., 2022)

Classification	Description
Advertising	Domains associated with marketing or advertising, e. g., Mopub.com
Streaming	Domains for television, movie streaming or music streaming such as spotify.com, youtube.com, or rte.ie
Education	Domains for which the primary purpose is for education or is used in education at university, such as wikemedia.com or dropbox. Inc
Gaming	Websites that are associated with video games or betting, such paddypower.com or king.com
Search	This classification includes websites that are used for internet searches, e. g., Google.com
Shopping	Websites for which the primary purpose is shopping, such as Amazon.com, Ebayinc.com, exotik.com Alibaba-inc.com
Social Media	Websites used for social interaction and communication, Twitter.com, facebook.com, telegram.Org
Other	Websites that do not naturally sit in any of the other categories, e. g., AitaleabiamoGlobal.com, aib.ie

A user session describes each user's activity when logged on to the WiFi. It is a one-dimensional vector with nine numeric values representing the number of flows in each classification (O'Brien et al., 2022). Sample user sessions are described in Table 10.

Table 10.

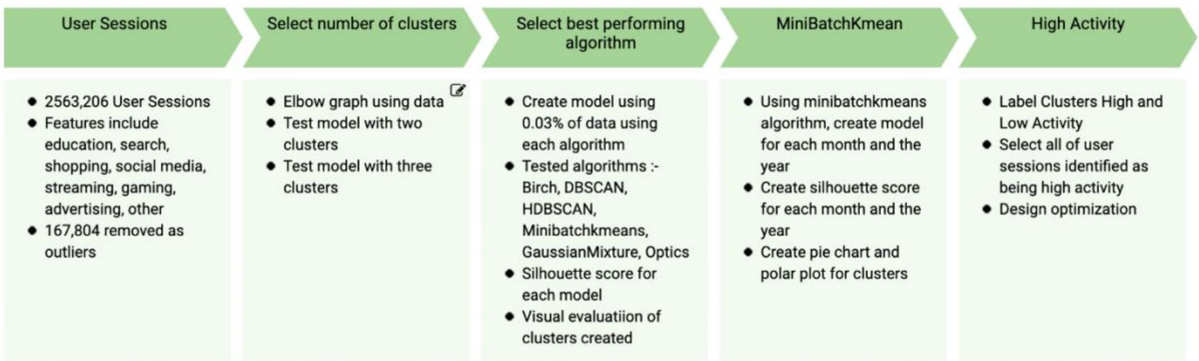
Samples of User Sessions. Each Details the Number of Flows in Each Category of Activity for a User

Id	Search	Social Media	Shopping	Education	Streaming	Advertising	Other	Gaming
1	1565	613	404	426	0	422	43	10
2	742	294	188	185	0	150	21	5
3	1242	392	200	4	12	0	0	14
4	436	118	74	2	6	0	0	6
5	3793	1653	1127	483	71	234	172	47
6	1674	580	469	183	33	94	68	21

Using unsupervised machine learning on the user session data enabled patterns in the data to be identified by clustering or grouping data together based on inherent similarities in the data (Saxana et al., 2017). Figure 4. describes the process to develop an unsupervised machine learning model.

Figure 4.

Unsupervised Learning , Identifying Number of Clusters and Selecting Unsupervised Learning Algorithm



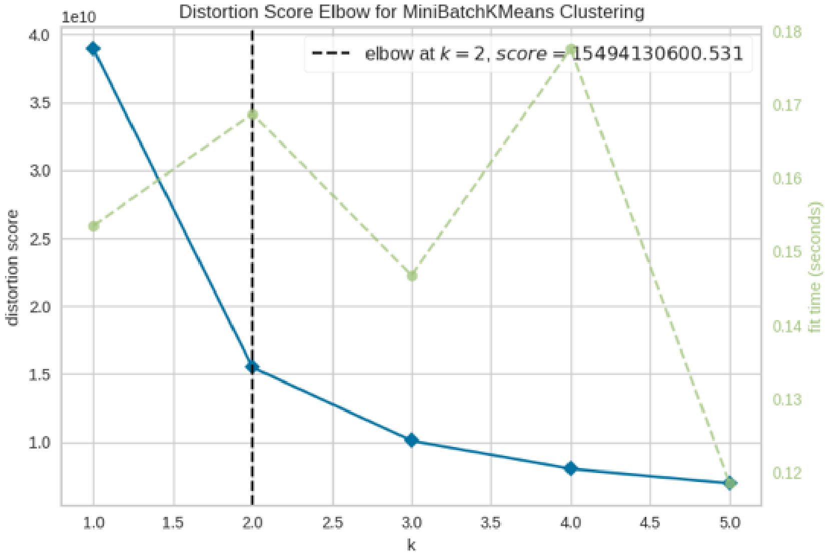
Extreme outliers were first removed (174 user sessions) from the set of user sessions by creating a box plot for each feature and identifying feature values outside the standard range of a bar plot for that feature, after which user sessions that had features that were three standard deviations away from the norm for that feature were removed (167,710 user sessions). In total, 167,884 sessions were removed from the 2,563,206 user sessions.

In order to identify patterns in the user sessions unsupervised machine learning techniques were used. Clustering identifies data patterns so that data can be divided into subsets and data with similar patterns are clustered together. Hence, a cluster can be used to designate a subset of the population sampled (Maimon & Rokach, 2010). There are many clustering techniques. Centroid-based clustering identifies the similarity between data points. Similarity is computed as the distance to centroids of a user-defined number of clusters, where those centroids are iteratively re-located to minimise the distance between the point and other points in the cluster and maximise the distance between points in other clusters. Kmeans is a centroid-based clustering algorithm and MiniBatchKmeans is an adaption of Kmeans to effectively manage big data (Hicks et al., 2021, Sculley, 2010). In distribution clustering, the data are allocated to clusters based on probability distributions. As the distance from a data point to the centre of a cluster or distribution increases, the probability of that point being allocated to that cluster decreases. The Gaussian Mixture Models (GMM) (Pernkopf & Bouchaffra, 2005) are one of the most widely used distribution clustering algorithms. Hierarchical clustering algorithms, such as Birch or HDBSCAN, operate either using a top-down (divisive) or a bottom-up (agglomerative) approach of assigning data to clusters until the stopping criterion is met. In the top-down approach, every data point is in the same cluster and consecutive divisions based on similarity or dissimilarity between different points lead to division of the data into smaller clusters (Rodriguez, 2019). In a bottom-up approach, every data point is assigned a unique cluster, which is merged with other clusters based on data similarity as the algorithm progresses. Density-based clustering algorithms, such as DBSCAN and OPTICS are based on the identification of clusters where data points are concentrated. Data in areas where concentration is sparse are considered noise (Rodriguez, 2019). Given the variety of potential algorithms that can be used to develop an unsupervised model, there is a need to identify and select the most appropriate machine learning algorithm for a particular application by evaluating and testing different algorithms with the data set.

The optimum number of clusters for the unsupervised machine learning algorithms can be effectively identified using the Elbow method (Syakur et al., 2018). Using the Elbow method the sum of squared errors (SSE) was calculated for increasing number of clusters and the SSE vs the number of clusters was plotted see Figure 5. Inflections points in the graph identified two or three clusters as optimum. Both two and three clusters were trialled with the algorithms. Two was found to be optimum by visual examination and assessment of the meaning of the patterns identified in the clusters (Aggarwal & Reddy, 2013).

Figure 5.

Elbow Graph to Identify Optimum Number of Clusters



A selection of centroid-based, distribution-based, hierarchical and density-based algorithms were selected for testing, to identify the algorithm that would be most effective in finding clusters in the data set. Each of the unsupervised learning algorithms, Birch, DBSCAN, Gaussian Mixture, HDBSCAN, MiniBatchKmeans and Optics were tested. Models were developed with 0.02% of the data set (50,506 user sessions), a sample of the dataset was used to manage the processing requirements of the computationally intensive algorithms and so that a result was delivered for each model within a day. The processing was done on a Dell machine running Ubuntu 20.04 LTS, Memory 62.5 GiB, 3 * Intel Core 19-109000X with 3.7TB disk. The silhouette scores were considered and a visual examination of the clusters created in a polar plot and pie chart was done, to identify the most appropriate clustering algorithm for the data set. A silhouette score ranges from a value of -1 to 1. The silhouette score rates the strength of cohesion in a cluster compared to its separation from other clusters. The closer the value is to 1, the stronger the indication that data are well matched to their own cluster and poorly matched to neighbouring clusters. The results from testing the various models developed are displayed in Table 11. The strongest silhouette score was returned by the Birch and HDBSCAN algorithms; however, only 0.03% or less of the data was allocated to the second or third clusters, which identified more than 97% of the user sessions with the same pattern of usage. MiniBatchKmeans had a strong silhouette score of 0.73 and identified a distinct usage pattern for 11.3% of the user sessions. MiniBatchKmeans is designed to manage big data effectively, thus was selected to train the model.

Table 11.

Unsupervised Learning Algorithms Test Results

Algorithm	Cluster High Activity (% of total)	Silhouette Score
Birch	9.59%	0.698
DBSCAN	16.60%	-0.096
Gaussian Mixture	41.00%	0.313
HDBSCAN	<0.03%	-0217
MiniBatchKmeans	1620%	0.688
Optics	<0.06%	-0.378

MiniBatchKmeans is a variant of the Kmeans algorithm and uses mini-batches to reduce the computation time for large data sets such as the one used in this research, while still optimising the same objective function. Kmeans clusters data by trying to separate samples into *n* groups of equal variance, minimizing variation or spread within a cluster (inertia). Mini-batches are smaller sets of the input data, randomly selected in each training iteration. These mini-batches reduce enormously the amount of computation required to reach a local solution (Sculley, 2010). The algorithm iterates between two steps. Samples are selected randomly from the dataset to form a mini-batch, the mini-batch are assigned to the nearest centroid, then the centroids are updated. For each sample in the mini-batch, the assigned centroid is updated by taking the current average for the sample and all previous samples assigned to that centroid. Thus, decreasing the rate of change for a centroid over time. The two steps are performed until convergence, or a pre-set number of iterations is reached (Sculley, 2010).

A MiniBatchKmeans model was developed with the total data set, data on 2,563,206 individual user sessions on the university WiFi. Two distinct clusters were identified, and the model created had a silhouette score of 5.9. The model created predicted a cluster for each of the user sessions. The results from the classification were graphed using a polar plot and a pie chart, see Figures 6 and 7. A polar plot is a radial chart, which uses the polar coordinate system, where its x-axis looks like a circle with the origin point as a centre, and each point is determined by distance from a fixed point and angle from a fixed direction. The average value for each of the features in its clusters is represented on the polar line chart, see Figure 6 and further detailed in Table 12. The total percentage of users in each of the classifications over the year is represented in the pie chart, see Figure 7. The MiniBatchKmeans model identified two classes of users, one with low general usage and the other with high general usage, see Figure 6. The clusters were labelled high intensity and low intensity to reflect the characteristics of the clusters. The cluster labelled high intensity had a high volume of activity in particular in search, social media and shopping, while the cluster labelled low intensity had a low volume of interactions in these categories, see Figure 6. Approximately 18% of the user sessions were designated as high intensity, see Figure 7. There were 2,079,038 low intensity user sessions ~(82%). and 446,250 high intensity user sessions (~18%). The average education activity was calculated as the mean amount of activity in the education category over all user sessions. Of those low intensity user sessions, 179,829 (~9%) were involved in average education activity, while 1,899,209 (~91%) were not. Of those high intensity user sessions, 167,020 (~37%) were involved in average education activity, while 279,230 (63%) were not.

Figure 6

Polar Chart of Characteristics of Flow Intensity of Activities in Clusters Identified

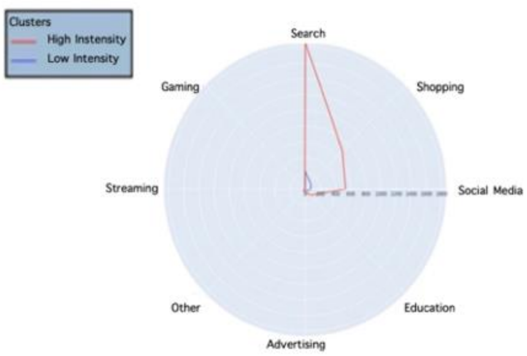


Figure 7

Pie Chart of Percentage of User Sessions in High Intensity (red) and Low Intensity (blue) Clusters

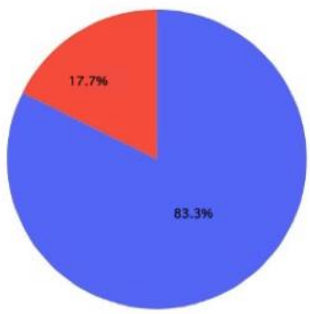


Table 12.

Average Intensity in Features of User Sessions in the Low Intensity and High Intensity Clusters

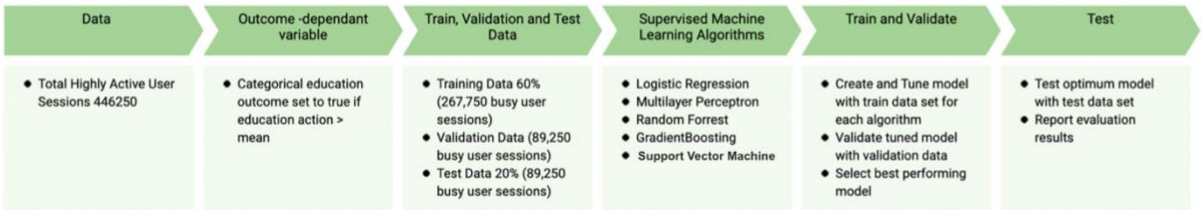
Cluster	Feature	Average Intensity	Cluster	Feature	Average Intensity
High Intensity	Search	1863	Low Intensity	Search	319
	Social Media	692		Social Media	150
	Shopping	534		Shopping	75
	Education	107		Education	31
	Advertising	38		Advertising	5
	Streaming	12		Streaming	2
	Gaming	7		Gaming	1
	Other	33		Other	7

In supervised learning, the machine is given a sequence of desired outputs, the goal is to train a model to identify the correct output given a previously unseen input. Logistic regression is one of the fundamental classification algorithms where a log odds in favour of one of the classes is defined and maximized via a weight vector. Random forest (RF) algorithms (Breiman, 2001) create an ensemble of multiple classifiers built over different subsets of columns of the input data. Gradient Boosting (Friedman, 2001) is a boosting algorithm, where over iterations error is predicted and subtracted from the output of the classifier. Selection of a model for machine learning requires identification of the most appropriate model and fine tuning of parameters for a particular problem (Yeteru, 2020).

A supervised learning model was developed to identify if usage of WiFi for education activities could be predicted for the users with high intensity usage of the WiFi. The process followed is outlined in Figure 8. A categorical variable was created that identified a user with educational activity above the mean volume of activity for all user sessions. The machine learning algorithms used most often in research for predicting academic success have been ANN, Naïve Bayes, Logistic Regression, SVM and Decision Tree algorithms thus an algorithm from each of these categories was tested (Sandra et al., 2021). A gradient boosting algorithm can improve accuracy of a decision tree or linear regression algorithm hence it was also considered (Fernández-Delgado et al., 2014). A supervised machine learning model using, logistic regression, random forest classifier (decision tree algorithm), multilayer perceptron classifier (ANN), gradient booster classifier and Support Vector Machine (SVM) were tuned and tested to determine if a model trained using the algorithm and high activity data could predict education activity. The features used to train the model were data from the user sessions on activity on social media, search, shopping, streaming, gaming, advertising and other. The categorical variable on Education activity was the output of the model or the value the model was trained to predict. The high activity user session data set, on 446,250 user sessions, was split into a training, validation and test data set based on a 6:2:2 ratio, thus adhering to a standard machine learning practise to avoid introducing bias by overfitting the model (Feurer et al., 2019). A set of models for each of the data set were trained with the training data, 10-fold cross validation and tuned with a set of parameters to find the optimum performing model for each algorithm. As SVM is a resource intensive algorithm a radial basis function variant was used to manage to improve performance with the big data set. (Razaque et al, 2021)

Figure 8.

Development of Supervised Machine Learning Model to Predict Education Activity



The optimum model for each algorithm was validated with the validation data and performance metrics were gathered

3.4 Ethical Issues

Ethical approval was obtained from Nottingham Trent University (NTU). An application for ethical approval of the research studies proposed was submitted to the NTU College of Business, Law and Social Sciences Research Ethics Committee (CREC). The application detailed every aspect of the research design and implementation, with particular focus on research-related ethical issues. The application detailed the aims and objectives of the research and the methods and procedures that would be followed in the research. Detailed information was submitted on the materials that would be used, how any issues relating to participants would be addressed, how anonymity and confidentiality of participation would be managed, how security in the retention of research data would be implemented, how informed consent from potential participants would be gathered, any risk of harm to participants was considered, the capacity of participants to give valid consent was addressed, process for recruitment of participants was detailed as well as any form of monetary compensation for participants that was offered, and generally how all ethical risks were managed was described in the application. Examples of information provided to the participants were submitted with the application, including requests for consent/participation and details on how to opt-out. Ethical approval was granted for this research by the CREC: (No. 2018/167) on October 10th 2018.

Any ethical issues related to the collection of data on user behaviour on the network was addressed using permission to analyse meta data given by students when accessing the network. All data collected from the network was anonymous ‘data about data’ and could not be connected to any individual user. The ethical issue of ensuring adult participants in the psychometric survey was managed by requiring participants to be over 18 years.

The three empirical studies completed for this research are presented in the next three chapters. The first of these chapters details the published study which gathered digital traces from a university WiFi over an academic year and identified characteristics in the patterns of activity on the internet.

Chapter 4. WiFi at University: A Better Balance Between Education Activity and Distraction Activity Needed.

4.1 Introduction

Internet use has become central to education and academic work and more so during the Covid-19 pandemic, as universities and colleges have moved to more online delivery of education (Qazi et al., 2020). Students often apply knowledge or new skills developed on the Internet to boost self-directed learning and academic performance (Rashid & Asghar, 2016; Zhu et al., 2011). However, time online is not restricted to academic activities (Demirtepe-Saygılı & Metin-Orta, 2020), and excessive use of the internet can become problematic and impact students negatively, reducing academic performance (Felisoni & Godoi, 2018; Xu et al., 2019) and reducing wellbeing (Bakioğlu, 2020; Ye & Lin, 2015). Universities provide WiFi access to the internet to enhance users learning experience, however it is necessary to understand how WiFi is actually used, to understand whether its provision is enriching or impoverishing the educational experience (Henderson et al., 2015).

Research on internet use has often used cross-sectional psychometric assessment, which quantifies experiences with internet technology as opposed to assessing actual behavior (Ellis et al., 2019). Self-assessment of internet use can be limited in effectiveness by recruitment and sample size, the number of questions that can be asked, the choice of psychometric test and the identification of the activities a user engages in. Such studies are also vulnerable to self-serving bias and systematic patterns of misreporting, such as overreports of internet use (Busch & McCarthy, 2021; Ryding & Kuss, 2020). Thus, more reliable research conclusions might draw on assessment of actual behavior and complementing evidence from self-report studies.

Existing research on actual user behavior on the internet in an educational environment has assessed users activity to understand the frequency of use and time spent on a phone in a classroom environment (Kim et al., 2019), other studies have tracked lecture attendance and punctuality (Zhou et al., 2016). Data on actual behavior which identified the applications and

intensity with which applications are being used have had limited number of participants (<200) and depended on a tracking application on the phone (Jayarajah et al., 2015; Wang et al., 2014).

Unobtrusive passive measurement of behavior on the internet is frequently used for monitoring user behavior for security and network management purposes (Maier et al., 2009; Trevisan et al., 2020).

Internet usage behavior can be deduced from digital traces of activities on the internet. Using digital traces, it is possible to gather data consistently and frequently with greater fidelity at a fraction of the effort and cost. Moreover, the data precision and realism of digital traces ensures that the generalisability of findings across the population is maximised (Chang et al., 2014). Extracting meaningful information from the large data set required technical skills and subject matter expertise, technical skills to manage and exploit the big data as well as interdisciplinary knowledge to interpret the meaning in a specific functional domain (Espinosa et al., 2019). Spatial-temporal research into digital technology is needed to understand how we balance the potential benefits and harms of digital technologies in education (Melo et al., 2020).

Unobtrusive passive measurement using digital traces of all internet activity of all users in a university in this study provided detailed information on the range of activities users are engaged with and information on the intensity of the engagement with those activities, over an academic year. This data can be used to identify if the patterns of behavior suggest Healthy Internet Use or Problematic Internet Use (PIU).

While Healthy Internet Use has been defined as using the internet to achieve a specific aim, within an appropriate time frame, with no conceptual or behavioral difficulties (Davis, 2001), there is no standardized definition for PIU. Nevertheless, it is commonly conceptualized as compulsive internet behavior, and associated cognitions, that results in marked distress in daily life (Spada, 2014; Young, 1996). PIU has been linked to heavy and consistent use of the internet by a user for distraction activities or for activities without a purpose (Davis, 2001; Moreno et al., 2013). PIU can also develop with overuse for work, study or other purposes. There is debate over what defines PIU; however, there is agreement that it is internet behavior that a person identifies as negatively affecting their life (Caplan, 2010; Chen et al., 2003). Research has found that internet use that has become problematic may not only adversely affect student academic performance, but also their overall wellbeing (Elhai et al., 2019; Hebebci & Shelley, 2018;). Impacts of PIU on health and wellbeing have been recognized by The European Parliamentary Research Service (Brey & Gauttier, 2019). Thus, it is important to understand how the internet is being used by students in particular on the university provided WiFi and whether the use of this technology is likely to be beneficial to the educational experience.

The I-PACE model explains the development and maintenance of PIU as a result of predisposing factors and choices to alleviate offline world stresses or psychosocial problems which together with reduced inhibitory control and instrumental conditioning lead to the development and maintenance of PIU (Brand et al., 2019). Wellbeing factors may be identified as predisposing psychological factors which motivate individuals to use the internet to alleviate or escape from offline stressors (Chang & Lin, 2019; Reer et al., 2019). Moderators of PIU in the I-PACE model are cognitive biases or coping strategies, thoughts about the internet and experiences on the internet which influence the decision to use it. Wellbeing may be considered a moderator or mediator in the I-PACE model, a cognitive or affective reaction to a situational trigger. For instance, images of others enjoying themselves on social media may generate an affective reaction of loneliness or unhappiness and create or strengthen the decision to use social media to alleviate anxiety (Elhai et al., 2018; Hebebci & Shelley, 2018). Using the internet can become a coping mechanism to distract from distress, which gratifies or compensates and reinforces thoughts about the internet as an effective coping strategy.

Gratification on the internet according to the I-PACE model reinforces cognitive biases about internet use as a coping strategy and may motivate to spend more time online (Brand et al., 2016; Young & Brand, 2017). For example, using the internet as a coping strategy to manage loneliness by making new social connections online may be effective, however negative effects of using the internet excessively to manage loneliness can increase loneliness and lonelier people appear to have more negative effects, possibly as a result of neglect of offline relationships (Ceyhan, 2011; Wohn & Larose, 2014). Individuals who are not psychosocially healthy have difficulty not only maintaining healthy social interaction in their real lives, but also regulating their internet use (Kim et al., 2009). Reduced wellbeing may be a cause or effect or both of PIU, however the consistent correlations found in research between wellbeing and PIU suggest addressing PIU is worth considering as a means to improve wellbeing.

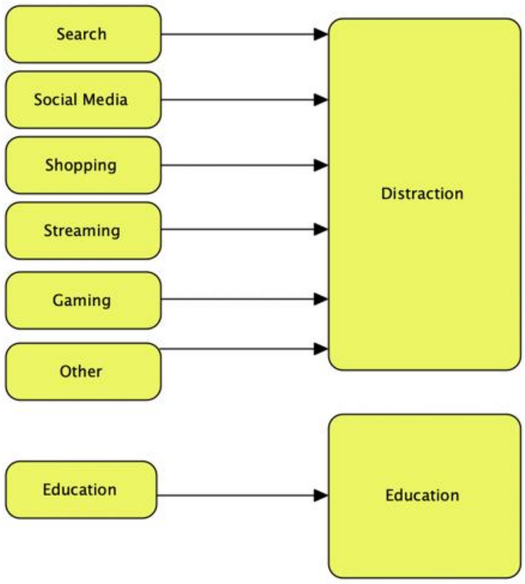
In the current research an interdisciplinary team of academics from computer science and psychology used the digital traces collected from the university WiFi for an academic year, to identify the patterns of behavior in university WiFi usage. The research model is represented in Figure 9. Data gathered using Netflow digital traces in this research detailed the WiFi transaction rather than the content of the transaction and identified ‘a user’ rather than ‘the user’, thus anonymity of the user identity is preserved and data privacy concerns are addressed.

The data were analysed to answer the following questions:

- To what extent do the patterns of actual behavior identified on a university WiFi over an academic year suggest it is used for education?
- To what extent do users of a university WiFi spend their time on distraction or educational activities?

Figure 9.

Research Model Representing Components of Internet Behavior and the Relationship with Education and Distraction



4.2 Materials and Methods

This study collected data on user behavior from a university WiFi for an academic year. The WiFi is used to access the internet from mobile devices such as phones and laptops when users are on a university campus. Approximately 12,000 students and 1,000 staff use the university WiFi, for details of demographics see Appendix B. Users automatically or manually connect to the network using their devices when on site in any of the four university campuses.

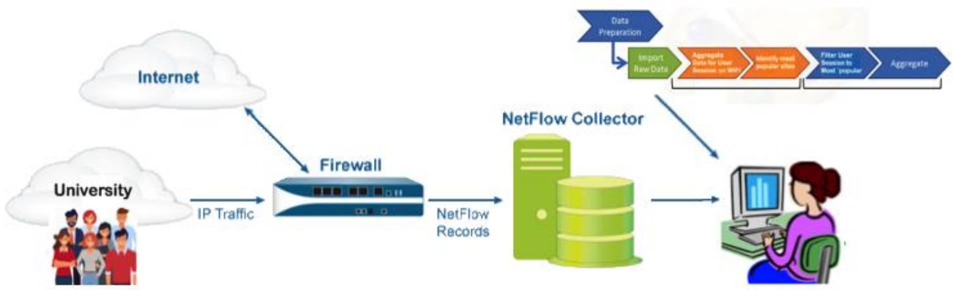
Data were also collected from an electronic survey. Emails were sent to the university email accounts of approximately 12,000 students in the university. The email contained information about the study as well as the link to an online questionnaire. The online questionnaire consisting of questions on demographics, general internet behavior and validated psychometric scales had a total of 119 questions. There were 834 valid responses. The mean age of participants was 22.46 years (*SD* = 6.48 years), with a range from 17 to 62 years. A total of 45% of the sample was male. The psychometric tests used included the Smartphone Addiction Scale – Short Version (SAS-SV) (Kwon, Kim, et al., 2013), the Problematic Internet Use Questionnaire (PIUQ-SF) (Demetrovics et al., 2016), the Bergen Social Media Addiction Scale (BSMAS) (Andreassen et al., 2017), Internet Gaming Disorder Scale–Short-Form (IGDS9-SF) (Pontes & Griffiths, 2015), the Problematic Pornography Consumption Scale (PPCS-18)

(Bőthe et al., 2018), the Personal Wellbeing Index (PWI) (The International Well Being Group, 2013), the UCLA Loneliness Scale (Version 3) (Russell et al., 1980) and the FOMO scale (Przybylski et al., 2013).

The WiFi network is built on CISCO hardware and software which allows statistics on network traffic to be gathered using NetFlow, see Figure 10. The Netflow traces of internet traffic can be used to identify levels of activity and patterns of behavior on the internet (Medeiros et al., 2020). The data collected over time represent a comprehensive log that allows an accurate, longitudinal assessment of internet usage in a university environment.

Figure 10.

Conceptual Diagram Representing University WiFi and NetFlow data Collection.



4.2.1 Netflow Data Collection

NetFlow data were gathered from the university Network between September 2018 and May 2019. The NetFlow data were generated by student, staff, and guest activity on the fixed and WiFi network. The fixed network activity is from devices physically connected to the network and includes personal computers (PCs) in labs and offices where it is likely students are supervised and supervision could impact behavior. Research has found that students who pass their exams use more fixed PC connections to the internet (Xu et al., 2019). To study unsupervised behavior this research focuses on collecting usage activities data from university WiFi network as it is more likely to reflect student behavior when unsupervised.

NetFlow is embedded within Cisco Software to characterize network operation, allowing administrators to understand who, what, when, where, and how network traffic is flowing (Introduction to Cisco IOS NetFlow - A Technical Overview - Cisco, n. d.). A NetFlow enabled device creates a packet of information on all network traffic it encounters. A flow is a communication between two devices each identified by a unique IP address. A single flow shares the same information for the fields in Table 13, for which packets and bytes are tallied. A NetFlow record is output if the flow has been active for 5 minutes or when the flow is finished. In this research, a flow or statistic is explained as a set of interactions between a user and destination on the internet.

Table 13.

Format and Meaning of Data in a Netflow Record ("Introduction to Cisco IOS NetFlow - A Technical Overview - Cisco," n. d.).

Field Type	Description
Src IP Address	The source IP address for the communication
Dst IP Address	The destination IP address
Flows	Number of flows that were aggregated.
Src Port	Source Port Number
Dst Port	Destination Port Number

The volume of NetFlow data generated by user activity varies depending on date and time. Date and time determine the number of staff and students on-site in the university and the activities ongoing at the university, see Appendix C. Approximately half a billion data points or 8GB of data is generated on a weekday when students are in the university.

The volume of NetFlow data generated by the system has made it challenging to store and process the data (Medeiros et al., 2020). There were times over the academic year when data were not collected because of technical issues encountered on the network or lack of storage capacity. These time slots were from September 8, 2018, to September 13, 2018, and from January 18, 2019, to January 21, 2019.

4.2.2 Data Processing

The percentage of male and female student responses to the psychometric tests which indicated problematic internet use or low wellbeing or loneliness was calculated using the psychometric test scores and the standard cut-off points in use for each psychometric test, see Appendix D. Also, it was calculated that 70% of the students that responded to the survey indicated that they felt their internet use was probably not or definitely not good for their health.

Netflow data processing is discussed and implemented in previous research (Gill et al., 2011; Medeiros et al., 2020). In this research activity to a total of 186 websites were analysed, (see Appendix E). The 186 websites identified in Appendix E, include the 120 most accessed sites for each of the nine months of the academic year. This focused approach reduced the number of features in the data set by approximately 98%, while losing less than 3% of the information on user behavior. Investigation of the WiFi internet traffic identified a total of approximately 9000 different websites that were accessed by users each month.

To identify the patterns of behavior in internet activity it was necessary to characterise the types of activities the users were engaging in. The IP address in the NetFlow records were translated to domain names and each domain name was classified. In this way, an individual website domain name can be grouped together with other websites which share the same classification to get an overview of internet use. Explanation of group classifications and examples of assignments of individual domain names to the different classifications are provided in Appendix F. The domain name and sub domains for an IP address were identified using IP-info's IP reverse look up service (Comprehensive IP Address Data, IP Geolocation API and Database - IPinfo. Io, n. d.). If there were subdomains for a domain name and the subdomains were identifiable, it was understood that the primary domain was an internet service provider, and the subdomains identified the destination domains. For example, Amazon.com provides both shopping and website hosting services. In this research when Amazon.com is returned without a list of subdomains it is assumed it is a shopping website and when a list of subdomains are provided it is assumed it is acting as a hosting service.

Classifications were based on the Internet advertising Board (IAB) digital content classification standard (Content Taxonomy - IAB Tech Lab, n. d.). In order to choose the appropriate classification for a website domain, see Appendix F, the website was manually visited, the classification from the IAB Taxonomy was checked on the website 'Zvelo.com'. The website could also be further examined using the website 'brandfetch.com' and a Google search. Classifications were assigned based on what appeared to be the primary functionality of the service. For example, a YouTube access was classified as streaming. Sites that did not belong to one of the nine service classifications identified were included in the "other" class (Gill et al., 2011).

The classification 'cloud and technology' identifies network activities that were considered as enabling technology used to deliver a website. And as such does not add information on user behavior. The goal of the user is to access the website, technology used to deliver the website is collateral activity and is not considered as an indicator of user behavior. This classification decision was based on analysis of the websites and discussion with the university technical team. However, it could be that some of these websites are used by the students and reflect user behavior. It was expected to see strong correlations between this classification with all other classifications, however there was a weak correlation with “streaming and gaming”. This may be explained as the websites in these classifications could use different enabling technology for which the comparative level of activity is low.

Approximately 4% of total activity was to the Apple website. This activity was not included in the analysis as the level of activity did not appear to be related to actual user behavior. It was explained by automated backup of Apple phone data to the cloud when a phone connected to the WiFi network and as such would not contribute to the understanding of behavior.

To process the data, programs in C and Python were developed. The binary files which were generated on the network by Netflow were converted to User Sessions (US). A US is a one-dimensional vector with nine numeric values representing the number of flows in each classification. Each US describes a user’s activity on the internet for the duration they were logged on to the university WiFi see Appendix G for example user sessions. An overview of the process for cleaning and preparing the data is given in Appendix H.

The Data set was vast, containing details of 2,563,206 user sessions. Each user session measured nine categories of activity see (Appendix G). Principal Component Analysis (PCA) was used to reduce the dimensionality of the data and identify the key factors in the data (Jolliffe, 2002). The appropriateness of applying PCA was verified by reviewing the correlation of the features in the data set (see Appendix I) to ensure there were adequate correlations between the variables a Bartlett's test of sphericity was conducted. The p-value calculated was <0.1 which confirmed that PCA was appropriate.

Data were standardised prior to PCA to ensure the high-variance variables would not dominate the first few principal components (Jolliffe, 1990). Standardised data have a mean of 0 and range between 1 and –1. Outliers were removed after standardisation. An outlier was identified as a feature with a value that was greater than 3 standard deviations from the mean. Data in a US were considered to be an outlier if the number of flows in a category was more than three standard deviations from the mean.

$$z = (x - \mu) / \sigma >= 3$$

The number of user sessions removed as outliers for the year was 128,422; see Appendix J for details.

PCA did not require the data in the features to have a normal distribution (Jolliffe & Cadima, 2016) so, although the data were skewed after standardising and after outliers removed, the data were not normalised. PCA analysis was implemented using scikit-learn (a popular Python data analytics library). As indicated in the Elbow graph in Appendix K, two was chosen as the number of components for the PCA (Cangelosi & Goriely, 2007).

PCA Analysis was performed on the data for the full year and individually for each month.

4.3 Results

The PCA loadings show some variation as a function of the month. The features and loadings for each component were analysed (Appendix L, Figure L1 and Figure L2). Factor loadings for a principal component with the same sign contributed in the same direction, while those with opposite signs contributed in the opposite direction. The principal component analysis was performed on the correlation matrix. The loadings of the principal components describe how each of the classifications of the user session contributes to the component.

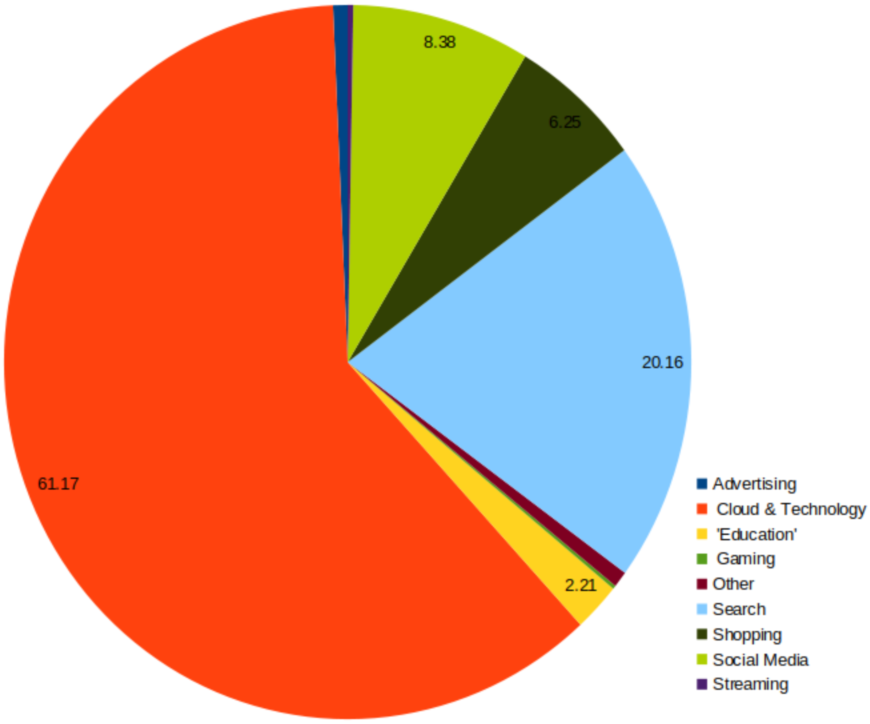
Principal component 1 (PC1) had strong positive loadings for search, social media, shopping and 'cloud and technology'. The loading for cloud and technology reflects network activity that is considered as enabling technology used to deliver a website. This activity does not add information on user behavior. Hence, as education is the business at hand in a university, PC1 is named distraction which describes search, social media and shopping activities, activities that are not directly related to education see (Appendix L, Figure L1 and Figure L2), distraction explains between 62% and 70% of the variance in the data depending on the month see Appendix M.

Principal component 2 (PC2) is dominated by a strong negative loading for social media. It has positive loadings of varying strengths for education, search, streaming and shopping. Of particular note for this research which is analysing user behavior on a university WiFi is the inverse correlation between internet activity in education and social media. As social media activity increases education activity decreases see (Appendix L, Figure L1 and Figure L2). This principal component describes user activity that is low in social media use see Appendix L, Figure L1 and Figure L2. The second principal component 'Not social media' explains between 8% and 15% of the variance in the data depending on the month see Appendix M.

The activity on the network for the year was examined. The percentage of activity in each classification over the year is represented in Figure 11.

Figure 11.

University WiFi Activity Classified for the Academic Year 2018/19



Note. Slices with percentage less than 1% are not labelled

The maximum variation in the level of activity on the university WiFi, in a classification in a month was 5%. In January education activity increased by 5% and search activity decreased. The second Semester did not begin until the 28th of January so the total activity for the month of January was reduced and all activity was likely to be dominated by staff behavior. The classifications where the greatest volume of activity took place over the year were ‘cloud and technology’ (61/62%), ‘search’ (17/19/20%), ‘social media’ (8/9%), ‘shopping’ (6/7%) and ‘education’ (2/3/6%) of total activity. The number of user sessions in each month, in each category, in each semester is described in Appendix N, Figures N1, N2, N3 and N4. The number of users’ active was greatest in October, November, February, March and April, the months when most students are expected onsite in the academic year. The number of students active on the WiFi was reduced in September, December, January and May, the months starting and ending the semesters.

The average activity for a user in a session in each category in each semester is presented in Appendix N. The mean number of flows was calculated by dividing the total number of flows for the users which were active in each category.

$$\mu = \sum_{i=1}^{n} \frac{x_i}{n}, x_i \neq 0$$

The average intensity of user activity across all months was greatest in 'cloud and technology', followed by search, social media, and shopping, with a drop in intensity in all other classifications. While activity in 'cloud and technology' was most intense, the category represents backend activity to deliver the website so the category explains little about user behavior.

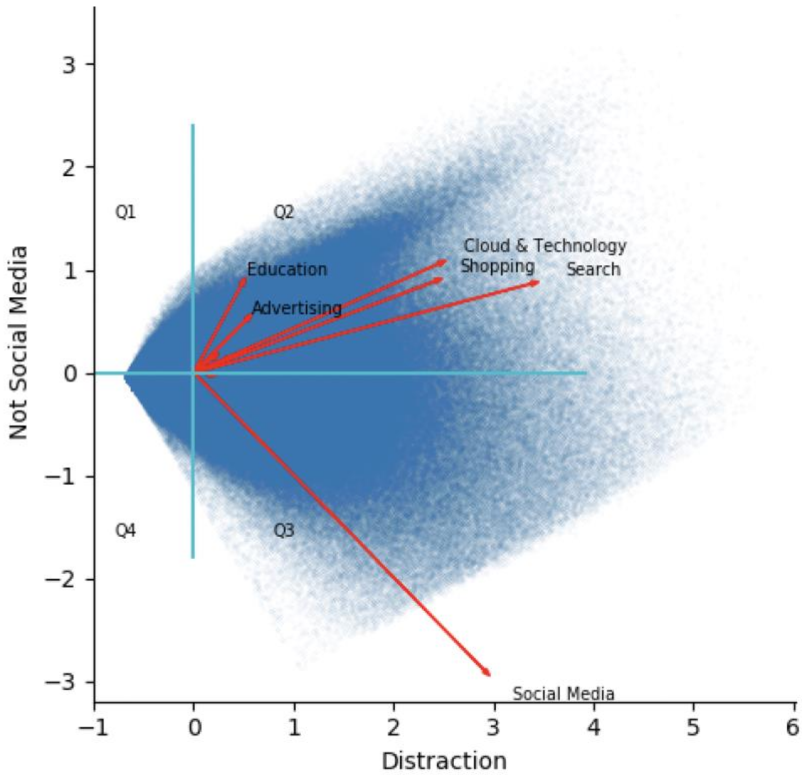
The details of the three websites, most accessed in each classification for the academic year, are listed in Appendix O. The percentage of total activity is calculated by dividing the flows to an individual website by the total of the flows to the top websites accessed, see Appendix E. Activity to the cloud and technology category was dominated by the university's internet service provider Heanet.ie. In the search category, Google was used most often. In social media activity, Facebook dominated, followed by Twitter, which had less than 3% of the activity of Facebook. Third on the list of most active social media websites was Onionflix, which is a Facebook news and media website. The most accessed website in the category shopping was Amazon.com. The website most accessed in the category education was the university website. The university website is hosted on Amazon.com. The most used websites in the category gaming were King.com and paddypowerbetfair.com, one a gaming website and the other gambling. In the category streaming, Netflix was the most used website, followed by Spotify which had only 35% of the activity of Netflix.

Search activity accounted for approximately 19% of the total activity analysed. Google accounted for almost 95% of this activity over the academic year see Appendix O. Social media activity accounted for approximately 7.5% of the total internet activity on university WiFi and Facebook accounted for over 93% of this total see Appendix O, Facebook social media usage may include Instagram and WhatsApp as the level of usage of these websites were surprisingly low and this may be explained if Facebook as the company owning these websites identifies the majority of its servers as Facebook, even if the servers are delivering services for WhatsApp or Instagram or other Facebook owned apps. Shopping activity accounted for approximately 6% of the total internet activity on university WiFi and Amazon accounted for over 97% of all shopping see Appendix O.

A biplot of the principal components was used to guide the interpretation of PCA (Kohler & Luniak, 2005). Biplots lines represent the features of the dataset, and points represent the observations. In Figure 12 below, each point represents a user session on the WiFi with the point (Distraction, Not social media) and the lines represent the features that were input to the principal component analysis. The length of the lines approximates the variances of the variables, the longer the line, the higher the variance (Kohler & Luniak, 2005).

Figure 12.

Biplot of User Sessions for the Year, 'Distraction' vs. 'Not Social Media' Components



Note. Lines representing features with low variance were not labelled

Combined, the first two principal components represent approximately 79% of the total variation in the dataset, hence the two-dimensional bi-plot given in Figure 12, is a good approximation of the original scatterplot in nine-dimensional space. In Figure 12, social media and search are represented by the longest lines and therefore are the features with the highest variance. In Figure 12, 'distraction' (PC1) is represented by the x-axis and 'Not social media' is represented by the y-axis. Those points centered around (0,0) represent the users whose activity in distraction is close to the mean. In the diagram, quadrants were created around the mean. The activity on the left upper quadrant represents users who are involved in less distraction, less social media and more educational activity (Q1). The activity on the right upper quadrant represents users who are involved in more distraction activity; however fewer social media and more educational activities (Q2). The activity on the left lower quadrant represents users who are involved less in general distraction, more social media and less educational activity Q4). The activity on the right lower quadrant represents users who are involved in more general distraction activity and more social media activity (Q3). The major source of variation in the dataset is between users when the (weighted) average activity in distraction is high and users where this average activity is low (Jolliffe, 1990).

4.4 Discussion

The current research aimed to determine if the use of the university WiFi is enhancing the educational experience in a university by identifying the patterns of behavior of users of the university WiFi over an academic year.

The research examined the intensity and type of websites engaged with, in over 2.5 million user sessions using the Netflow data on a university WiFi. User behavior was analysed by classifying the websites accessed by a user in a session on the WiFi and identifying the volume of activity of the user's activity on each website in each classification. This classification allowed identification of patterns of users' behavior and potential PIU.

Prior work in identifying patterns of internet behavior have relied on psychometric tests and/or had a relatively small set of users and/or required participants to use specific software (Jayarajah et al., 2015, Wang et al., 2014) and/or have not provided information on the range of activities a user is engaged in and focused on a narrow range of behaviors (Kim et al., 2019; Zhou et al., 2016). Such studies suffer from sporadic and partial observability. In contrast, the observations reported in the present paper are generated based on the full suite of behavior of more than 13,000 users on the university campuses over an academic year.

Only 2% of the total internet activity on the university WiFi was classified as 'education'. The low level of activity in the education classification on a university WiFi was of concern. There was four times more social media activity, 10 times more search activity and three times more shopping activity over the academic year. Some of the activity on searching, social media, streaming, and shopping may have been related to education. While the actual items searched for or shopped for could not be identified, the positive correlations between shopping and education and search and education (< 0.3) suggest that shopping and search activity may have some link to education activity. However, the correlations less than or equal to 0.1 between streaming and education, and social media and education would indicate that neither streaming nor social media had any significant link to activity in education (Appendix J). Hence, we can surmise based on the correlations between the activities that, while some of the shopping and search activity are likely to have some education focus, the social media and streaming activity are unlikely to be related to education. Thus, it appears that the university WiFi may be used for some shopping, searching and educational activities which may support academic objectives, however it appears that social media activities and streaming activities often do not. The majority of user activity can be considered a distraction from educational activities. By providing ubiquitous access to WiFi, universities are enabling users to engage in distraction activities. Effective strategies to reduce the level of distraction activity and increase the level of education activity on the university WiFi could be expected to have a positive impact on student academic performance.

In the survey of the students at the university where the WiFi data were gathered the students estimated that approximately 60% of their time on the internet was spent on distraction, less than what was identified as distraction activity on the university WiFi in this research. Most students rated their general internet use (69% male, 71% female) as problematic, smartphone (47% male, 61%female) use as addictive, while approximately 15% of students (8% male and 21% female) felt their social media use was addictive see Appendix D. A total of 70% of students in response to a question in the survey indicated that their internet use was probably not or definitely not good for their health.

The results of the survey from the student body highlighted that more than half the student body felt that their internet use was unlikely to be good for their health, and in particular their general internet use and smartphone use may be problematic. The results from the survey suggest that there is a need for mechanisms to support students so that they can successfully use the internet, smartphones and social media for their studies and avoid the negative consequences that can result from overuse for distraction.

This research confirms the findings of Gill et al. (2011) that much of the network traffic in an organisation is directed to and from a small number of websites. In this research, over 97% of the internet activity on the university WiFi each month was to 120 websites and there was consistency in the websites accessed from month to month. Approximately 61% of all activity was classified as cloud and technology which is understood as backend activity not reflecting user behavior. Of the remaining 39% of activity, over 31% was in search, social media and shopping. Thus, in excess of 79% of total activity that reflects user behavior on the university WiFi in an academic year was activity in search, social media and shopping. Over 93% of this 79% was managed by three technology companies, Google, Facebook and Amazon. This evidence highlights the small number of technology companies that have a major influence on content delivered to users on a university WiFi (Appendix O). Governments are developing legislation to protect users from harmful content and practises (Cusumano et al., 2021; Online Safety Bill, 2021), however comprehensive legislation is not yet in place, in Ireland, the UK or Europe. If technology companies are not guided by legislation on what is acceptable to society to sustain user attention and protect users from harms, technology companies as economic entities are likely to focus on profit potentially to the detriment of their users' wellbeing and student wellbeing in a university environment.

PCA was used to synthesize the multiple features of the users' behavior on the internet and identified the key components of the behavior as 'distraction' and 'Not social media'. These two components facilitated comprehension of the patterns of behavior. The PCA of user behavior on the WiFi in the university identified that users predominantly spent their time on the internet on 'distraction'. In this research a distraction was considered as any internet activity which reflected user behavior and was not classified as 'education'. According to distraction Conflict Theory (Sanders et al., 1978), internet activity not related to the task at hand, which in university students is education, may cause stress when it is interesting and/or hard to ignore (Baron, 1986). Thus, if some university students are spending excessive time on the internet on non-educational activities at the expense of educational activities, it may be causing stress. What is excessive for an individual is self-assessed however previous research has found that heavy and consistent use of the internet for distraction activities can be problematic for students and can have a negative effect on their academic performance and wellbeing (Elhai et al., 2019; Stead & Bibby, 2017). Hence, the analysis of actual behavior on a university WiFi over an academic year which identified use of the internet predominantly for 'distraction' provides robust evidence of the risk of PIU in the student body.

The second principal component of user behavior identified in the PCA in the research as 'Not social media' showed an inverse relationship between social media activity and education, shopping or search activity. The component 'Not social media' differs from the 'distraction' component as it shows an inverse relationship between social media and other classifications. Of particular interest and concern in a university environment was the negative relationship between 'education' and 'social media'. PC2 'Not social media', suggests that the pattern of user behavior on the university WiFi indicates that activity in 'education' or 'shopping' or 'search' may decrease with an increase in 'social media' activity. Previous research identified a negative relationship between facebook usage and academic performance, the negative relationship identified between educational activity and social media activity in this research could provide an explanation (Busalim et al., 2019; Rouis et al., 2011). In a university environment consideration should be given to mechanisms to reduce social media usage given its contribution to the high level of distraction activity and it's links with reduced education activity, academic performance and wellbeing.

Strategies to reduce the time on distraction, activity and increase time on education on the university WiFi could improve student wellbeing and improve students' academic performance. Practical options to address potentially problematic WiFi use could include filtering, blocking or time limiting website use. Distraction use might be reduced by limiting access to non-educational websites by time, filtering or blocking. Given the level of interaction with Google, Facebook and Amazon, websites hosted by these companies could be a key focus for these interventions. Education websites could be promoted on the WiFi. Encouraging users to engage with educational websites might also help rebalance the use of WiFi towards education (Lee et al., 2019). The introduction of an official taxonomy for website classification would enable effective access control and monitoring. Educational programs could also be effective in promoting healthy internet use (Throuvala et al., 2018).

Analysis of the patterns of user behavior when accessing the internet on a university WiFi identified a level of distraction activity which highlights a risk for problematic internet usage. Given the links identified in research between PIU and loneliness, anxiety, reduced wellbeing, FOMO and academic performance, the students' pre-occupation with distraction activity generally and use of social media particularly on a university WiFi should be of concern to university and other educational institutions (Elhai et al., 2017; Price & Smith, 2019).

4.5 Limitations and Future Research

Although television and other media use an official standard to rate content, no such standard is available for websites or social network sites or streaming services (Lee et al., 2019). This rating would not only have been useful for classifying the websites the users visited in this research, it would also be useful for classifying or filtering appropriate content. In the absence of this official classification, a classification system that has been developed by technology companies was used. The Interactive advertising Board is a group of technology company representatives who provide publishers with a classification system for website content (Content Taxonom– - IAB Tech Lab, n. d.). Introducing an official content Taxonomy and requiring website providers to implement it would ensure correct identification of a website's purpose. Correct identification of a website's purpose and content would have many positive effects including enabling effective screening options for institutions, students and others.

This research assessed actual behavior that was anonymised and did not assess how each individual user felt about the impact of their behavior. Research which simultaneously analysed a user's actual behavior and how that users assessed their behavior would aid identification of patterns of PIU. Further analysis is warranted of actual student internet usage and the student assessment of the impact of potentially problematic behavior. Studies which linked actual student behavior to student outcomes would also be of particular interest, it was not possible to link the data in this study to individual students to examine if or to what degree academic performance could be predicted by internet behavior.

This research focused on unsupervised behavior on the university WiFi and does not consider user behavior when accessing the internet from the fixed network or other unsupervised behavior when using the internet. Internet users access the internet using their personal internet provider, as such this research in examining internet use on WiFi is examining only one of the key components which a user can be expected to use to access the internet.

The behavioral activity was generated by staff and students in the university, see Appendix B. Internet behavior of staff and students is likely to be different. The increased loading in PCA for education in January when students are not expected on campus is evidence that supports this. Future research should focus on internet behavior of students only. It would also be interesting to consider behavior of students from different demographics; particularly the year in college would be of interest as students face many challenges when they begin college and may therefore be at greater risk of PIU (Wohn & Larose, 2014).

This research was focused on user behavior in a university environment where access to mobile devices and to WiFi is ubiquitous. Future research should consider monitoring actual behavior in other educational settings such as schools where access to mobile devices and the WiFi is limited and generally provided for an educational purpose. This type of provision could be expected to reduce time in distraction as the student would likely be engaged in an activity in a supervised environment.

The vast majority of the users' behavior on the university WiFi was interacting with websites controlled by three technology companies. Technology companies compete on the internet to capture and exploit users' attention and to do so effectively may design their products in ways that render them addictive by using techniques such as the use of intermittent variable rewards, design features that take advantage of our desires for social validation and social reciprocity and platform designs that erode natural stopping cues or directing users to sites that reinforce their beliefs (Bhargava & Velasquez, 2020; “Ledger of Harms,” 2021). The dominance of Google, Facebook and Amazon in user behavior highlights Google, Facebook and Amazon’s influence in the attention economy, where a measure of success is ability to sustain user attention (Canales, 2020). There are concerns that Google, Facebook, Amazon and other technology companies are not sufficiently governed by legislation in what they can do to attract user attention and can exploit any means to achieve their goal (Department for Digital, Culture, Media and Sport, and the Home Office,2019). The present research found that more than 75% of all user behavior on the university WiFi was hosted by three technology companies. This statistic that suggests they are very effective in sustaining user attention. Future research could further investigate how and why students are using these websites on the university WiFi.

The research findings suggest that universities should consider strategies to manage PIU. Future research on an effective program on PIU prevention could develop interest in meaningful activities outside of the internet, give training on awareness and impacts of problematic behavior or develop a practice of internet abstinence. A program could be delivered as part of a broader harm prevention curriculum that could be expected to bear academic performance benefits (Throuvala et al., 2018). Future research could also measure how effective a program of time limiting, filtering and blocking could be in rebalancing WiFi usage.

4.6 Conclusion

The patterns of actual behavior identified on a university WiFi over an academic year suggest that WiFi usage is focused on distraction and is unlikely to enhance the users educational experience.

This research proposes a new process to identify patterns of behavior on the internet using digital traces. This study is a fine-grained, longitudinal study of a large-scale group of university WiFi users’ behavior on the internet. The data enabled identification of the range of internet activities and the intensity of engagement with these activities, of 13,000+ users. Classification of the activities and PCA enables the users’ behavior patterns to be identified. The scope and scale of the study illuminates previously unidentified patterns of user behavior, which are valuable inputs to determining if provision of ubiquitous access to the internet via WiFi technology is likely to be of benefit to users’ educational experience in a university or to be harmful. This research highlights how spatial-temporal research into the use of digital technology in educational environment illuminates its impact (Henderson et al., 2015; Melo et al., 2020).

The behavioral analysis identified several key findings. User behavior on university WiFi is predominantly in distraction which is likely to be problematic in an educational Institution and negatively affect student wellbeing and performance. Users of the university WiFi are less likely to be engaged in other activities when engaged in social media , most notably education activity, which is of particular concern in a university environment. Google, Facebook and Amazon host over 75% of all user behavior on a university WiFi. The current findings have important practical implications for educational institutions and could be used to guide policy.

The research findings show that internet behavior on a university WiFi is dominated by distraction activity, a risk for problematic use. Excessive time on distraction activity on the internet has been found to have negative effects in previous research (Elhai et al., 2019; Think Tank European Parliament, 2019). The pattern of distraction activity may provide part of the explanation for the high level of problematic internet, smartphone and social media use that was self-assessed in the electronic survey in the same student body.

Internet use is central to education; however, using it in a way that promotes student wellbeing and improves student academic behavior is vital. The negative link found in this research between education activity and social media activity, which supports previous findings, is of concern, in particular as there was four times more activity in social media than education. Also of concern on a university WiFi was over 90% of all social media use was to Facebook controlled sites when Facebook use, in particular, has been linked to reduced academic performance (Busalim et al., 2019; Feng et al., 2019).

The present research suggests that Universities need to consider how WiFi is used and the extent to which providing ubiquitous access to the internet is beneficial to students. Action is required to reduce distraction activity and increase educational activity by users of WiFi in Universities. Existing research on prevention of PIU suggest both environmental and psychosocial competencies or promoting harm reducing factors should be considered (Lee et al., 2019). Environmental actions include legislation to define acceptable mechanisms to attract and maintain attention on the internet. Although technology companies are likely to be averse to regulation, effective mechanisms to reduce internet harm including regulation are necessary (Kuss, 2021; Lee et al., 2019). By understanding WiFi activity, universities could introduce policies to limit distraction activity or consider other mechanisms such as education programs to encourage focus on education, if needed (Lee et al., 2019; Throuvala et al., 2018).

The need for an official content taxonomy for internet use was identified in this research. Exact identification of a website's purpose and content may have many positive effects when analysing behavior patterns, but may also enable effective screening options for institutions, students and others. Introducing an official content taxonomy and requiring website providers to implement it may ensure correct identification of a website's purpose with certainty, in a way this is not currently possible. The focus of this study was actual internet behavior, the next study in chapter 5 investigates how a subset of the students, in the university where the objective data was gathered, assessed their internet use and their wellbeing.

A link to the published paper is included in Appendix P.

Chapter 5. Problematic Internet Use Understood Using the I-PACE Model, Partial Network Correlation and Variance Partitioning

5.1 Introduction

Problematic internet use (PIU) can be conceptualized as a behavioral pattern of internet use marked by preoccupation and unregulated and excessive use which leads to significant negative consequences not accounted for by any other disorder (Kuss & Pontes, 2019). General PIU, problematic smartphone use, problematic social media use, problematic gaming, and problematic pornography use are some of the subtypes of Problematic Internet Use (PIU). The European Parliamentary Research Service has recognised the harmful impact of Problematic Internet Use (PIU) on health, wellbeing and general normal functioning (Think Tank European Parliament, 2019). To manage the harmful impacts of PIU, it is necessary to understand the concept of PIU, how it is developed and maintained, the associated psychological risk factors and the resulting behaviors. However, currently there is no standardised agreement on what constitutes PIU, in part due to the many different forms or subtypes of problematic internet use and the lack of clarity on the associations between the subtypes (Caplan, 2010; Kwon, Kim, et al., 2013; Young, 1996). College life can be challenging as students cope with managing their time, studies, health, finances and often new home environments (Murphy, 2017). Approximately 35% of third-level students in Ireland have reported feeling lonely often or all of the time (Price & Smith, 2019). Loneliness is frequently closely associated with FOMO, a person's concern that others are having rewarding experiences which they are not a part of, which creates a need to stay constantly connected, often by using social media (Przybylski et al., 2013; Elhai et al., 2018). Disconnection can result in a sense of loneliness, and those suffering the negative impact of being alone can be vulnerable to FOMO. Loneliness, FOMO and PIU are negatively correlated with wellbeing (Elhai et al., 2018; Hebebci & Shelley, 2018; Moberg & Anestis, 2015; Stead & Bibby, 2017). Hence, understanding the relationship between student wellbeing, loneliness, FOMO and PIU may have important implications for supporting mental health and wellbeing in students. As internet use is central to education (Murphy, 2017), students tend to be frequent users and may thus be particularly prone to PIU

. Students are also prone to loneliness and FOMO. Psychological factors such as wellbeing, loneliness and the fear-of-missing-out (FOMO) may be relevant to the development and maintenance of PIU. The roles that these factors play need to be clarified. Hence, the current study primarily seeks to understand associations between wellbeing, loneliness, FOMO and PIU in university students.

There is variation in the incidence rate of PIU. In European studies, rates of PIU in university students varied from 1-13.9% (Andrie et al., 2019; Gómez et al., 2017; Macur et al., 2016; Foresight, 2019; Panel for the Future of Science and Technology, 2020). Variation in the incidence rate might reflect the types of PIU studied and sex differences in PIU. For example, a recent systematic review suggested men were often found to be influenced more by generalised PIU, while women often had higher incidence of specific forms or subtypes, such as problematic smartphone usage or problematic social media usage (Baloğlu et al., 2020).

The Interaction Person Affect Cognition Execution (I-PACE) model is a model of behavioral addiction. The model is a useful aid in understanding and explaining PIU development and maintenance. The I-PACE model explains behavioral addictions as a result of predisposing psychological and biological factors as well as moderating and mediating factors such as cognitive affect and reactions to situational triggers, cognitive biases and coping strategies. These factors, combined with reduced inhibitory control, instrumental conditioning and accessibility of a behavior, can be associated with developing and maintaining an addiction (Brand et al., 2019). The I-PACE model (Brand et al., 2019) is used in the current study to provide a theoretical framework to coalesce the findings on wellbeing, loneliness, FOMO and PIU subtypes. In the I-PACE model (Brand et al., 2019) biological factors, such as gender, and psychological variables, such as loneliness and FOMO, maybe linked to PIU. Moderating and mediating variables, such as internet-related cognitive or attentional bias or using the internet as a coping strategy and reduced inhibitory control and/or instrumental conditioning, can contribute to or be affected by PIU in an addiction process. The gratification experienced when using the internet, the ubiquitous availability of the internet, and the affordability of access to the internet may accelerate the development of problematic behavior on the internet (Brand et al., 2019). The I-PACE model suggests the development and maintenance of PIU is affected by the interaction of predisposing, moderating and mediating variables (Brand et al., 2019). Identifying and developing understanding of the relationships between moderating and mediating variables, such as loneliness, FOMO and wellbeing on PIU is important in identifying and managing PIU and developing healthy internet use behaviors (Elhai, Yang, Dempsey et al., 2020). Analysing the relationships between PIU subtypes and associated psychological variables in a network may provide important insight into the centrality of specific domains and the patterns of relationships (Chen et al., 2021). A network approach to understanding PIU involves analysis of the associations between PIU subtypes and wellbeing, loneliness and FOMO. A partial correlation network would aid comprehension by giving a visual representation of the relationships between the variables. Modelling the network of relationships using partial correlation networks will clarify the associations in the network. Understanding the network of relationships between PIU subtypes and wellbeing, loneliness and FOMO can enable those managing PIU to identify and focus on the variables with greatest influence when trying to reduce PIU, loneliness and FOMO and improve wellbeing. Variance partitioning can be used to quantify the contribution of nodes in the network, in explaining the variance in loneliness, FOMO and wellbeing.

The current research examines university students' reported experience on the internet using the results of psychometric tests on PIU subtypes (general PIU, problematic smartphone addiction, problematic social media use, problematic gaming, problematic pornography use) as well as results from psychometric tests on loneliness, wellbeing and FOMO. The partial correlation network clarifies the complex pattern of relationships between the subtypes of PIU and wellbeing, loneliness and FOMO. Variance partitioning further explains the relationships between the subtypes and associated psychological variables for males and females (Hevey, 2018). This study aims to clarify the associations between PIU subtypes in males and females. The study will also explore if men and women differ regarding the associations between wellbeing, loneliness and FOMO and the PIU subtypes. The study will identify the subtypes of PIU that are most influential in the relationships between PIU subtypes and wellbeing, loneliness and FOMO. Specifically, the following hypotheses are tested.

- *Hypothesis 1:* The relationships between the PIU subtypes, wellbeing, loneliness and FOMO differ for males and females.
- *Hypothesis 2:* Men in comparison to women have a higher level of generalised PIU.
- *Hypothesis 3:* Women in comparison to men have a higher level of problematic smartphone usage and problematic social media usage.
- *Hypothesis 4:* Decreased student wellbeing is explained by the interaction between loneliness and general PIU.
- *Hypothesis 5*: Student loneliness is explained by the interaction between general PIU, problematic smartphone use, and problematic social media use.
- *Hypothesis 6:* Student FOMO is explained by the interaction between general PIU and problematic smartphone use.

5.2 Methods

5.2.1 Design

This study used a cross-sectional online data gathering technique. Emails were sent to the university email accounts of all students in an Irish university; approximately 12,000 students are enrolled in the university. The email contained information about the study as well as a link to an online questionnaire. The online questionnaire consisted of some questions on demographics, internet use and validated psychometric scales, had a total of 119 questions and required approximately 15 minutes to complete. The students were offered an opportunity to enter a raffle for three Oneforall vouchers worth 50 Euros each as an incentive to participate in the survey.

5.2.2 Participants

A convenience sample of *N*=1060 students from the emailed students responded. Of the 1060 respondents, data from 834 were processed; the remaining 216 had not answered sufficient questions in the survey or had not answered questions in a meaningful way, e. g., answered all questions with the same response. The mean age of participants considered in the analysis was 22.46 years (*SD* = 6.48 years), with a range from 17 to 62 years. The mean age of male participants was 22.44 years (*SD* = 626 years) and female participants was 22.15 years (*SD* = 6.09 years). In terms of gender distribution, approximately 45% of the sample was male and 55% female. The majority (80%) were studying for an undergraduate degree, with 18.5% studying for a post-graduate degree and the remainder studying as part of an apprenticeship program. Most students identified engineering and science as their faculty (48%), with business and humanities being identified by 31%, approximately 0.5% identified the Art and Design College, National Maritime College and School of Music. The remaining 19.5% identified 'Other' as their faculty. On average the students had studied 2.05 years (*SD* = 1.18 years) at MTU.

5.2.3 Materials

In addition to basic demographic information and general questions on internet behavior detailed in Appendix A. The online survey comprised of a number of different psychometric tools to assess Problematic Internet Use (PIU), FOMO, wellbeing and loneliness. The demographic information, the internet use information and the data from the responses to the psychometric tests were used in this study.

Psychometric tests to measure PIU

In order to assess smartphone addiction, the Smartphone Addiction Scale – Short Version (SAS-SV) (Kwon, Kim, et al., 2013) was used. The internal consistency of the SAS-SV for the data was verified based on the data from the current study with a Cronbach's alpha of 0.85. The scale is a brief self-report instrument based on the Smartphone addiction scale (SAS) (Kwon, Lee, et al., 2013). In the self-report scale, participants respond to statements including 'Having a hard time concentrating in class, while doing assignments, or while working due to smartphone use', 'Won't be able to stand not having a smartphone' or 'Feeling pain in the wrists or at the back of the neck while using a smartphone'. The responses are given on a six-point Likert scale (ranging from 1: ‘‘strongly disagree’’ and 6:‘‘strongly agree’’). The symptoms measured are salience, withdrawal, negative consequences, compulsive use and tolerance. The SAS-SV is a 10-question scale based on the SAS to measure smartphone addiction in teenagers in South Korea, however it has also been found to be an effective measure of smartphone addiction in American young adults (Harris et al., 2020). The SAS-SV scale proposes a cut-off point (31) for males which is lower by two points than the female cut-off point (33), to identify the extent to which usage is potentially pathological from a diagnostic point of view (Kwon, Kim, et al., 2013). The 10 questions used accumulate a score ranging from 10 to 60 which is used to determine if the participants’ smartphone usage behavior can be categorized into normal or potentially addictive.

The PIUQ-SF-9 (Koronczai et al., 2011) was used to identify internet users at risk of developing problematic Internet use and those not at risk. The internal consistency of the PIUQ-SF-9 for the data was verified based on the data from the current study with a Cronbach's alpha of 0.85. The 9-item scale measures negative consequences of internet use, preoccupation/withdrawal and excessive usage. In the self-report scale, participants respond to statements including ‘How often do you feel tense irritated or stressed if you cannot use the internet for as long as you want to’, ‘ Do you feel more irritability, anxiety and/or sadness when you try to either reduce or stop using the internet?’ or ‘Do you feel the need to spend increasing amount of time engaged online in order to achieve satisfaction or pleasure?’. The responses are given on a five-point Likert scale (ranging from 1: ‘‘never’’ to 5:‘‘always/almost always”). The scale was found to be able to discriminate those at risk of PIU and those not at risk, using a statistically established cut-off point of 22, above which use is considered problematic. Scores range from 9 to 45 (Koronczai et al., 2011).

The Bergen Social Media Addiction Scale (BSMAS), which is adapted from the Bergen Facebook Addiction Scale (Andreassen et al., 2017), consists of six items. The participants are asked to respond, by rating how often in the last year they felt in response to statements including ‘You feel an urge to use social media more and more’, ‘Used social media in order to forget about personal problems’ or ‘Tried to cut down on the use of social media without success’. The responses are given on a 5-point Likert scale ranging from 1 (very rarely) to 5 (very often). The internal consistency of the BSMAS was verified based on the data from the current study with a Cronbach's alpha of 0.87. The BSMAS applies the six core addiction components (salience, mood modification, tolerance, withdrawal, conflict, and relapse) proposed by Griffiths (2005) to assess the experience of using social media over the last year. A higher score on the BSMAS indicates stronger addiction to social media. A BSMAS score over 19 in scores that range from 5 to 30 was suggested to identify an individual is at-risk of developing problematic social media use (Bányai et al., 2017).

The nine-item Internet Gaming Disorder Scale–Short-Form (IGDS9-SF) (Pontes et Griffiths, 2015) is a short self-report screening measure based on the nine Diagnostic and Statistical Manual of Mental Disorders (DSM-5) criteria for Internet Gaming Disorder (American Psychiatric Association, 2013). The participants are asked to respond to questions such as ‘Do you feel more irritability, anxiety or even sadness when you try to either reduce or stop your gaming activity?’, ‘Do you feel the need to spend increasing amount of time engaged gaming in order to achieve satisfaction or pleasure?’ or ‘Have you continued your gaming activity despite knowing it was causing problems between you and other people?’. The responses are on a 5-point Likert scale ranging from 1 (never) to 5 (very often). The internal consistency of the IGDS9-SF was verified based on the data from the current study with a Cronbach's alpha of 0.91. The IGDS9-SF assesses subtypes and prevalence of IGD by examining both online and/or offline gaming activities occurring over a 12-month period. It has been widely used to assesses subtypes and prevalence of Internet Gaming Disorder (IGD) in a general population. A cut-off point of 32 was established (Qin et al., 2020). Scores above this cut-off are indicative of problematic gaming. The scale produces a final score with a range between 9 and 45.

The Problematic Pornography Consumption Scale (PPCS-18) (Bőthe et al., 2018) was used to measure problematic pornography use. The internal consistency of the PPCS-18 was verified based on the data from the current study with a Cronbach's alpha of 0.94. Responses were recorded on the following 7-point scale: 1 = never, 2 = rarely, 3 = occasionally, 4 = sometimes, 5 = often, 6 = very often, 7 = all the time. PPCS-18 consists of 18 items, and assesses the six core components of addiction: salience, mood modification, conflict, tolerance, relapse, and withdrawal. Statements that are rated include ‘I felt that I had to watch more and more internet porn for satisfaction’, I unsuccessfully tried to reduce the amount of porn I watch’ or ‘I became stressed when something prevented me from watching porn’. A cut-off score of 76 on the scale was used to distinguish normal and problematic use in scores that range from 18 to 126; scores that are greater than or equal to 76 are indicative of problematic use.

Mental health measures

The Personal Wellbeing Index (PWI) (The International Well Being Group, 2013) is derived from the Comprehensive Quality of Life Scale (ComQol) which was originally developed by Cummins (1997). It is used internationally to measure subjective wellbeing (SWB). Cronbach’s alpha based on the data from the current study for the scale was 0.88. The scale is used to question how satisfied people are with seven life domains. The seven questions identify standard of living, personal health, achievement in life, personal relationships, personal safety, community-connectedness and future security (Lau et al., 2005). Sample questions are ‘How satisfied are you with your standard of living?’, ‘How satisfied are you with what you are achieving in life?' or 'How satisfied are you with your personal relationships?'. The scale uses an 11-point satisfaction scale ranging from 'No Satisfaction At All' (0) to 'Completely Satisfied' (10). The total score is calculated and converted to a percentage of 70. The Australian normative range of scores suggested for individuals is 50-100 points (The International Well Being Group, 2013), so a cut-off point of 50 was chosen. Scores above this cut-off were considered as indicating a normal level of wellbeing.

The UCLA Loneliness Scale (Version 3) (Russell et al., 1980) is a 20-item scale most commonly used to measure subjective feelings of loneliness as well as feelings of social isolation. Cronbach's alpha calculated based on the data from the current study was 0.93. Participants answer questions including 'How often do you feel that you are "in tune" with the people around you?', 'How often do you feel that you lack companionship?' or 'How often do you feel alone?'. Participants rate each item on a scale from 1 (Never) to 4 (Often). The test has been found to be reliable and effective for measuring loneliness in a variety of populations. The cut-offs for loneliness severity in the UCLA-3 scale used in this research, were identified for this scale in Loneliness: human nature and the need for social connection.(2008), total score < 28 = no/low loneliness, Total score 28 - 43 = moderate loneliness, and Total score >43 = high loneliness.

The FOMO scale developed by Przybylski et al. (2013) was used. It is a 10-item measure with a Likert scale ranging from "1 = Not at all true of me" to "5 = Extremely true of me. ". Sample statements that are evaluated are 'I fear others have more rewarding experiences than me. ', 'I fear my friends have more rewarding experiences than me. ' or 'I get worried when I find out my friends are having fun without me. '. The scale is a brief self-report assessment that minimizes participant burden and provides maximal information about an individual's level of FOMO. The internal consistency of the FOMO scale based on the data from the current study was verified with the data with a Cronbach's alpha of 0.85. Items reflect apprehension from missing out on experiencing or learning about friends' rewarding experiences. The total scores from the scale (Przybylski et al., 2013) correlate negatively with psychological need satisfaction, positive mood and life satisfaction; and positively with social media engagement. There was no recommended cut-off point for FOMO; a higher score on the scale in the range 5 to 50 indicates higher levels of FOMO.

5.2.4 Process

The percentage of male and female student responses to the psychometric tests which indicated PIU or low wellbeing or loneliness was calculated using the psychometric test scores and the standard cut-off points in use for each psychometric test, see Table 14. Details of the mean and standard deviations in the scores for males and females are presented in Table 15. Shapiro Wilk tests indicated that the model of the psychometric tests for males and females were not normally distributed. Therefore, Mann-Whitney tests were used to identify differences in responses in males and females for each psychometric test, see Table 15.

This research uses R and the bootnet library (R Core Team, 2020) to generate a partial correlation network with regularization techniques to gain insight into relationships between the variables measured in the study (Bhushan et al., 2019; Epskamp & Fried., 2018). The network represents the strength of relationships between variables, and is useful to explore whether these are in line with theory. The partial correlation network can reveal unique relationships between variables that were not anticipated as the interaction between the many variables in the network may not have been examined in combination before (Bhushan et al., 2019).

The regularized partial correlation networks were generated using Extended Bayesian Information Criterion (EBIC) and graphical lasso (Foygel Barber & Drton., 2010). Nodes in the graph represent the psychometric tests and the edges represent a statistical relationship that is estimated using partial correlation techniques. These techniques have been shown to perform well in retrieving the network structure between variables that are interdependent (Friedman et al., 2008). The observed variables (nodes) may influence one another and edges represent a partial correlation among two nodes when all other variables under consideration are controlled for (Epskamp & Fried, 2018). The strength of the partial correlation is directly related to the strength of the regression coefficient. Unlike what can be seen from a multiple regression analysis of a single dependent variable, the partial correlation network also highlights which other variables have an impact. By linking separate multiple regression models, partial correlation networks allow for mapping out linear prediction and multicollinearity among all variables (Epskamp et al., 2017). In order to prevent overinterpretation, spurious connections or edges that represent very small partial correlations are limited. Minimizing EBIC has been effective in identifying the relationships between nodes in the network (Foygel Barber & Drton, 2010, 2015; van Borkulo et al., 2014). In this research, the hyperparameter is set at 0.5 as a more parsimonious model is preferred and expected to highlight the more important relationships (Foygel Barber & Drton, 2010). When observed variables are continuous, but not normally distributed, the variables can be transformed to have a marginal normal distribution. A nonparanormal transformation was applied to the data (Liu, Lafferty et al., 2009).

To estimate the importance of a variable, the centrality measures node strength, closeness and betweenness were calculated (Barrat et al., 2004; Boccaletti et al., 2006; Opsahl et al., 2010). Expected influence calculates the strength of connections between nodes, however it takes account of negative edges (Robinaugh et al., 2016). ‘Node strength’ describes the participation of a node within the network and is calculated by summing the number of connections with the sum of the strength of the connections of a node to all other nodes. ‘Closeness’ is calculated as the inverse sum of the shortest paths between a node and all other nodes. Closeness’ is an indication of how easy it is to access other nodes in the graph from the node of interest. The ‘Betweenness’ is calculated by counting how frequently a node of interest is included on the shortest path between two nodes. Hence, a high score on betweenness suggests that a node is highly connected with other nodes in the network (Oldham et al., 2019).

The partial correlation network shows the unique bivariate relationship between the PIU subtypes and the correlates after partialling out all other effects in the network. To further understand the shared contribution of the PIU subtypes and correlates on a dependent variable, the relationships in the partial correlation network were analysed using variation partitioning, in particular the relationships between PIU subtypes and correlates with wellbeing, loneliness and FOMO were considered. VP was introduced by Borcard (1992) and is often used in ecological analysis and modelling (Bienhold et al., 2012, Dray et al., 2012). VP tries to “partition” or resolve the explanatory power of independent variables identified in matrices in relation to the same response or dependent variables defined in another matrix. The effect of a variable is calculated using the square of the semi-partial correlation between a given independent variable and the dependent variable. Thus, if independent variables are all uncorrelated, then independent variable importance can be entirely determined by ranking the unique effects. When independent variables are correlated, as in this research, the common effects can indicate the extent and pattern of the independent variables’ shared variance in predicting variance in the dependent variable (Nimon & Oswald, 2013).

This research uses R and the vegan library for variation partitioning (Oksanen et al., 2020). Variation partitioning partitions the variation in data using two, three, or four explanatory tables in redundancy analysis ordination (RDA) or distance-based redundancy analysis. If the response variable is a single vector, partitioning is by partial linear regression (Oksanen et al., 2020).

To prepare the data for analysis, information from any survey respondent that did not have a valid score for all the psychometric tests was removed. Of the 834 responses with valid data, only 672 had a valid score for every survey and were therefore included in the partial correlational and variance partitioning analysis.

5.3 Results

The *N*=834 participants estimated their total internet time daily on average as 6.89 hours, 4.18 hours (*SD* = 2.71 hours) on entertainment and 2.73 hours (*SD* = 2.35 hours) on internet use with a purpose, e. g., education. Of the participants, 70% answered probably not or definitely not when asked whether their internet activities were beneficial to their physical health. In response to a question on whether their internet activities were beneficial to their mental health, 49% answered probably not or definitely not. The number of male and female students who responded to each psychometric test is displayed in Table 14. The number and percentage of male and female students who scored above the cut-off point for each of the psychometric tests except for the test measuring FOMO are displayed. Increasing scores in the test indicate an increase in FOMO. The number of male and female students who responded to each psychometric test as well as the median and standard deviation in the scores for male and female students in each of the psychometric tests were calculated and are displayed in Table 15. Results of Mann-Whitney tests were used to determine if there were significant differences in the male and female responses to the psychometric tests and results are displayed in Table 15. There was a significant difference between male and female scores on the psychometric tests SAS-SV, IGDS9-SF, BSMAS, FOMO, PPCS-18 and PWI. Thus, it was decided to analyze male and female response data separately. The scores of problematic gaming and pornography use in the student body were low. There were 1% or less in both male and female respondents that scored above the cut-off for either psychometric test.

Table 14.

Percentage Above Cut-off in Psychometric Tests

. Gender	*Male*			*Female*				
Psychometric Test	N	N Above Cut-off	%Above Cut-off	N	N Above Cut-off	% Above Cut-off	Cut-off	Valid Range
SAS-SV	362	169	47	469	284	61	33 female, 31 male => potentially addictive smartphone usage	6 to 60
PIUQ-SF-9	341	80	23	449	123	27	>=22 => potential problematic general internet usage	9 to 45
IGDS9-SF	331	3	1	435	1	0	>=32 => potential internet gaming disorder	9 to 45

BSMAS	326	25	8	442	91	21	>=19, potentially addicted social media usage	5 to 30
PPCS-18	289	3	1	396	0	0	>=76 => potentially problematic internet pornography consumption	5 to 50
FOMO	322	N/A	N/A	432	N/A	N/A	N/A	0 to 100
PWI	362	220	61	469	267	57	< 50 => suggests wellbeing is less than normal	20 to 80
UCLA	308	204	66	428	305	71	>= 43 indicator of moderate or high degree of loneliness	18 to 126

Table 15.

Descriptive Statistics and Results of Mann-Whitney Test to Identify Significant Differences in Survey Responses for Males and Females

Gender	Male			Female			Mann Whitney U Test	
Psychometric Test	N	Mdn	Std	N	Mdn	Std	W	P
SAS-SV	362	29.5	9.08	469	35	9.08	57591	*p* < =.001**
PIUQ0-SF-9	341	17	6.18	449	18	6.41	71276	0.952
IGDS9-SF	331	14	624	435	9	4.36	38094	*p* < =.001
BSMAS	326	10	5.05	442	14	527	46250	*p* < =.001
PPCS-18	289	31	14.6	396	20	6.85	19982	*p* < =.001
FOMO	362	20	9.56	469	22	10.11	73758	*p* < =.001
PWI	319	55	1123	427	54	11.67	61520	*p* <.05
UCLA	308	48.5	13.38	428	51	1329	61040	0.087

Note 1: Shapiro Wilk Test identified each independent set of data as non-normal

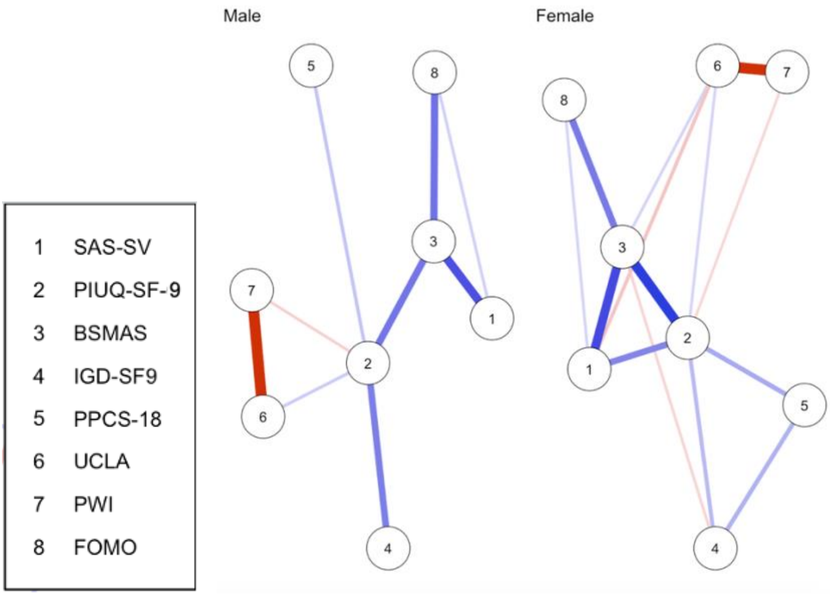
A partial correlation network was calculated for the male and female responses and represents the significant partial correlations between nodes. Each node represents a measurement of the users' experience as self-reported in responses to a psychometric test and the edge represents the strength of the partial correlation between the nodes when the impact of all other variables in the network is controlled. A blue edge represents a positive correlation and red indicates a negative correlation. The weight of the edge represents the strength of the correlation. There were n=390 female responses, and n=281 male responses with a valid score for all of the psychometric tests.

A partial correlation network for males and females PIU subtypes and, the correlates loneliness, wellbeing and FOMO is displayed in Figure 13. The graph is parsimonious due to LASSO estimation. In the partial correlation networks, several links are identified for both males and females. For both males and females there was a strong negative correlation between Node 6 (UCLA) and Node 7 (PWI) and Node 7 (PWI) and Node 2 (PIUQ-SF-9), while there were positive correlations between Node 6

(UCLA) and Node 2 (PIUQ-SF-9); Node 8 (FOMO) and Node 3 (BSMAS), Node 8 (FOMO) and Node 1 (SAS-SV); Node 2 (PIUQ-SF-9) and Node 5 (PPCS-18) and Node 2 (PIUQ-SF-9) and Node 4 (IGD-SF9). Some links exist on the partial correlation network for females only; Node 6 (UCLA) was positively linked to Node 3 (BSMAS), Node 6 (UCLA) was negatively linked to Node 1 (SAS-SV), and Node 5 (PPCS-18) was linked to Node 4 (IGD-SF9), and Node 4 (IGD-SF9) was negatively linked to Node 3 (BSMAS) for females only.

Figure 13.

Partial Correlation Network of Subtypes for PIU and Correlates Wellbeing and Loneliness and FOMO



Note 1: Smartphone Addiction Scale Short Version (SAS-SV), Problematic Internet Use Questionnaire Short Form (PIUQ-SF-9) (Koronczai et al., 2011), Bergen Social Media Addiction Scale (BSMAS) (Andreassen et al., 2017), Internet Gaming Disorder-Short Form (IGD-SF9) (Pontes et Griffiths, 2015) , Problematic Pornography Consumption Scale (PPCS-18) (Bőthe et al., 2018), UCLA Loneliness Scale Version 3 (UCLA) (Russell et al., 1980), Personal Wellbeing Index (PWI) (The International Well Being Group, 2013), Fear of Missing Out Scale (FOMO) (Przybylski et al., 2013).

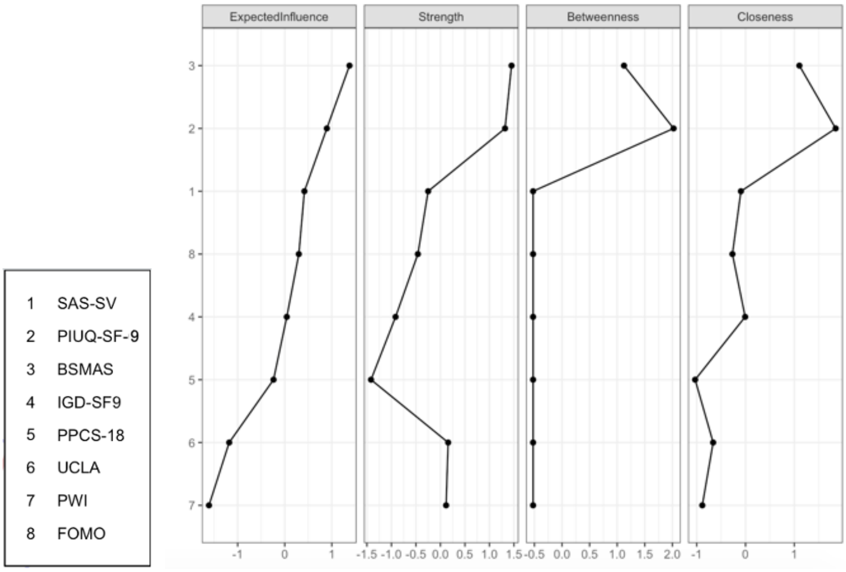
The centrality estimates of the importance of the nodes in the partial correlation network representing the subtypes of PIU and the covariates loneliness, wellbeing and FOMO are displayed in Figure 14, and confidence of estimates are reported in Figure 15. The Expected Influence centrality measure is the sum of the weightings of the edges touching a node on the graph. Expected Influence considers negative associations, while the Strength centrality measure is the sum of absolute values. A node in a network that has negative edges may diminish activation in other subtypes and should not be considered as a highly problematic node (Robinaugh et al., 2016). The centrality estimates in Figure

14, identify Node3 (BSMAS) and Node 2 (PIUQ-SF-9) as the nodes with the greatest expected influence and strength in the partial correlation networks for both males and females.

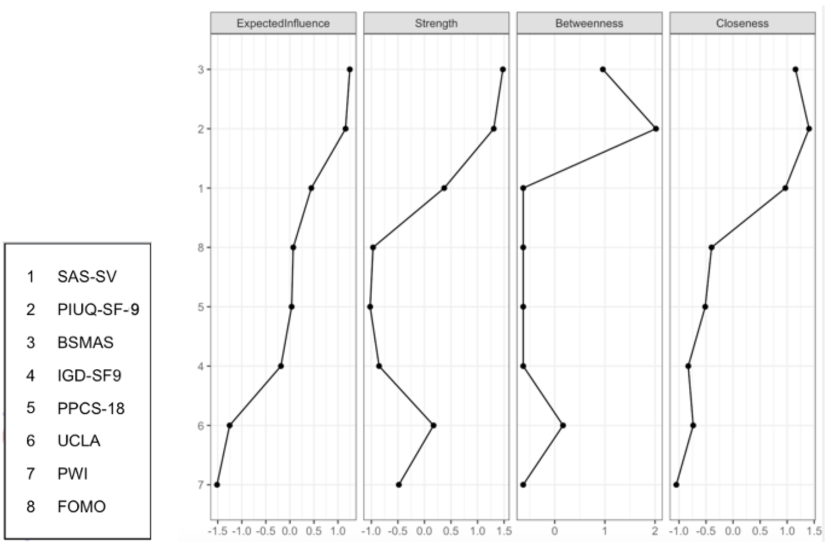
Figure 14.

Centrality Estimates of Subtypes of PIU and Wellbeing and Loneliness and FOMO

<u>Male</u>



<u>Female</u>



Note 1: Smartphone Addiction Scale Short Version (SAS-SV), Problematic Internet Use Questionnaire Short Form (PIUQ-SF-9) (Koronczai et al., 2011), Bergen Social Media Addiction Scale (BSMAS) (Andreassen et al., 2017), Internet Gaming Disorder-Short Form (IGD-SF9) (Pontes et Griffiths, 2015) , Problematic Pornography Consumption Scale (PPCS-18) (Bőthe et al., 2018), UCLA Loneliness Scale Version 3 (UCLA) (Russell et al., 1980), Personal Wellbeing Index (PWI) (The International Well Being Group, 2013), Fear of Missing Out Scale (FOMO) (Przybylski et al., 2013).

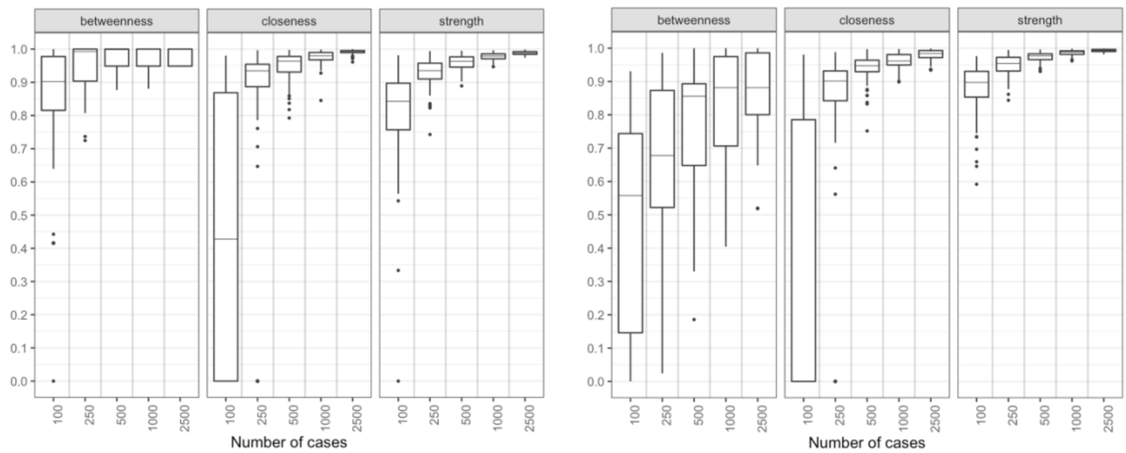
* z-scores are shown on x-axis rather than raw centrality indices.

The confidence in the estimates of centrality depend on the number of respondents or cases examined, and this analysis included 281 males and 390 females. There was good confidence for both males and females in all estimates of centrality (>0.7) except for female betweenness for which the confidence was less than 0.7, as can be seen in Figure 15.

Figure 15.

Partial Correlation Graph Confidence of Estimates of Centrality

Male **Female**



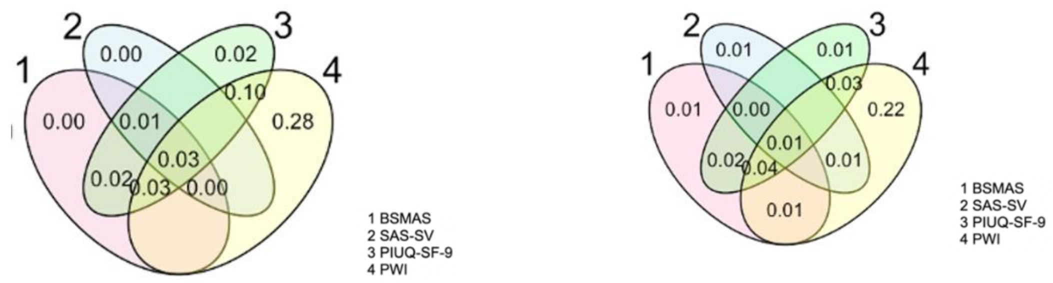
Variance partitioning was used to quantify the percentage of the variance in wellbeing, loneliness and FOMO explained by the relationships identified in the partial correlation graph in Figure 13.

The Venn diagram in Figure 16 presents the results of variance partitioning where PIUQ-SF-9, SAS-SV and BSMAS and PWI are the independent variables and UCLA (Loneliness) is the dependent variable. The diagrams shows that 48% of the variance in UCLA for males and 35% of UCLA for females is explained by the variance in the independent variables. The Venn diagrams also highlight the variance explained by the interaction between the variables. From the diagram, the variance in male and female UCLA appears to be heavily explained by PWI and PIUQ-SF-9 and their interaction. Approximately 52% of the variance in male and 65% of the variance in female loneliness is not explained by the variation in PIUQ-SF-9, SAS-SV, BSMAS and PWI Variation in male loneliness is explained by PWI independently (28%) and then by the combined effect of PWI and PIUQ-SF-9, BSMAS, SAS-SV (16%). Variation in female loneliness is explained by PWI independently (22%) and then by the combined effect of PWI and PIUQ-SF-9, BSMAS, SAS-SV (13%).

Figure 16

Variance in Loneliness Explained by Independent Variables BSMAS, SAS-SV, PIUQ-SF-9 and PWI

Male **Female**



Note 1: Male residuals 0.52
Note 2: Values < 0 not shown

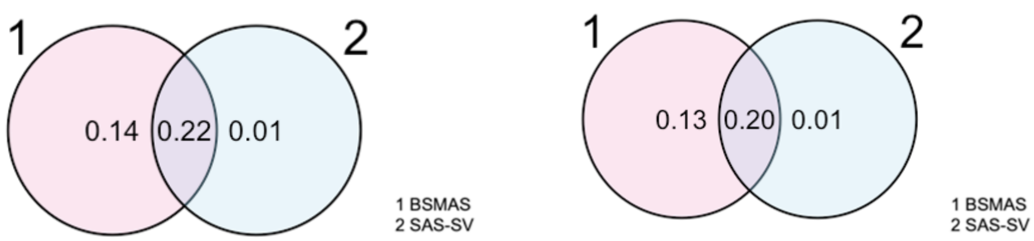
Note 1: Female residuals 0.65
Note 2: Values < 0 not shown

The Venn diagrams in Figure 17 are generated by variance partitioning where BSMAS and SAS-SV use are the independent variables and FOMO is the dependent variable. The diagram shows that 37% of the variance in FOMO for males and 33% of the variance for females is explained by the independent variables SAS-SV and BSMAS. The Venn diagram also identifies the variance explained by the interaction between SAS-SV and BSMAS. SAS-SV alone accounts for 1% of the variance; the interaction between SAS-SV and BSMAS accounting for 22% in males and 20% in females. The influence of BSMAS on its own in predicting FOMO Is 14% for males and 13% for females. A total of 63% of the variance in male and 67% of the variance in female FOMO is not explained by the variance in SAS-SV and BSMAS.

Figure 17

Variance in FOMO explained by Independent Variables BSMAS and SAS-SV in Males and Females

Male **Female**



Note 1: Male residuals 0.52
Note 2: Values < 0 not shown

Note 1: Female residuals 0.65
Note 2: Values < 0 not shown

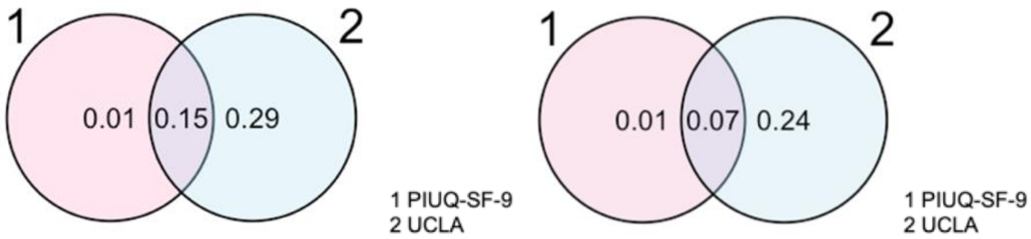
The Venn diagrams in Figure 18 are generated by variance partitioning, where PIUQ-SF-9 and UCLA are the independent variables and PWI (Wellbeing) is the dependent variable. The diagram shows that

45% of the variance in PWI for males and 32% of the variance for males is explained by the independent variables PIUQ-SF-9 and UCLA. PIUQ-SF-9 accounts for 1% of the variance independently; the interaction between PIUQ-SF-9 and UCLA accounting for 15% of variance in wellbeing for males and 7% in females. The influence of UCLA on its own in explaining the variance in PWI is 29% for males and 24% for females. A total of 55% of the variance in male and 68% of the variance in female PWI was not explained by the variables PIUQ-SF-9 and UCLA.

Figure 18

Variance in Wellbeing Explained by Independent Variables PIUQ-SF-9 and UCLA in Males

Male **Female**



Note 1: Male residuals 0.55
Note 2: Values < 0 not shown

Note 1: Female residuals 0.68
Note 2: Values < 0 not shown

5.4 Discussion

Hypotheis 1 was supported, gender differences in the relationships between PIU subtypes (general PIU, problematic social media use, problematic smartphone use, problematic gaming, problematic pornography use) and wellbeing, loneliness and FOMO were identified. The gender differences were identified by comparing male and female partial correlation networks. These networks represented the variables and the relationships between them. Differences in the male and female network manifested in the existence of relationships and the strength of relationships. There were three relationships that existed between the PIU subtypes in the female partial correlation network that did not exist in the male partial correlation network. Positive associations existed for females between problematic smartphone use and general PIU. Positive associations also existed for females only between problematic pornography use and problematic gaming, a relationship found in previous research for both males and females (Rozgonjuk, 2021). There was also a negative association between problematic social media use and problematic gaming for females which was not found in other research investigating female problematic gaming (Lopez-Fernandez et al., 2019), the relationship may not have been considered. These relationships which exist for females but not for males confirmed hypothesis 1, gender differences exist in the relationships between PIU subtypes and wellbeing, loneliness and FOMO.

Hypothesis 2 was not supported by the research findings, this research did not find that men in comparison to women had a higher level of generalised PIU. It was expected that males would have a higher level of general PIU as found in previous studies (Kim et al., 2018; Wartberg et al., 2020). In the current study, the level of general PIU was not found to differ significantly between males and females. However previous studies which found male PIU significantly greater considered problematic gaming in assessing general PIU (Wartberg et al., 2020), the level of problematic gaming was also significantly different for males and females in this research. Other research that found gender differences may have used a different psychometric assessment instrument to measure general PIU (Kim et al., 2018). Findings on gender differences in general PIU are not consistent (Baloğlu et al., 2020). Previous research on general PIU in Ireland also found no significant difference in male and female levels (Su et al., 2019). However, in the present study, the impact of general PIU in explaining the variance in male wellbeing was higher for males. The percentage of variation in wellbeing explained by the interaction between general PIU and loneliness for males was 15%. For females, it explained only 7%. The variance in loneliness explained by the interaction between general PIU and wellbeing was also higher for males at 16%, double the 8% variance in female loneliness explained by the same interaction. Thus, while the level of general PIU was not found to differ significantly between males and females, the impact of general PIU when combined with loneliness or reduced wellbeing explained considerably more variation in male wellbeing and loneliness than in females. General PIU alone explained much less of the variation in loneliness than general PIU and wellbeing interactions. Thus, general PIU is of concern, in particular for males, for lonely people and for those with reduced wellbeing. Supporting previous research findings (Elhai et al., 2018; Hebebci & Shelley, 2018; Moberg & Anestis, 2015; Stead & Bibby, 2017). Reducing general PIU could have a significant positive effect on wellbeing and reduce loneliness. Equally it may be that reducing loneliness or increasing wellbeing may significantly reduce general PIU. Clarifying gender differences on the inter-relationships between general PIU, wellbeing and loneliness, highlights a link with problematic internet use for particular demographics. The findings highlight the need for internet use to be part of the conversation when considering student wellbeing and loneliness.

Hypothesis 3 was supported, as found in previous research (Aparicio-Martínez et al., 2020; Baloğlu et al., 2020); women in comparison to men reported a significantly higher level of problematic smartphone usage and problematic social media usage. There was a positive association between loneliness and problematic social media use for females. Considering, the level of problematic social media use in females found in this and previous research is significantly higher for females than for males (De-Sola et al., 2019; Kırcaburun et al., 2018; Ostendorf et al., 2020; Victorin et al., 2020), the direct link between problematic social media use and loneliness for females is of particular concern. Other research has found direct links between problematic social media use and loneliness for both males and females (Atroszko et al., 2018; Martila et al., 2021). A negative association between loneliness and problematic smartphone use also existed for females only. A negative link between loneliness in females and problematic smartphone use was also identified in previous research (Hebebci & Shelley, 2018). Thus, smartphones may be used by females to make connections that help manage loneliness or lonelier females use smartphones less (Hebebci & Shelley, 2018). Smartphones have been found to be particularly effective in managing loneliness for those who use smartphones to communicate feelings or anxieties online (Karsay et al., 2019). However, the negative effects of overuse of the internet to cope with loneliness can increase loneliness and lonelier people appear to have more negative consequences, possibly because of neglect of offline relationships (Ceyhan, 2011; Wohn & Larose, 2014).

The fourth, fifth and sixth hypotheses were tested by examining the relationships which were identified in the partial correlation networks between PIU subtypes and wellbeing, loneliness and FOMO and then variance partitioning was used to quantify the variance explained by those relationships in loneliness, wellbeing and FOMO. Variance partitioning identified that the variation in wellbeing that was explained by the interaction between general PIU and loneliness was 15% for males and 7% for females. Thus, student wellbeing was explained by the interaction of PIU and loneliness, supporting hypothesis 4. Variance partitioning identified that the variation in student loneliness explained by the interaction of problematic social media use, problematic smartphone use, general PIU and loneliness was 21% for males and 11% for females. Hence, student loneliness was explained by the interaction of general PIU, problematic smartphone use, problematic social media use and wellbeing, supporting hypothesis 5. Variance partitioning identified that the variation in FOMO that was explained by the interaction between problematic smartphone use and problematic social media use was 22% for males and 20% for females. These findings support hypothesis 6, student FOMO was explained by problematic smartphone use and problematic social media use.

Problematic social media use followed by general PIU were distinguished, using centrality estimates, as the most influential subtypes of PIU for both males and females. The network of relationships between PIU subtypes for males in the partial correlation network existed in the female partial correlation network. These consistencies in the male and female correlation graphs highlighted commonality in the inter-relationships between PIU subtypes for males and females. Examination of the male and female partial correlation graphs suggests for both males and females the strongest relationships between variables were between problematic smartphone use and problematic social media use, between general PIU and problematic social media use and between problematic smartphone use and FOMO. These common inter-relationships for males and females may indicate a latent variable that suggests a pattern where general PIU, problematic social media use, problematic smartphone use and FOMO are developed and maintained together. The I-PACE model (Brand et al., 2019) can be used to interpret these findings in the context of a behavioral addiction. General PIU, problematic social media use, problematic smartphone use and FOMO relate to each other. Smartphone use may enable easy access to the internet, resulting in social media or other activity on the internet, which in turn may generate FOMO. The experience of FOMO may lead to decisions to use social media or internet activity to reduce FOMO, resulting in gratification on the internet which could lead to further use of the internet, which through instrumental conditioning may develop into PIU into an addictive process (Brand et al., 2019). Thus, it may be necessary to address problematic smartphone use, problematic social media use, general PIU and FOMO concurrently to address PIU.

This research and previous research linked problematic social media use and FOMO (Casale et al., 2018; Liu & Ma, 2018b), problematic social media use and general PIU (Kittinger et al., 2012, Primi et al., 2021), problematic social media use and problematic smartphone use (Liu & Ma, 2018b). Other research found a direct link between problematic social media use and wellbeing, a link that was mediated by general PIU in this research (Hawi & Samaha, 2019, Primi et al., 2021). Centrality estimates identified problematic social media use as the most influential node in the partial correlation network analysis of PIU subtypes and wellbeing, loneliness and FOMO for both males and females. As such, reducing problematic social media usage may have a considerable effect in weakening the relationships in the network. Problematic social media use should be a key consideration in addressing and managing PIU for males and females.

In the partial correlation network, both male and female FOMO are linked to increased problematic social media use, supporting previous research (Casale et al., 2018; Hunt et al., 2018). Male and female FOMO were also linked to problematic smartphone use, which was also found in previous research (Elhai et al., 2018; Elhai et al., 2019; Elhai ,Yang, Dempsey et al., 2020; Servidio, 2021). More that 32% of the variance in FOMO can be explained by problematic social media use and problematic smartphone use see Figure 17. The interaction between the problematic smartphone use and problematic social media use accounted for over 20% of the variation in FOMO for both male and females. Thus, use of social media on a smartphone in particular may increase FOMO. Other research found direct links between FOMO and wellbeing measures, a relationship which was not identified in this research (Casale et al., 2018; Elhai et al., 2019; Stead & Bibby, 2017). Addressing problematic smartphone use and problematic social media use may assist students experiencing FOMO or addressing FOMO may assist students reduce problematic smartphone use and problematic social media use.

Theory on the development and maintenance of PIU in the I-PACE model (Brand et al., 2019) can frame the findings in this study. Potential predisposing biological and psychological differences which could influence the development and maintenance of PIU were identified. Gender is a potentially predisposing biological factor. Wellbeing, loneliness and FOMO may be considered pre-disposing, moderating or mediating psychological factors of PIU. In this research, FOMO was directly linked to problematic social media use and problematic smartphone use for both males and females. Loneliness was linked to reduced wellbeing and general PIU. The relationship between loneliness and the PIU subtypes suggests that loneliness may be a moderator or mediator of PIU and/or vice versa. Wellbeing was also negatively linked to general PIU, and as such wellbeing may also be a moderator or mediator of PIU and/or vice versa. Internet or social media-related cognition, internet or social media-related attentional bias, use of the internet as a coping strategy or instrumental conditioning are measured in this research using psychometric tests of PIU subtypes and are explained in the I-PACE model as potential moderators and mediators of PIU (Brand et al., 2019). The interrelationships between the PIU subtypes in the partial correlation network also suggest that PIU subtypes may be moderators or mediators of PIU. The accessibility of the addictive behavior is also considered in the I-PACE model (Brand et al., 2019). The ubiquitous and cheap access to the internet via the smartphone may support the development and maintenance of PIU in an addictive process and explain the identification of the smartphone subtype of PIU as the third most central subtype in the partial correlation network. A smartphone is portable and gives access to the internet. Approximately 95% of those aged 16 to 19 years in Ireland use a smartphone and have cheap and easy access to the internet via WiFi or a network service provider (Central Statistics Office, 2018).

A large percentage of the students who participated in this study felt their internet use was probably not beneficial to their mental (49%) or their physical health (70%). The percentage of problematic smartphone use (SAS-SV) (Kwon et al., 2013) in this report was 47% for males and 61% for females, higher than reported in other studies which also used SAS-SV with similar cutoff points. Research found percentages in studies from US (college students, cutoff 31 male 33 female), China(adults, cutoff 31 male 33 female), Europe (adults, cutoff 31 male 33 female), and Brazil (adolescents, cutoff 33) ranged from 12 to 53% (Andrade et al., 2020; Harris et al., 2020; Lopez-Fernandez, 2017; Luk et al., 2018). The percentage of general PIU (PIUQ-SF-9) (Koronczai et al., 2011) reported in this research was 23% for males and 27% for females, also higher than reported by Koronczai et al. (2011), who reported a rate of 11% for adults' and 18% for high school students' general PIU in Hungary, assessed with a cut-off point of 22. The percentage of problematic social media use reported in this research was 8% for males and 21% for females, also high in comparison to previous studies which also used the BSMAS (Andreassen, et al., 2017) to assess problematic use, reporting rates of 4.5% in a study of Hungarian students using a cut-off point of 19 (Bányai et al., 2017), 4.9% in a study of Polish students using a polythetic approach to identify those addicted, (Balcerowska et al., 2020) and 17% in a Chinese study using a combined polythetic approach and cut-off of 19 (Hou et al., 2019). Of the survey participants 61% of the male students and 57% of the female students assessed their wellbeing to be normal or above, thus 39% of the male students and 43% of female students rated their wellbeing as below normal. Of the survey participants 66% of the male students rated their loneliness as moderate/high and 71% of the female students rated their loneliness as moderate/high also higher than 35% reported in previous research which used a self-developed questionnaire (Price & Smith, 2019). The findings from this research suggest that many students are lonely and/or have reduced wellbeing and may have difficulties with their general internet use, social media use and smartphone use which have negative consequences for them. The findings also suggest that reducing problematic social media use, general PIU and problematic smartphone use may positively affect wellbeing, loneliness and FOMO in students or vice versa. The findings suggest students may need supports in order to effectively regulate and effectively manage social media usage, their general internet use and smartphone use.

5.5 Limitations and future studies

The present study is not without limitations. First, data were collected using self-report measures; therefore, the reliability of the results depends on respondents' integrity and precision and their interpretation of items. Participants included only university students from a single university in Ireland, which may limit the generalisability of the findings. The analysis using partial correlation network and variation partitioning is not done routinely in research in psychology and would benefit from further investigation.

The assessment of PIU subtypes, wellbeing and loneliness were conducted using responses to psychometric tests and could be further investigated in interviews with students. The participants in this study were recruited and participated electronically. The electronic method of participation may have attracted participants with higher levels of PIU.

The centrality and importance of general PIU in the partial correlation network representing subtypes of PIU and the covariates wellbeing, loneliness and FOMO can be partially explained by the questions on the PIUQ-SF-9 (Koronczai et al., 2011) encompassing information that is used to answer questions on the BSMAS (Andreassen, et al., 2017), PPCS-18 (Bőthe et al., 2018), IGD-SF9 (Pontes & Griffiths, 2015) and SAS-SV (Kwon, Kim, et al., 2013). General internet use and specific internet use overlap; time on the internet for example includes time on social media or the smartphone. This potential overlap would benefit from further investigation.

5.6 Conclusions

This research highlights links between internet use and negative consequences for student wellbeing, loneliness and FOMO. The students who participated in the research reported high levels of general PIU, problematic smartphone use and problematic social media use. Roughly half of the students surveyed reported that internet use was probably not good for their mental or physical health. The students also reported high levels of loneliness and reduced wellbeing. Relationships between PIU, loneliness, wellbeing and FOMO identified in this research as well as the variance in wellbeing, loneliness and FOMO explained by the interaction with PIU subtypes suggest that students experiencing loneliness, reduced wellbeing or FOMO may need to change how they use the internet, their smartphones and social media.

This research highlights a direct link between general PIU and reduced wellbeing and between general PIU and increased loneliness. This is an important finding in university students who need to use the internet to support their studies and who as a group have identified with low wellbeing and high loneliness. General PIU was identified as having a strong link with reduced wellbeing and loneliness particularly for males, while problematic social media use was central in the male and female networks of relationships and at a level of particular concern in females. A potential latent variable for PIU was also identified which linked general PIU, problematic smartphone use, problematic social media use and FOMO, a variable which could be explained in the development and maintenance of PIU as a behavioral addiction using the I-PACE model (Brand et al., 2019).

Universities and institutions need to consider support for students which can help develop awareness of their internet use and the potential negative consequences for their wellbeing. There are strategies in place to address concerns with student wellbeing in Ireland (Price & Smith, 2019) such as the Higher Education Healthy Campus Charter & Framework for Ireland 2020–2025 (Department of Health and the HSE,2020). This strategy for promoting student wellbeing in education institutions requires implementation of health and wellbeing actions, which create connections between health, learning and the campus. Formulation of a policy on internet use to support student health could be guided by the evidence of the need for action, identified in this research. The health and wellbeing of the campus community could be improved by introducing supports in everyday teaching and learning to reduce problematic general internet use, problematic social media use and problematic smartphone use for students. The evidence found in this research suggests that addressing PIU in students should be a particular focus for student mental health as the issue may be addressable in a way that few other issues affecting health are and the affect may be considerable. These research findings highlight a need for universities to support students by looking at options on how best to protect students from developing PIU. Research on prevention of PIU suggests both environmental and psychosocial competencies or promoting harm-reducing factors should be considered (Lee et al, 2019). Less problematic use of smartphones, social media and the internet could potentially impact student wellbeing significantly. Although, as the relationships identified in this research were not causal, any initiatives which improve student wellbeing and/or loneliness could also have a positive effect on general PIU, problematic social media use and problematic smartphone use.

This research clarified the inter-relationships between PIU subtypes (general PIU, problematic social media use, problematic smartphone use, problematic gaming, problematic pornography use) and wellbeing, loneliness and FOMO using a partial correlation network and variance partitioning. The analysis and findings demonstrate the potential usefulness of a network correlation analysis and variance partitioning in psychology research. The analyses are effective in clarifying the inter-relationships between combinations of variables and enabled understanding of the inter-relationships between PIU subtypes and wellbeing, loneliness and FOMO. Variance partitioning was effective in clarifying the contribution of PIU subtypes and associated psychological variables in explaining the variance in wellbeing, loneliness and FOMO.

The focus of the first experimental study in chapter 4 was an analysis of actual internet behavior on a university WiFi, this study investigated how a subset of the students in the university where the objective data was gathered, assessed their internet use and their wellbeing. The final study in chapter 6 will examine how machine learning using the same objective data as used in the first experimental study in chapter 4 on actual internet behavior on a university WiFi can give insight into the patterns of behavior on the internet in a university and enable prediction of education activity on the internet from other activities on the internet.

Chapter 6. University WiFi Activity Modelling and Analysis to Identify Behavior Patterns and Predict Education Usage

6.1 Introduction

Among the member countries of the Organisation for Economic Cooperation and Development (OECD), an average of 62% of gross domestic product is spent on education (OECD, 2007). Education is highly valued and hence, understanding what impacts education, such as reduced academic performance and student wellbeing, should also be valued (Poropat, 2009). Internet use has become central to education and academic work (Murphy, 2017; Qazi et al., 2020). However, time online is not restricted to academic activities, internet use can become problematic. As previously stated, problematic internet use (PIU) can be conceptualized as a behavioral pattern of internet use marked by preoccupation and unregulated and excessive use which leads to significant negative consequences not accounted for by any other disorder (Kuss et Pontes, 2019). PIU has been linked to reduced academic performance (Xu et al., 2019) and poor wellbeing (Elhai et al., 2019; Price & Smith, 2019). The current study proposes that behavioral patterns of internet use in a university environment can identify user groups at risk of PIU at an institutional level.

Unobtrusive passive objective monitoring is the collection of data in a manner that does not impact the participant, without active data entry by the participant, as such it allows for continuous data collection over longer periods of time (Asselbergs et al., 2016; Bentley et al., 2019). Digital traces of WiFi activity can be gathered using unobtrusive passive monitoring. Patterns in the big data gathered from WiFi digital traces in an institution could be used to understand and predict internet behavior in the institution from the granular details of actual usage (Fischer et al., 2020). WiFi digital traces are an accurate record of behavior and can be gathered at a fraction of the cost of other data collection methods such as surveys. Moreover, the data precision and realism of WiFi digital traces ensures that generalisability across the population is maximised (Chang et al., 2014). Recent reviews evaluating passive monitoring have highlighted how real-time measurement can enable assessment of variables more accurately in a less intrusive manner than self-report measures (Bentley et al., 2019; Cornet & Holden, 2018). Self-assessment tools have been used very effectively in psychological research and in research on problematic internet use as they can be convenient, inexpensive, easy to use, quick to administer, give direct testimony and can be standardised and validated (McDonald, 2008). However, data gathered from self-assessment has limitations. Rather than capturing data from all users in a domain, it captures data from those that agree to participate. Self-assessment instruments identify a number of questions in a domain, which are focused on a suite of activities a user engages in while digital traces can be generated for all users and all activities in a domain. Self-reported data can be vulnerable to self-serving bias, as individuals may assess their behavior in a positive light and patterns of over-reports have been found in estimates of internet use when compared with actual use (Busch & McCarthy, 2021; Ryding & Kuss, 2020). To strengthen research findings on internet behavior there is a need to measure internet behavior using objective data as well as by self-assessment (Nie et al., 2007). Findings from analysis of objective data on internet can complement research findings from self-assessment. A transparent and verifiable process to collect objective data on internet behavior ensures a sound foundation for analysis in research. The use of objective data to assess behavior can make research findings more robust to criticism than research findings that rely exclusively on the accuracy of self-report. However, the consequences of behavior for an individual requires self-assessment and cannot be assessed using digital traces alone. Assessment of actual behavior on the internet can identify patterns of behavior at an institutional level and identify characteristics of internet use in an institution. Knowledge of behavior patterns and the characteristics can contribute to identifying behavioral patterns that suggest risk of PIU, however self-assessment is required to identify PIU.

Producing meaningful information from a large data set requires technical skills to manage the data and subject matter expertise to interpret the meaning in a functional domain (Espinosa et al., 2019). Unobtrusive, passive measurement of behavior on the internet is already frequently used for monitoring behavior for security and network management purposes (Marquez et al., 2017; Trevisan et al., 2020). Digital traces have been used to understand patterns of internet use and patterns of engagement with education activities in a university environment (O'Brien et al., 2022). Individual behavior on the internet can be measured by dividing activities into categories, such as search, social media, shopping, education, gaming, streaming and measuring the intensity or volume of activity in each category for a period of time or session (O'Brien et al., 2022).

Machine learning might be used to more accurately classify and predict behavioral and subjective responses. Machine learning can complement statistical inferential analysis, as results for unseen data can be realistically estimated. Usually maximum precision in prediction is enabled with highly complex non-interpretable models, such as xGboost, Random Forest and Neural Networks (Orrù et al., 2020). Big data sets such as the one used in this research are useful in machine learning; the larger a sample, the more representative it is of the population from which it is drawn. As sample size grows, it becomes more difficult for a statistical model to identify patterns that occur in the training data, but not in the broader population. Hence, smaller effects from larger samples are preferable to larger effects from smaller samples (Yarkoni & Westfall, 2017). The use of machine learning methods and big social data has great potential in research however there is a challenge as machine learning analyses do not easily map onto theory, such as the I-PACE model. The internals of machine learning models, for example neural networks, are often uninterpretable, performing complex procedures that produce outputs that are to be trusted. Thus, performance of the model should not be the only consideration in machine learning research applications (Radford & Joseph, 2020).

Data on student activity in online education resources, such as virtual learning environments, has been effectively used to predict student withdrawal (Kuzilek et al., 2018; Hassan et al., 2019) and/or academic performance (Peach et al., 2019; Heuer & Breiter, 2018). Research has identified patterns of behavior that highlights influences for student success. Those students in the Open University that used the virtual learning environment intensively around assessement periods ie. for cramming, had less success academically (Peach et al., 2019). Studies also found that data on student activity on the virtual learning environment from the open university could predict student academic performance and academic success (Heuer & Breiter, 2018; Kuzilek et al., 2018; Hassan et al., 2019). The open university, has a particular dependence on its virtual learning environment as students are restricted to virtual engagement thus the findings may not be replicated in an environment that is dominated by student participation onsite. However, even in a typical university where students participate onsite, usage of the WiFi for educational purposes may be a valuable predictor of student engagement.

In the current research, data which describes the usage of a university WiFi, in 2,563,206 user sessions, are modelled using unsupervised and supervised machine learning. The hybrid approach will be used to identify clusters of users with similar behavior patterns on the WiFi. The study will also predict education engagement from engagement in other activities on the internet. This research uses machine learning to identify user internet behavior patterns to answer the following research questions:

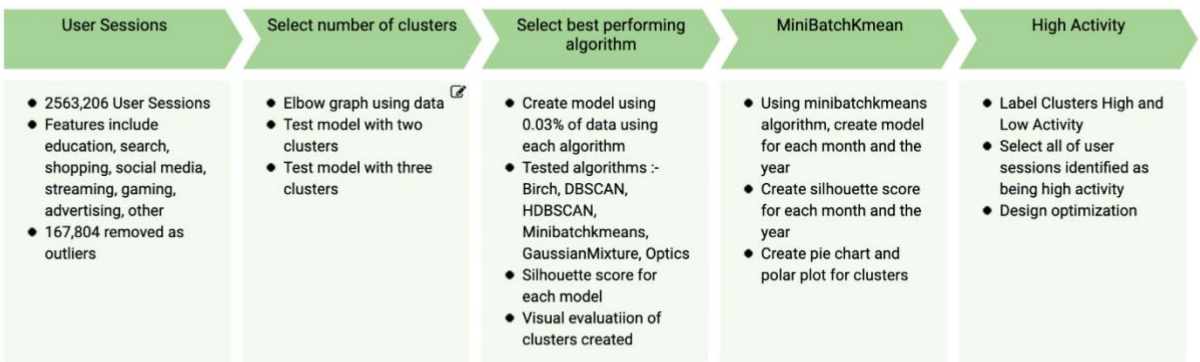
1. Are there groups of users whose behavior pattern of internet usage on a university WiFi distinguishes them from each other?
2. To what extent does the pattern of user WiFi behavior enable prediction of education-related WiFi-activity at university?

6.2 Method

In this study unsupervised and supervised machine learning was used to analyse data on user internet activities collected on a university Wi-Fi over an academic year. The data for this study was cleaned and prepared in a previous study (O'Brien et al., 2022). A total of 2,563,206 user sessions, which describe the internet activities engaged in by 13,000 users on the university WiFi were gathered between September 2018 and May 2019. The method used to analyse this data is described in detail in chapter 3 section 3.3.6. Unsupervised machine learning was used in this study to identify patterns in the data by clustering or grouping data together based on inherent similarities in the data (Saxana et al., 2017). Figure 19. describes at a high level the process to develop an unsupervised machine learning model.

Figure 19

Unsupervised Learning , Identifying Number of Clusters and Selecting Unsupervised Learning Algorithm



MiniBatchKmeans was selected to develop the unsupervised machine learning model, as it was fast and generated useful clusters. A MiniBatchKmeans model was developed for the 2,563,206 individual user sessions on the university WiFi. Two distinct clusters of users were found in the data. The model created had a silhouette score of 5.9 which indicated a good cohesiveness between the user sessions in a group and good distinction from the user sessions in the other group. The group for each user session was identified and added to the data for each user session. The results were graphed using a polar plot and a pie chart, see Figures 20 and 21. The average value for each of the features in its clusters is represented on the polar line chart, see Figure 20 and further detailed in Table 16. The percentage of users in each of the two clusters is represented in the pie chart, see Figure 21. The MiniBatchKmeans unsupervised model, creates two classes of users, one with low general usage and the other with high general usage, see Figure 20. The clusters were given the names high intensity and low intensity to reflect the higher usage and the lower usage that users in the cluster have. Users sessions in the high intensity cluster had a high volume of activity in particular in search, social media and shopping, while user sessions in the cluster labelled low intensity had a low volume of interactions in these categories, see Figure 20. Approximately 18% of the user sessions were identified as high intensity, see Figure 21. The quantity of low intensity user sessions was 2,079,038 while there were 446,250 high intensity user sessions (~18%). sessions. Of the low intensity user sessions only 179,829 (~9%) were involved in average education activity, while 1,899,209 (~91%) were not. Of the high intensity user sessions, 167,020 (~37%) were involved in average education activity, while 279,230 (63%) were not.

Figure 20.

Polar Chart of Characteristics of Flow Intensity of Activities in Clusters Identified

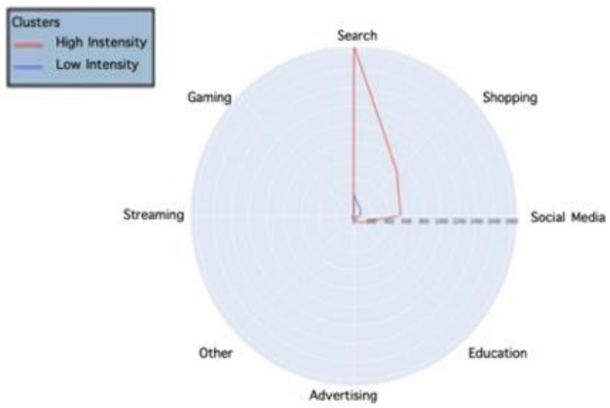


Figure 21.

Percentage of User Sessions in High Intensity (red) and Low Intensity (blue) Clusters

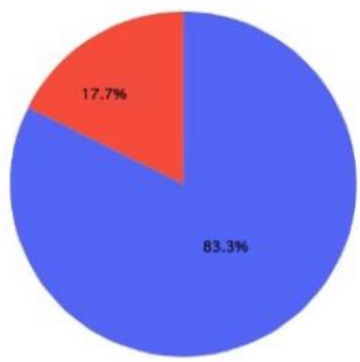


Table 16.

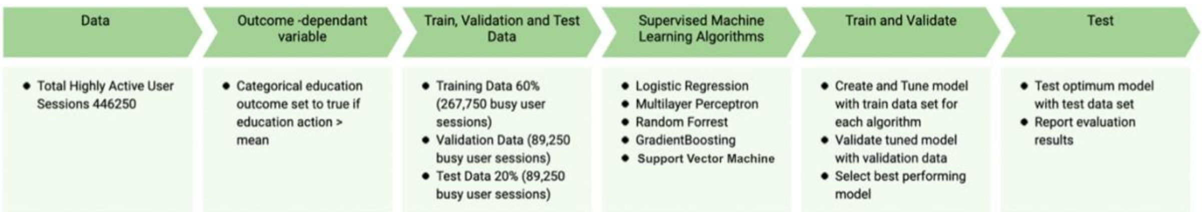
Average Intensity in Features of User Sessions in the Low Intensity and High Intensity Clusters

Cluster	Feature	Average Intensity	Cluster	Feature	Average Intensity
High Intensity	Search	1863	Low Intensity	Search	319
	Social Media	692		Social Media	150
	Shopping	534		Shopping	75
	Education	107		Education	31
	Advertising	38		Advertising	5
	Streaming	12		Streaming	2
	Gaming	7		Gaming	1
	Other	33		Other	7

Using supervised learning, a model was developed to identify average education activity given a previously user session data on search, social media, shopping, advertising, streaming, gaming and other as input. Thus the developed model could identify if usage of WiFi for education activities could be predicted for the users with high intensity usage of the WiFi. The process followed is outlined in Figure 22. A categorical variable was created in a user session that identified if a user engaged with at least the average amount of educational activity. The categorical variable on Education activity was the output of the model or the value the model was trained to predict. The high activity user session data set, on 446,250 user sessions, was split into a training, validation and test data set on a 6:2:2 ratio. Using this ratio avoids introducing bias by overfitting the model (Feurer et al., 2019). A set of models for each of the data set were trained with the training data, 10 fold cross validation and tuned with a set of parameters to find the optimum performing model for each algorithm. Each of the algorithms tested were among those highlighted as most used in predicting academic performance (Sandra et al., 2020), gradient boosting can improve accuracy of a decision tree or linear regression algorithm and was also tested (Fernández-Delgado et al., 2014). SVM is a resource intensive algorithm thus a radial basis function variant was used to manage the big data set when training(Razaque et al, 2021).

Figure 22.

Development of Supervised Machine Learning Model to Predict Education Activity



6.3 Results

Using an unsupervised machine learning model based on the MiniBatchKmeans algorithm on a data set describing the WiFi activity of 13,000 users at a university over an academic year, two distinct patterns of user behavior were identified. Confidence in the unsupervised machine learning model, trained with the MiniBatchKmeans algorithm, which was developed to identify the patterns, was established with a silhouette score = 0.59 and a visual inspection of the clusters using a polar plot and pie chart, see Figure 20 and Figure 21. The polar plot highlighted the characteristics of the user behavior and enabled the labelling of the two clusters identified as 'High intensity' and "Low intensity' see Table 16. The high intensity cluster represented approximately 17.7 % of the user sessions and had higher intensity of activity in all feature categories, while the low intensity cluster represented 82.3% of the user sessions with less internet activity in each category see Figure 21 and Table 16.

High activity users had concentrated activity in search, social media and shopping in particular, see Table 16. Low activity users, although also active in search, social media and shopping, were active at a much lower intensity. The average high activity user was 17.4 times more active in search, 6.5 times more active in social media and five times more active in shopping than in education. The average low activity users were 10 times more active in search, five times more active in social media and 2.3 times more active in shopping relative to education. There were 17.7% of user sessions with the high activity pattern of behavior over the academic year.

The best performing supervised learning model was identified as Random Forrest see Table 17. While both of the models developed using Random Forrest and Gradient Boost performed better than all the models validated with the validation data however Random Forrest had a much faster execution time.

Table 17.

Performance Metrics of Optimum Model Configurations Tested Using Validation Data Set

Model	Accuracy	Precision	Recall	F1 Score – Weighted Average	Number of 0s and 1s in total of 89250 sessions
Logistic Regression(LR)	0.68	0.64	0.34	0.65	55935/33315
Support Vector Machine(SVM)	0.70	0.70	0.67	0.67	55935/33315
Multilayer Perceptron (MLP)	0.70	0.67	0.41	0.68	55935/33315
Random Forest (RF)	0.71	0.67	0.46	0.70	55935/33315
Gradient Boosting (GB)	0.71	0.67	0.46	0.70	55935/33315

The best performing algorithm was selected based on Accuracy (number of correct predictions / total number of predications) and F1 score (harmonic mean of Precision and Recall) as the goal of the model was to identify engagement in education or not effectively. Both the Random Forrest and Gradient Boosting model produced equivalent results for these measures on the validation set and were both used with the test data to determine how effectively they could be expected to predict education activity. The Random Forrest model developed reported Precision = 0.67 (number of true positives / total number of positive predictions), Recall = 0.46 (number of true positives/total number of positives), resulting in F1-score = 0.70 (weighted average of precision and recall). The Gradient boosting model developed reported Precision = 0.67 (number of true positives / total number of positive predictions), Recall of 0.46 (number of true positives/total number of positives), resulting in F1-score = 0.70 (weighted average of precision and recall). The support or number of user sessions with positive education activity were 51,574 and negative were 62,105. In comparison to the baseline performance prediction, all user sessions were not active in education, which had a precision = 0.546. The machine learning model developed effectively identified education activity with an F1-score = 0.70.

Supervised machine learning was used to develop a model with the 446,250 high intensity user sessions. A categorical variable for education identified that 167,020 of those sessions had education activity less than the mean. Of the low intensity user sessions, approximately 9% were involved in average education activity, while 1,899,209 (~91%) were not. Of the total high intensity user sessions, 167,020 (~37%) were involved in average education activity, while 279,230 (63%) were not. The Random Forrest machine learning model that was trained, validated and tested to predict average education activity for high intensity users had an F1 score for accuracy or harmonic mean for accuracy = 0.71, higher than the baseline score 0.546 calculated on the prediction that all high activity user sessions are not involved in education.

6.4 Discussion

The research used machine learning to identify internet behavior patterns at an institutional level. The research found groups of users whose behavior pattern of internet usage on a university WiFi distinguished them, high intensity users were distinguished from low intensity users. The research also found it was possible to predict of education-related WiFi-activity in the university from other internet activities on the WiFi. A supervised machine learning model developed from the data on high intensity users enabled prediction of education activity on the WiFi from WiFi activity in other areas. Using the model it was possible to predict with 71% accuracy education activity for the high intensity users.

Digital traces gathered from a university WiFi over an academic year were used to train an unsupervised machine learning model. The model identified two clusters of internet users on the university WiFi, high intensity and low intensity. This research highlighted that 17.7% of WiFi user behavior can be categorised as high intensity, and high intensity usage is identified by particularly high usage in search, social media and shopping activities. The pattern of engagement in non-education activities identified in the characteristics of the user behavior may be of concern in a university environment where there is an expectation of high activity in education to support academic learning. Previous research has found a similar pattern of user behavior on the internet although on a much smaller dataset, where 25% of 504 users' internet behavior fell into the high intensity category (Vayre & Vonthron, 2019). Overuse of the internet is a risk for problematic internet use (PIU), and those users with a high intensity usage pattern could be at risk of PIU. Identification of high intensity internet users in a university environment could enable universities to estimate the need for supports in the university to ensure users are using the internet in a way that promotes their wellbeing and academic performance. Quantifying the percentage of users in the high intensity category could also support universities quantifying the amount of resources needed to address potential PIU. The effectiveness of supports that are introduced could also be measured by analysing data from digital traces after the supports have been implemented, comparing the results with the results from before the supports were implemented and examining the percentage that remain at risk and the characteristics of the behavior patterns for change.

A high intensity user was at least four times more active in each category of internet use on the WiFi than a low intensity user. A high intensity user was on average 17 times more active in search than education, six times more active in social media than education and five times more active in shopping than in education, supporting previous findings on analysis of behavior on WiFi in this university (O'Brien et al., 2022). Thus, it appears that activity for high intensity users on a university WiFi is not in education and universities should evaluate whether ubiquitous access to the WiFi in university supports students achieving their educational objectives.

Approximately 37% of the users with high activity were likely to be involved in the average amount of education activity, while 9% of users with low activity were likely to be engaged in the average amount of education activity. In determining if it was possible to predict education activity in the high intensity group, a supervised machine learning model using a random forest algorithm was developed. The model predicted activity in education for high intensity users based on their activity in other areas on the WiFi with 71% accuracy. Other research has found that student activity on online education resources, such as virtual learning environments, can predict student withdrawal (Kuzilek et al., 2018; Hassan et al., 2019) or predict academic performance (Heuer & Breiter, 2018). Previous research was based on open university data and demonstrated that machine learning could be effectively used with measures of student engagement for prediction of academic performance or withdrawal in a university which exists exclusively online. In the current study data was generated by students who engage in the university both onsite and online and related to the full suite of internet activities rather than just activity on the virtual learning environment. Students who are not engaging in educational activities on the university WiFi may still be at risk of withdrawal or reduced academic performance. Lack of engagement with education activities on the internet by high intensity internet users found in this study may also be a risk for poorer academic performance as found in previous studies (Kuzilek et al., 2018; Hassan et al., 2019). Identification of those with high intensity usage of a university WiFi but who do not engage significantly in education activities on the WiFi may enable universities an opportunity to look for ways to engage these users.

6.5 Limitations

A key limitation of this research is the restriction of the analysis to internet behavior on the university WiFi. In a university, users are likely also to be accessing the internet using their telecom network access provider and the university's fixed network. This research is limited to one access point to the internet however would give a more accurate picture of a user's behavior if it considered all three.

6.6 Conclusion

Analysis of actual user behavior on a university environment identifies two distinct categories of users, high intensity and low intensity. Approximately 18% of user sessions are high intensity. A high intensity user is at least four times more active than a low intensity user and at least five times more active in search, shopping and social media than in Education. Quantifying the percentages of users in each category and describing the characteristics of users in each category gives an overview of internet behavior on a university WiFi.

This analysis of behavior a university WiFi could enable universities to identify the percentage of users at risk of PIU in the institution. Thus, identifying a risk for student wellbeing and academic performance. Prediction of high intensity WiFi users' engagement in education could also enable identification of users at risk of withdrawal. Behavior on a university WiFi could enable universities to estimate supports required to manage PIU and also measure performance of those supports.

This research contributes to the general understanding of internet use patterns by using objective data on actual behavior to identify two distinct patterns of internet use on a university WiFi over an academic year. The percentage of user sessions in each category is also quantified. Thus, establishing a baseline of a pattern of behavior on the internet using objective data. This research finds that it is possible to predict education activity from activities in other areas on the internet suggesting that other activities on the WiFi may be a distraction from academic activities. Hence providing ubiquitious access to these activities in a university environment with WiFi may not benefit student's academic performance and increase the risk of PIU. Having investigated the patterns of actual user behavior on a university WiFi and student self-assessment of the behavior, in the final chapter the research aims, outcomes and achievements are reviewed and summarised.

Chapter 7. General Discussion

7.1 Summary of Research Aims

Internet use has become central to education and academic work, so much so that during the Covid-19 pandemic, many universities and colleges moved exclusively to online delivery of education (Qazi et al., 2020). However, there can be negative consequences from overuse. PIU can have a variety of detrimental outcomes for students. This doctoral research project aimed to understand patterns of behavior on the internet in a university environment and the relationships between PIU, wellbeing, loneliness and FOMO for students. To identify patterns in internet activity in the university, data on all of the activity on the university WiFi over an academic year was gathered and analysed. The analysis highlighted patterns of internet behavior that had not been previously identified in psychology research. The prevalence of PIU in the student body and the relationship of PIU to wellbeing, FOMO and loneliness in the student body were assessed using survey data gathered from the student body. The survey included psychometric tests on general PIU, problematic smartphone use, problematic social media use, problematic pornography use, problematic gaming, wellbeing, loneliness and FOMO. The inter-relationships between the PIU subtypes, wellbeing, loneliness and FOMO were investigated using a partial correlation network and variance partitioning. By examining actual behavior of users on the internet and self-assessment data from a subset of the same users, it was possible to get a comprehensive overview of patterns of internet behavior and the indications of PIU in a university. The research findings were interpreted using the I-PACE model (Brand et al., 2019) which offered an explanation of the associations between the PIU subtypes, wellbeing, loneliness and FOMO in a behavioral addiction model.

7.2 WiFi at University: A Better Balance between Education Activity and Distraction Activity Needed.

In the first study, presented in Chapter 4, unobtrusive passive monitoring gathered a vast amount of data on actual user behavior on the internet from a university WiFi over an academic year. A need for more research on internet use behavior based on objective data had previously been identified (Ryding & Kuss, 2020). The WiFi behavior was examined using data on more than two and a half million user sessions from the university WiFi. The scope and scale of the data gathered in the study illuminated patterns of user internet behavior not previously identified. To identify the patterns of behavior in internet activity, it was necessary to classify the types of activities the users were engaging in. Internet activity on websites that shared a purpose were labelled with a classification, e. g., 'Search' for activity on 'Google' or 'Bing', 'Shopping' for activity on 'Amazon' or 'Ebay' and 'Social Media' for activity on 'Facebook' or 'Twitter'. The analysis of internet activity on the university WiFi confirmed the findings of Gill et al. (2011) that much of the network traffic in an organisation is directed to and from a small number of websites. Principal Components Analysis (PCA) was used to identify the most important dimensions of users' behavior. Distraction was the label used to describe internet activities in search, social media and shopping, activities that were not directly related to education, which is expected to be the focus in a university. Over the year and relative to use for education, users were 10 times more active in search, four times more active in social media and three times more active in shopping. Excessive time on distraction activity on the internet has been found to have negative effects in previous research (Elhai et al., 2019; Think Tank European Parliament, 2019). The study also found that an increase in education activity was linked to reduced social media activity. Previous research had already identified a negative relationship between Facebook usage and academic performance, which may be explained by the negative correlation between social media and education which was found in this research (Busalim et al., 2019; Rouis et al., 2011). Use of the WiFi predominately for distraction and overuse of social media particularly on a university WiFi is of concern in educational institutions (Elhai et al., 2017; Price & Smith, 2019). The study highlights the need for innovations in institutional and governmental mechanisms to reduce internet harm including regulation (Kuss, 2021; Lee et al., 2019). By understanding WiFi behavior, universities are better able to introduce policies to manage behavior or consider other mechanisms such as education programs to encourage WiFi users to focus on education and avoid potentially PIU (Lee et al., 2019; Throuvala et al., 2018).

7.3 Problematic Internet Use Understood using the I-PACE model, Partial Network Correlation and Variance Partitioning

The second study, in Chapter 5, was a phenomenological exploration of the correlations in the subtypes of PIU, general PIU, problematic smartphone use, problematic social media use, gaming, pornography and wellbeing, loneliness and FOMO. Data from a survey of 834 students in the same university as the objective data were gathered were collected and analysed. The survey included psychometric tests on PIU subtypes, general problematic internet use, problematic smartphone use, problematic social media use, problematic gaming, and problematic pornography use, as well as psychometric tests on wellbeing, loneliness and FOMO. Analyses were performed on the data for males and females separately, as significant differences in the levels of problematic smartphone use, problematic social media use, problematic gaming, problematic pornography use and FOMO for the sexes were identified. Although there has previously been much research on the subtypes of PIU and their relationship with wellbeing, loneliness and FOMO, the relationships between the PIU subtypes and the other assessed variables were not clear.

This research leveraged a partial correlation network and variance partitioning analysis. The partial correlation networks and variance partitioning used in this study extended existing knowledge with a coherent network representation of the relationships between PIU subtypes and wellbeing, loneliness and FOMO. The partial correlation network was useful to identify commonalities and differences in the associations between the nodes in the networks of relationships for males and females. A latent variable linking general PIU, problematic social media use and problematic smartphone use and FOMO identified a pattern of associations which was similar for both males and females. The latent variable was interpreted using the I-PACE model (Brand et al., 2019). The associations were explained using the model, as students may use their smartphones to access the internet, engage in social media or general internet use, which may generate FOMO. The experience of FOMO may lead to decisions to use social media or internet activity to reduce FOMO. The internet activities may result in gratification which leads to further use of the internet, and through instrumental conditioning, the use may develop into PIU in an addictive process (Brand et al., 2019). Graph theory centrality estimates, generated from the partial correlation network identified problematic social media use and general PIU as the most influential nodes in the network of relationships. Problematic social media use and general PIU nodes had the greatest expected influence, strength, betweenness and closeness of all nodes in the network for both males and females. However, differences were also identified. When considering supporting males who are dealing with PIU and low wellbeing (including loneliness), general PIU in particular should be a focus for interventions. For females, social media use should be of particular concern and a focus for interventions.

The findings in this research suggest high levels of problematic smartphone usage, general PIU, problematic social media usage, loneliness and below average wellbeing in the student body surveyed. These findings suggest that students may need to be supported in order to effectively manage social media usage, their general internet use and smartphone use. This study re-emphasises the need identified in the first study for innovations in institutional and governmental mechanisms to reduce internet harm including regulation (Kuss, 2021; Lee et al., 2019). By understanding the level of PIU and the types of PIU and the relationships with wellbeing, loneliness and FOMO, institutions are better able to develop policies to manage behavior or consider other mechanisms such as education programs to develop awareness and avoid potential PIU (Lee et al., 2019; Throuvala et al., 2018). By clarifying the differences between the relationships for males and females beyond the significant differences reported in the levels of PIU, this study differentiates areas of particular concern for men and women that may require additional support.

7.4 University WiFi Activity Modelling and Analysis to Identify Behavior Patterns and Predict Education Usage

In the third study, presented in chapter 6, WiFi behavior was examined, using the data on more than two and a half million user sessions on the university WiFi, which were gathered in the first study. Using unsupervised machine learning, two distinct clusters of user sessions were identified. The clusters represented groups of user sessions based on two distinct patterns of behavior. The clusters were labelled as high intensity and low intensity. There were 17.7% of the user sessions in the cluster labelled as high intensity. The high intensity users were at least four times more active in each category of internet use on the WiFi than low intensity users. A high intensity user on the university WiFi was on average 17 times more active in search than in education, had 6.5 times higher activity in social media than education, and five times higher activity in shopping than in education, supporting previous findings on behavior on the WiFi in this university (O'Brien et al., 2022). Quantifying the percentages of user sessions that are classified as high intensity and low intensity and describing the characteristics of users in each classification identifies the patterns of internet behavior on a university WiFi. A high intensity user of the WiFi is a user whose use may be problematic. Previous research has found a similar pattern of user behavior on the internet, although on a much smaller dataset, identifying 25% of 504 users whose internet behavior was classified as high intensity (Vayre & Vonthron, 2019). Analysis of behavior on a university WiFi in this way can enable universities to estimate the percentage of users at risk of PIU in the institution.

Using the high intensity user sessions, a supervised machine learning model was developed to predict a user's education activity on the WiFi from other activity on the WiFi. The model predicted activity in education for high intensity users based on their activity in other areas on the WiFi with 71% accuracy. Other research has found that student activity on online education resources, such as virtual learning environments, can predict student withdrawal (Kuzilek et al., 2018; Hassan et al., 2019) or predict academic performance (Heuer & Breiter, 2018). Lack of engagement with education activities on the internet may be a risk for poorer academic performance (Kuzilek et al., 2018; Hassan et al., 2019). Analysis of user behavior on a university WiFi and prediction of lack of engagement with education activities may enable universities at an institutional level to develop policies to deliver infrastructure in particular access to the internet in such a way that supports student academic performance and wellbeing.

7.5 The I-PACE model

The Interaction Person Affect Cognitive Execution (I-PACE) (Brand et al., 2019) is a model which outlines the processes underlying development and maintenance of behavioral addictions. The present research does not provide any indication about predisposing factors as no longitudinal analyses were performed. However, relationships were identified which could be either cause or effect. Predisposing factors for PIU development and maintenance may be psychological or biological. The associations between PIU and gender suggest gender may predispose to PIU as gender cannot be affected by PIU. The links between PIU and loneliness, reduced wellbeing and/or FOMO suggest they may predispose to PIU or be an effect of PIU. Factors such as cognitive reactions to situational triggers may affect choices to use the internet. Other factors, such as cognitive and attentional biases, may also affect the choice to use the internet as a coping strategy. Gratification or compensation when using the internet to alleviate loneliness or FOMO or to distract from offline life stresses offer an explanation for the associations found with PIU in this research. PIU subtypes, particularly social media and general PIU, are associated with other PIU subtypes, FOMO, loneliness and wellbeing. Compulsive use of the internet may be linked with reduced inhibitory control and may be enabled by cheap and easy access to the internet. The I-PACE model (Brand et al., 2019) can frame findings on PIU to enable greater understanding. The treatment of PIU should be focused on potential mediating and moderating factors according to previous research (Elhai, Yang, Dempsey et al., 2020). While cause and effect or moderators and mediators were not established in this research, the factors general PIU and problematic social media use were identified as central factors in the network of relationships between PIU subtypes and wellbeing, loneliness and FOMO and as such could be the focus of treatment of PIU.

7.6 Limitations

Several limitations in this research were identified. This succinct summary section will highlight a number of those, over and above the ones presented in each of the empirical chapters. The present research is cross-sectional and therefore offers insights into the associations between the assessed variables, and does not determine causal relationships. Research efforts that would establish the direction of the relationships between the variables examined in this research are needed to shed further light upon the etiology of PIU and the relationships between PIU and wellbeing, loneliness and FOMO.

In this research, the pattern of behavior of individual users on the university WiFi and the student response to the psychometric survey were not linked. This link could have enabled other valuable insights and comparisons of a particular individual's actual behavior and the individual's self-assessment of the behavior.

7.7 Future research

Problematic social media use was found as the most influential node in the network of relationships between PIU subtypes and wellbeing, loneliness and FOMO from the survey data. Reasons for and consequences of this influence need to be further discerned. This research also found an inverse relationship between social media Wi-Fi use and educational Wi-Fi use in the pattern of actual behavior. The inverse relationship suggests that those who use social media attend to educational activities less or vice versa. To establish whether this is in fact the case, further research is required.

The potentially negative effects of problematic general internet use on loneliness and wellbeing are another avenue for study. This research project has indicated that general PIU is central in the network of relationships between PIU subtypes. The research also found that general PIU was directly linked to reduced wellbeing and increased loneliness in student populations. In order to establish whether this is indeed the case, additional research is required. Research could link individual actual internet behavior with self-assessment data to further explore the relationships. The research highlighted that for males the variance in wellbeing and loneliness that was explained by the interaction between general PIU and wellbeing or general PIU and loneliness was twice that for females. Research into the effect of general PIU on males and the associations with reduced wellbeing or increased loneliness could further explain this finding.

A number of relationships which existed for females that did not exist for males could be further investigated. The negative correlation between problematic smartphone use and loneliness for females could be investigated to determine if problematic smartphone use can reduce loneliness for females or vice versa. This research also found an inverse relationship between problematic social media use and problematic gaming and between problematic pornography use and problematic gaming; relationships that could be further examined and understood. Problematic gaming may be less likely to be an issue for females who have issues with problematic social media use or problematic pornography or vice versa. The negative correlations between these variables in particular would benefit from further scientific evaluation.

7.8 Implications

This research has implications for prevention, research, and clinical practice. This doctoral research project elucidates the level of PIU in university students and the phenomenology of PIU in university students. The research investigates and clarifies the relationships between PIU and student wellbeing, loneliness and FOMO. The research has also illuminated the pattern of actual internet behavior of users of the WiFi in a university environment and identified aspects of that behavior that may put people at risk of PIU. Thus, this research highlights the need to consider PIU or excessive use of the internet in a university environment as PIU can result in significant impairment and distress for some individuals and generally negative consequences (Brey & Gauttier, 2019).

The research findings suggest that university WiFi is principally used for distraction activities and thus expected educational benefits may not be achieved. Excessive use of the internet for distraction is a potential harm for students. While internet use is central to education, using it so that it promotes student wellbeing and improves student academic behavior is critical. The present research suggests that Universities need to re-consider how WiFi is delivered to students, how it is used and the extent to which providing ubiquitous access to the internet is beneficial to students. The negative link found in this research between education activity and social media activity, which supports previous findings, is of concern. It was concerning that on a university WiFi over 90% of all social media use consisted of Meta-controlled sites. Facebook use, in particular, has been linked to reduced academic performance (Busalim et al., 2019; Feng et al., 2019). Measures are required to reduce distraction activity and increase educational activity by users of WiFi in Universities. Universities could consider practical solutions to reduce internet distraction, such as education programs to develop awareness of the risks of Problematic Internet Use (PIU) and/or filtering, blocking or time limiting use of distraction-related websites on a university WiFi and/or restricting availability of WiFi to particular locations on the university campus.

This research found high levels of PIU, a large percentage of students with reduced wellbeing and a very high percentage of students that were lonely. Most students surveyed felt that internet use did not benefit their physical health and approximately half felt it did not benefit their mental health. PIU has been found to generally adversely affect student wellbeing (Casale et Fioravanti, 2011; Elhai et al., 2021; Elhai et al., 2018; Hebebci & Shelley, 2018; Reer et al., 2019; Stead & Bibby, 2017) and academic performance (Truzoli, 2019). The level of PIU, the percentage of university students with wellbeing below par, and the level of loneliness and FOMO identified in this study suggest that university students may need to be supported in order to effectively manage social media usage, their general internet use and smartphone use. Managing problematic social media use and general PIU in particular could positively affect wellbeing and negatively affect loneliness and FOMO. Thus, universities need to consider how the internet resources they provide are used, the level of PIU in the student body, how PIU affects university students' wellbeing and academic performance and how students with potential PIU are supported.

The recognition of the existence of PIU in university students and recognition of the potential negative consequences for students in particular on their level of loneliness and wellbeing can serve as evidence to highlight a need to develop and initiate targeted preventions and focused support initiatives. These can be informed by the findings of the present research, as it has indicated that (i) high levels of general PIU, problematic social media use and problematic smartphone use exist in student populations, (ii) PIU is associated with lower wellbeing, increased loneliness and FOMO, (iii) there are two distinct patterns of internet usage on a university Wifi; almost 20% of user sessions highlight a high intensity pattern of usage, (iv) it is possible to predict internet education activity from other internet activities in a university environment, (v) there is an inverse relationship between social media use and education activity on a university WiFi, (vi) the vast majority of activity on a university WiFi consists of distraction activity, (vii) commercial for profit entities host the vast amount of interactions on university WiFi. All of the research findings indicate that focused management and support to address PIU in university students is needed and such supports could promote student wellbeing and academic success.

As previously stated, the high level of PIU reported by students highlights the need for innovations in institutional and governmental mechanisms to reduce internet harm including regulation (Kuss, 2021; Lee et al., 2019). Support for students in education institutions may include policies to manage behavior or other mechanisms, such as education programs to encourage WiFi users to focus on education (Lee et al., 2019; Throuvala et al., 2018). The clarification of the relationships between PIU subtypes, wellbeing, loneliness and FOMO will allow clinicians to consider the nuances of PIU in males and females and the relationships with wellbeing, loneliness and FOMO and thus, offer more focused treatment for PIU, reduced wellbeing, loneliness and FOMO.

The analysis of actual behavior performed in this study can enable institutions to approximate the percentage of students in an institution that are at risk of PIU. The percentage of users at risk of PIU can be estimated using the percentage of WiFi sessions that are of high intensity. Changes in the percentage of user sessions that indicate high activity or a pattern of usage of high activity users can measure the potential impact of support aimed to reduce PIU at an institutional level.

From a mental health perspective, it is important to identify the factors that contribute to the risk of PIU and also recognise those factors that have a protective function. Ultimately, this research furthers a general understanding of why and how PIU is developed and maintained. The findings can facilitate the initiation of targeted and more nuanced support that is focused where it may be effective. These findings may help policy efforts in universities to prevent PIU when considering how best to protect students. Initiatives to improve student wellbeing and/or loneliness could also have a positive effect on general PIU, problematic social media use and problematic smartphone use. Many factors that affect student loneliness, wellbeing and FOMO would be beyond the scope of a university to address. However, it could be expected that support to help manage general PIU and problematic social media usage could be provided. The findings in this research suggest that increased general PIU and problematic social media usage are a cause or an effect or both cause and effect of increased loneliness, reduced wellbeing and increased FOMO. Effective support to enable university students to manage general PIU and problematic social media usage could have broad and very positive benefits.

Existing research on prevention of PIU suggests an individual's environment, social factors and individual thought and behaviour should be considered as well as promoting harm-reducing factors (Lee et al., 2019). Environmental actions could include legislation to define acceptable strategies to attract and maintain an individual's attention on the internet. Although technology companies are likely to be opposed to regulation, measures to reduce internet harm including regulation may be necessary (Kuss, 2021; Lee et al., 2019). By recognising patterns in users' activity on the university WiFi, universities may better understand their students behavior on the internet and its potential impacts. Where necessary universities could introduce focused policies to limit distraction activity or consider other mechanisms, such as education programs to encourage focus on education (Lee et al., 2019; Throuvala et al., 2018).

The need for an official content taxonomy to categorise the website content for all websites was also identified in this research. Identification of a website's purpose and content could have many positive effects when analysing behavior patterns, and could enable effective screening options for institutions, students and others. Government policy, creating an official content taxonomy and requiring website providers to register the purpose of their website using the taxonomy when making a website accessible on the internet could ensure correct identification of a website's purpose with certainty, in a way that is not currently possible.

7.9 Final remarks

This doctoral research project emphasised the importance of understanding internet use and the potential relationships with wellbeing, loneliness and FOMO in universities. PIU in this research was understood as a behavioral pattern of internet use marked by preoccupation and unregulated overuse with negative consequences not accounted for by any other disorder (Kuss & Pontes, 2019). In this research university students reported high levels of problematic smartphone use, problematic social media use and general problematic internet use. In analysis of the patterns of actual internet behavior of the student body approximately 20% had a high intensity pattern of behavior that highlighted potential for PIU and the general pattern of internet use was unlikely to provide educational benefits. The student body reported high levels of loneliness and reduced wellbeing. Analysis of the data from the student survey identified links between PIU and wellbeing and loneliness. Given the negative consequences of PIU, the high levels of PIU reported, the concerning patterns of actual internet behavior identified, universities need as a matter of urgency to consider measures to address potential PIU in students.

References

Adiele, I., & Olatokun, W. (2014). Prevalence and determinants of Internet addiction among adolescents. *Computers in Human Behavior*, *31*(1), 100–110. https://doi.org/10.11016/j. chb2013.10.028

Aggarwal, C. C., & Reddy, C. K. (2013). *Data Clustering: Algorithms and Applications (Chapman & Hall/CRC Data Mining and Knowledge Discovery Series)* (1st ed.). Chapman and Hall/CRC.

Akbulut, Y, Dursun, Z. Z., Dönmez, O., & ŞAhin, Y. L. (2016). In search of a measure to investigate cyberloafing in educational settings. *Computers in Human Behavior*, *55*, 616–625. https://doi.org/10.1016/j.chb.2015.11.002

Albert, G., & Lotan,T. (2018). How many times do young drivers actually touch their smartphone screens while driving?, *IET Intelligent Transport Systems, 12*(6), 414-419, doi.org/10.1049/iet-its2017.0208

American Psychiatric Association. (2013). *Diagnostic and Statistical Manual of Mental Disorders, 5th Edition: DSM-5* (5th ed.). American Psychiatric Publishing.

Andión, J., Navarro, J. M., López, G., Álvarez-Campana, M., & Dueñas, J. C. (2018). Smart behavioral analytics over a low-cost IoT WiFi tracking real deployment. *Wireless Communications and Mobile Computing*, *1*(24). doi:10.11155/2018/3136471

Andrade, A. L. M., Scatena, A., Martins, G. D. G., Pinheiro, B. de O., Becker da Silva, A., Enes, C. C., & Kim, D. J. (2020). Validation of smartphone addiction scale - short version (SAS-SV) in Brazilian adolescents. *Addictive Behaviors*.1*10*(1). 106540.110.11016/j. addbeh2020.106540.

Andreassen, C. S., Pallesen, S., & Griffiths, M. D. (2017). The relationship between addictive use of social media, narcissism, and self-esteem: Findings from a large national survey. *Addictive Behaviors*, *64*, 287–293. https://doi.org/10.11016/j. addbeh2016.03.006

Andreassen, C. S., TorbjØrn, T., Brunborg, G. S., & Pallesen, S. (2012). Development of a Facebook addiction scale. *Psychological Reports*, *110*(2), 501–517. https://doi.org/102466/02.09.18. PR0.1102.501-517

Andreetta, J., Teh MSc, 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/10.11111/appy.12387

Andrie, E. K., Tzavara, C. K., Tzavela, E., Richardson, C., Greydanus, D., Tsolia, M., & Tsitsika, A. K. (2019). Gambling involvement and problem gambling correlates among European adolescents: results from the European network for addictive behavior study. *Social Psychiatry and Psychiatric Epidemiology*, *54*(11), 1429–1441. https://doi.org/10.11007/s00127-019-01706-w

Aparicio-Martínez, P., Ruiz-Rubio, M., Perea-Moreno, A. J., Martínez-Jiménez, M. P., Pagliari, C., Redel-Macías, M. D., & Vaquero-Abellán, M. (2020). Gender differences in the addiction to social networks in the Southern Spanish university students. *Telematics and Informatics*, *46*, 101304. https://doi.org/10.11016/j. tele2019.101304

Arpaci, I. (2020). Gender differences in the relationship between problematic internet use and nomophobia. *Current Psychology*. https://doi.org/10.1007/s12144-020-01160-x

Armstrong J. (2013) Positivism and constructivism. In: *Improving International Capacity Development. Palgrave Macmillan, London*. https://doi.org/10.11057/9781137310118_3

Association for Higher Education and Disability. (2016). Mental Health Matters - Mapping Best Practices in Higher Education. https://www. ahead.ie/userfiles/files/shop/free/Mental-Health-Matters-%20Online. pdf

Atluri, G., Karpatne, A., & Kumar, V. (2018). Spatio-temporal data mining. A*CM Computing Surveys, 51*(4), 1-41. doi:10.11145/3161602

Atroszko, P. A., Balcerowska, J. M., Bereznowski, P., Biernatowska, A., Pallesen, S., & Schou Andreassen, C. (2018). Facebook addiction among Polish undergraduate students: Validity of measurement and relationship with personality and wellbeing. *Computers in Human Behavior*, *85*, 329–338. https://doi.org/10.11016/j. chb2018.04.001

Babbage, C. (2020). Passages from the Life of a Philosopher. Independently published.

Bagby, R. M., Parker, J. D., & Taylor, G. J. (2020). Twenty-five years with the 20-item Toronto Alexithymia Scale. *Journal of Psychosomatic Research*, *131*, 109940. https://doi.org/10.1016/j.jpsychores.2020.109940

Baker, R. W., & Siryk, B. (1984). Measuring adjustment to college. *Journal of Counseling Psychology, 31*(2), 179–189. https://doi.org/10.1037/0022-0167.31.2.179

Bakioğlu, F. (2020). Internet addiction and social self-efficacy: The Mediator Role of Loneliness. *Anales de Psicología*, *36*(3), 435–442. https://doi.org/10.6018/analesps.394031

Balcerowska, J. M., Bereznowski, P., Biernatowska, A., Atroszko, P. A., Pallesen, S., & Andreassen, C. S. (2020). Is it meaningful to distinguish between Facebook addiction and social networking sites addiction? Psychometric analysis of Facebook addiction and social networking sites addiction scales. *Current Psychology*, *41*(2), 949–962. https://doi.org/10.1007/s12144-020-00625-3

Baloğlu, M., Şahin, R., & Arpaci, I. (2020). A review of recent research in problematic internet use: Gender and cultural differences. *Current Opinion in Psychology, 36,* 124–129. https://doi.org/10.11016/j. copsyc2020.05.008

Bányai, F., Zsila, G., Király, O., Maraz, A., Elekes, Z., Griffiths, M. D., Andreassen, C. S., & Demetrovics, Z. (2017). Problematic Social Media Use: Results from a Large-Scale Nationally Representative Adolescent Sample. *PLOS ONE*, *12*(1), e0169839. https://doi.org/10.1371/journal.pone.0169839

Baron, R. S. (1986). Distraction-conflict theory: Progress and problems. *Advances in experimental social psychology, 19*, 1-40. https://doi.org/10.1016/S0065-2601(08)60211-7

Barrat, A. & Barthelemy, Marc & Pastor-Satorras, Romualdo & Vespignani, Alessandro. (2004). The architecture of complex weighted networks. *Proceedings of the National Academy of Sciences of the United States of America. 101*(11). 3747-52.110.11073/pnas.0400087101.

Beck, A. T. (1967). *Depression: Clinical, Experimental, and Theoretical Aspects* (1st ed.). Hoeber Medical Division, Harper & Row.

Beck, A. T., Steer, R. A., & Brown, G. K. (1996). Manual for the Beck depression inventory-II. *San Antonio, TX: Psychological Corporation*.

Behfar, K., & Okhuysen, G. A. (2018). Perspective—discovery within validation logic: Deliberately surfacing, complementing, and substituting abductive reasoning in hypothetico-deductive inquiry. *Organization Science*, *29*(2), 323–340. https://doi.org/10.11287/orsc2017.1193

Bem, S. L. (1974). The measurement of psychological androgyny. *Journal of Consulting and Clinical Psychology*, *42*(2), 155–162. https://doi.org/10.1037/h0036215

Bertz, J. W., Epstein, D. H., & Preston, K. L. (2018). Combining ecological momentary assessment with objective, ambulatory measures of behavior and physiology in substance-use research. *Addictive Behaviors, 83*, 5-17. doi:10.11016/j. addbeh2017.11.027

Bhargava, V. R., & Velasquez, M. (2020). Ethics of the attention economy: The problem of social media addiction. *Business Ethics Quarterly*, 1–39. https://doi.org/10.11017/beq2020.32

Bhushan, N., Mohnert, F., Sloot, D., Jans, L., Albers, C., & Steg, L. (2019). Using a Gaussian graphical model to explore relationships between items and variables in environmental psychology research. *Frontiers in Psychology 10.* https://doi.org/10.3389/fpsyg2019.01050

Bienhold, C., Pop Ristova, P., Wenzhöfer, F., Dittmar, T., & Boetius, A. (2012): Biogeochemical measurements associated to deep-sea wood falls. *PANGAEA*. https://doi.org/10.11594/PANGAEA.802516 Supplement to: Bienhold, C et al. (2013): How deep-sea wood falls sustain chemosynthetic life. *PLoS ONE, 8*(1), e53590. https://doi.org/10.11371/journal. pone.0053590

Billieux, J., van der Linden, M., & Rochat, L. (2008). The role of impulsivity in actual and problematic use of the mobile phone. *Applied Cognitive Psychology*, *22*(9), 1195–1210. https://doi.org/10.1002/acp.1429

Blasi, M. D., Giardina, A., Giordano, C., Coco, G. L., Tosto, C., Billieux, J., & Schimmenti, A. (2019). Problematic video game use as an emotional coping strategy: Evidence from a sample of MMORPG gamers. Journal of Behavioral Addictions, 8(1), 25–34. https://doi.org/10.11556/2006.82019.02

Boccaletti, S., Latora, V., Moreno, Y, Chavez, M. & Hwang, D. U. (2006) Complex networks: Structure and dynamics. *Physics Reports, 424*, 175-308. http://dx.doi.org/10.11016/j. physrep.2005.10.009

Borcard, D., Legendre, P., & Drapeau, P. (1992). Partialling out the spatial component of ecological variation. *Ecology*, *73*(3), 1045–1055. https://doi.org/10.2307/1940179

Bőthe, B., Tóth-Király, I., Zsila, Á., Griffiths, M. D., Demetrovics, Z., & Orosz, G. (2018). The development of the problematic pornography consumption scale (PPCS). *Journal of Sex Research*, *55*(3), 395–406. https://doi.org/10.11080/00224499.2017.1291798

Brand, M., Wegmann, E., Stark, R., Müller, A., Wölfling, K., Robbins, T. W., & Potenza, M. N. (2019). The Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors: Update, generalization to addictive behaviors beyond internet-use disorders, and specification of the process character of addictive behaviors. *Neuroscience and Biobehavioral Reviews*, *104*(May), 1–10. https://doi.org/10.11016/j.neubiorev2019.06.032

Brand, M., Young, K. S., Laier, C., Wölfling, K., & Potenza, M. N. (2016). Integrating psychological and neurobiological considerations regarding the development and maintenance of specific

Internet-use disorders: An Interaction of Person-Affect-Cognition-Execution (I-PACE) model. *Neuroscience & Biobehavioral Reviews*, *71*, 252–266. https://doi.org/10.1016/j.neubiorev.2016.08.033

Brey, P. & Gauttier,S (2019). *Harmful internet use part II: Impact on culture and society.* Think Tank European Pariliment.

Brinker, J. K., & Dozois, D. J. (2009). Ruminative thought style and depressed mood. *Journal of Clinical Psychology*, *65*(1), 1–19. https://doi.org/10.1002/jclp.20542

Busalim, A. H., Masrom, M., & Binti Wan Zakaria, W. N. (2019). The impact of Facebook Addiction and self-esteem on students' academic performance: A multi-group analysis. *Computers & Education*, *142*, 103651. https://doi.org/10.1016/j.compedu.2019.103651

Busch, P. A., & McCarthy, S. (2021). Antecedents and consequences of problematic smartphone use: A systematic literature review of an emerging research area. *Computers in Human Behavior*, *114*, 106414. https://doi.org/10.1016/j.chb.2020.106414

Camacho, J., McDonald, C., Peterson, R., Zhou, X., & Kotz, D. (2020). Longitudinal analysis of a campus Wi-Fi network. Computer Networks, 170, 107103. https://doi.org/10.1016/j.comnet.2020.107103

Campbell, A. (1976). Subjective measures of well-being. *American Psychologist, 31*(2), 117–124. https://doi.org/10.1037/0003-066X.31.2.117

Canales, K. (2020, Sep 19). 11 things you can do to stop being manipulated by your phone, according to the tech experts on Netflix's 'The Social Dilemma'. Business Insider https://ntu. idm. oclc. org/login?url=https://University -proquest-com. ntu. idm. oclc. org/newspapers/11-things-you-can-do-stop-being-manipulated-your/docview/2444126944/se-2?accountid=14693

Cangelosi, R., & Goriely, A. (2007). Component retention in principal component analysis with application to cDNA microarray data. *Biology Direct 2*(2). https://doi.org/10.11186/1745-6150-2-2

Caplan, S. E. (2002). Problematic internet use and psychosocial wellbeing: Development of a theory-based cognitive–behavioral measurement instrument. *Computers in Human Behavio*r, *18*(5), 553–575. https://doi.org/10.11016/s0747-5632(02)00004-3

Caplan, S. E. (2010). Theory and measurement of generalized problematic internet use: A two-step approach. *Computers in Human Behavior, 26*(5), 1089–1097. https://doi.org/10.11016/j. chb2010.03.012

Carleton, R. N., Collimore, K. C., & Asmundson, G. J. (2007). Social anxiety and fear of negative evaluation: Construct validity of the BFNE-II. *Journal of Anxiety Disorders*, *21*(1), 131–141. https://doi.org/10.1016/j.janxdis.2006.03.010

Casale, S., & Fioravanti, G. (2011). Psychosocial correlates of internet use among Italian students. *International Journal of Psychology*, *46*(4), 288–298. https://doi.org/10.11080/002075942010.541256

Casale, S., Fioravanti, G., Flett, G. L., & Hewitt, P. L. (2014). From socially prescribed perfectionism to problematic use of internet communicative services: The mediating roles of perceived social support and the fear of negative evaluation. *Addictive Behaviors*, *39*(12), 1816–1822. https://doi.org/10.11016/j. addbeh2014.06.006

Casale, S., Lecchi, S., & Fioravanti, G. (2015). The Association Between Psychological Well-Being and Problematic use of internet communicative services among young people. *The Journal of Psychology*, *149*(5), 480–497. https://doi.org/10.1080/00223980.2014.905432

Casale, S., Rugai, L., & Fioravanti, G. (2018). Exploring the role of positive metacognitions in explaining the association between the fear of missing out and social media addiction. *Addictive Behaviors*, *85*(April), 83–87. https://doi.org/10.11016/j. addbeh2018.05.020

Central Statistics Office (CSO). (2018). Information Society Statistics - Households. https://www. cso.ie/en/methods/informationsociety/informationsocietystatistics-households/

Ceyhan, E., Ceyhan, A. A., & Gürcan, A. (2007). The Validity and Reliability of the Problematic Internet Usage Scale. *Educational Sciences: Theory and Practice. 7*.

Ceyhan, A. A. (2011). University students’ problematic internet use and communication skills according to the internet use purposes. *Kuram ve Uygulamada Egitim Bilimleri. 11*. 69-77.

Chang, R. M., Kauffman, R. J., & Kwon, Y. (2014). Understanding the paradigm shift to computational social science in the presence of big data. *Decision Support Systems*, *63*, 67–80. https://doi.org/10.1016/j.dss.2013.08.008

Chang, S. M., Hsieh, G. M. Y, & Lin, S. S. J. (2018). The mediation effects of gaming motives between game involvement and problematic Internet use: Escapism, advancement and socializing. *Computers and Education*, *122,* 43–53. https://doi.org/10.11016/j.compedu.2018.03.007

Chang, S. mei, & Lin, S. S. J. (2019). Online gaming motive profiles in late adolescence and the related longitudinal development of stress, depression, and problematic internet use. *Computers and Education*, *135*, 123–137. https://doi.org/10.11016/j.compedu2019.02.003

Cheek, J. M., & Buss, A. H. (1981). Shyness and sociability. *Journal of Personality and Social Psychology, 41*(2), 330–339. https://doi.org/10.1037/0022-3514.41.2.330

Chen, L., Luo, X., Bőthe, B., Jiang, X., Demetrovics, Z., & Potenza, M. N. (2021). Properties of the problematic pornography consumption scale (PPCS-18) in community and subclinical samples in China and Hungary. *Addictive Behaviors, 112*, https://doi.org/10.11016/j.addbeh.2020.106591

Chen, S. H., Weng, L. J., Su, Y. J., Wu, H. M., & Yang, P. F. (2003). Development of Chinese internet addiction scale and its psychometric study. *Chinese Journal of Psychology*, *45*, 251-266. 10.1037/t44491-000.

Chen, S. K., Lo, M. T., & Lin, S. S. J. (2015). Impulsivity as a precedent factor for problematic Internet use: How can we be sure? *International Journal of Psychology*, *52*(5), 389–397. https://doi.org/10.1002/ijop.12231

Cheng, C., & Li, A. Y. L. (2014). Internet addiction prevalence and quality of (real) life: A meta-analysis of 31 nations across seven world regions. *Cyberpsychology, Behavior, and Social Networking, 17*(12), 755–760. https://doi.org/10.11089/cyber2014.0317

Chi, X., Hong, X., Chen, X. (2020). Profiles and sociodemographic correlates of internet addiction in early adolescents in southern China. *Addictive Behaviors*, *106*, 106385. https://doi.org/10.11016/j. addbeh2020.106385

Chiorri, C., Bracco, F., Piccinno, T., Modafferi, C., Battini, V. (2015). Psychometric properties of a revised version of the ten item personality inventory. *European Journal of Psychological Assessment, 31*(2), 109–119. https://doi.org/10.11027/1015-5759/a000215

Coduto, K. D., Lee-Won, R. J., & Baek, Y. M. (2019). Swiping for trouble: Problematic dating application use among psychosocially distraught individuals and the paths to negative outcomes. Journal of Social and Personal Relationships, 37(1), 212–232. https://doi.org/10.11177/0265407519861153

Cohen, S., Kamarck, T., Mermelstein, R. (1983b). A Global Measure of Perceived Stress. *Journal of Health and Social Behavior*, *24*(4), 385. https://doi.org/10.2307/2136404

Comprehensive IP address data, IP geolocation API and database - IPinfo. io. (n. d.). Retrieved November 19, 2020, from https://ipinfo. io/

Constantino J.N. (2013) Social Responsiveness Scale. In: Volkmar F.R. (eds) Encyclopedia of Autism Spectrum Disorders. Springer, New York, NY. https://doi.org/10.1007/978-1-4419-1698-3_296

Content Taxonomy - IAB Tech Lab. (n. d.). Retrieved April 2, 2021, from https://iabtechlab.com/standards/content-taxonomy/

Cornet, V. P., & Holden, R. J. (2018). Systematic review of smartphone-based passive sensing for health and wellbeing. *Journal of Biomedical Informatics, 77*, 120–132. https://doi.org/10.11016/j. jbi2017.12.008.

Costa, P. T., & McCrae, R. R. (1992). Revised NEO personality inventory (NEO-PI-R) and NEO five-factor inventory (NEO-FFI). In *Odessa FL Psychological Assessment Resources*.

Crotty, M. (1998). The foundations of social research: Meaning and perspective in the research process (1st ed.). Routledge. https://doi.org/10.4324/9781003115700

Cummins, R. A. (1997). Self-rated quality of life scales for people with an intellectual disability: A review. *Journal of Applied Research in Intellectual Disabilities, 10*(3), 199–216. https://doi.org/10.11111/j.1468-3148.1997. tb00017.

Cupchik, G. (2001). Constructivist realism: An ontology that encompasses positivist and constructivist approaches to the social sciences. *Forum Qualitative Sozialforschung/Forum: Qualitative Social Research 2*(1).

Cusumano, M. A., Gawer, A., & Yoffie, D. B. (2021). Can self-regulation save digital platforms? *Industrial and Corporate Change*, *30*(5), 1259–1285. https://doi.org/10.1093/icc/dtab052

Dang, D. L., Zhang, M. X., Leong, K. K. H., & Wu, A. M. S. (2019). The Predictive Value of Emotional Intelligence for Internet Gaming Disorder: A 1-Year Longitudinal Study. *International Journal* *of Environmental Research and Public Health*, *16*(15), 2762. https://doi.org/10.3390/ijerph16152762

Davis, M. H. (1983). Measuring individual differences in empathy: Evidence for a multidimensional approach. *Journal of Personality and Social Psychology*, *44*(1), 113–126. https://doi.org/10.1037/0022-3514.44.1.113

Davis, R. (2001). A cognitive-behavioral model of pathological Internet use. *Computers in Human Behavior*, *17*(2), 187–195. https://doi.org/10.11016/s0747-5632(00)00041-8

Davis, R. A., Flett G. L., & Besser A. (2002). Validation of a new scale for measuring problematic internet use: Implications for pre-employment screen. . *Cybersychology and Behavior, 5*(4), 331-345,. https://doi.org/10.11089/109493102760275581

Demetrovics Z, Király O, Koronczai B, Griffiths MD, Nagygyörgy K, Elekes Z, et al. (2016). Psychometric properties of the problematic internet use questionnaire short-Form (PIUQ-SF-6) in a nationally representative sample of adolescents. *PLoS ONE 11*(8): e0159409. https://doi.org/10.11371/journal. pone.0159409

Demetrovics, Z., Szeredi, B., & Rózsa, S. (2008). The three-factor model of Internet addiction: The development of the problematic internet use questionnaire. *Behavior Research Methods*, *40*(2), 563–574. https://doi.org/10.3758/brm.40.2.563

Demirtepe-Saygılı, D., & Metin-Orta, I. (2021). An Investigation of cyberloafing in relation to coping styles and psychological symptoms in an educational setting. *Psychological Reports*, *124*(4), 1559–1587. https://doi.org/10.11177/0033294120950299

Department for Digital, Culture, Media and Sport, and the Home Office, Online Harms White Paper (2019). https://www.gov.uk/government/consultations/online-harms-white-paper/online-harms-white-paper

Department of Health and the HSE. (2020). *Higher Education Healthy Campus Charter & Framework for Ireland 2020–2025*. https://www. google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwjHgJrk96f3AhWNQUEAHbjwDLkQFnoECAMQAQ&url=https%3A%2F%2Fassets. gov.ie%2F138922%2F9c478bc4-42b7-45cf-aa62-d7e16b698ee6. pdf&usg=AOvVaw1nTSMzupzM34siWezysJKi

Derogatis, L R. (1992). The brief symptom inventory (BSI): Administration, scoring, and procedures manual II. Baltimore, MD:Clinical Psychometric Research. *Clinical Psychometric Research*.

Derogatis, Leonard R. (1993). BSI - Brief symptom inventory: Administration, Scoring, and Procedures Manual (4th ed). *Minneapolis MN: National Computer Systems*. https://doi.org/10.11037/t00789-000

De-Sola, J., Rubio, G., Talledo, H., Pistoni, L., van Riesen, H., & Rodríguez De Fonseca, F. (2019). Cell phone use habits among the Spanish population: Contribution of applications to problematic sse. *Frontiers in Psychiatry*, *10*. https://doi.org/10.3389/fpsyt2019.00883

de Vente, W., Majdandžić, M., Voncken, M. J., Beidel, D. C., & Bögels, S. M. (2014). The SPAI-18, a brief version of the Social Phobia and Anxiety Inventory: Reliability and validity in clinically referred and non-referred samples. *Journal of Anxiety Disorders*, *28*(2), 140–147. https://doi.org/10.1016/j.janxdis.2013.05.003

Diener, E., & Diener, M. (1995). Cross-cultural correlates of life satisfaction and self-esteem. *Journal of Personality and Social Psychology*, *68*(4), 653–663. https://doi.org/10.1037/0022-3514.68.4.653

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment*, *49*(1), 71–75. https://doi.org/10.1207/s15327752jpa4901_13

Dienlin, T., & Johannes, N. (2020). The impact of digital technology use on adolescent wellbeing. *Dialogues in Clinical Neuroscience, 22*(2), 135-142. doi:10.31887/DCNS2020222/tdienlin

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

Dissing, A. S., Jørgensen, T. B., Gerds, T. A., Rod, N. H., & Lund, R. (2019). High perceived stress and social interaction behaviour among young adults. A study based on objective measures of face-to-face and smartphone interactions. *PloS one*, *14*(7), e0218429. https://doi.org/10.11371/journal. pone.0218429

Do, H. N., Onyango, B., Prakash, R., Tran, B. X., Nguyen, Q. N., Nguyen, L. H., Nguyen, H. Q. T., Nguyen, A. T., Nguyen, H. D., Bui, T. P., Vu, T. B. T., Le, K. T., Nguyen, D. T., Dang, A. K., Nguyen, N. B., Latkin, C. A., Ho, C. S., & Ho, R. C. (2020). Susceptibility and perceptions of excessive internet use impact on health among Vietnamese youths. *Addictive Behaviors*, *101*, 105898. https://doi.org/10.11016/j. addbeh2019.01.043

Dray, Stéphane & Pélissier, Raphaël & Couteron, Pierre & Fortin, M. & Legendre, P. & Peres-Neto, Pedro & Bellier, Edwige & Bivand, Roger & Blanchet, F. Guillaume & Ceres, M. & Dufour, Anne-Béatrice & Heegaard, Einar & Jombart, T. & Munoz, François & Oksanen, Jari & Thioulouse, Jean & Wagner, Helene. (2012). Community ecology in the age of multivariate multiscale spatial analysis. *Ecological Monographs*.82257-275.110.11890/11-1183.1.

El Asam, A., Samara, M., & Terry, P. (2019). Problematic internet use and mental health among British children and adolescents. *Addictive Behaviors*, *90*, 428–436. https://doi.org/10.11016/j. addbeh2018.09.007

Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. *In Journal of Affective Disorders 207*, 251–259. https://doi.org/10.11016/j. jad2016.08.030

Elhai, J. D., Gallinari, E. F., Rozgonjuk, D., & Yang, H. (2020). Depression, anxiety and fear of missing out as correlates of social, non-social and problematic smartphone use. *Addictive Behaviors*, *105*, 106335. https://doi.org/10.1016/j.addbeh.2020.106335

Elhai, J. D., Levine, J. C., Alghraibeh, A. M., Alafnan, A. A., Aldraiweesh, A. A., & Hall, B. J. (2018). Fear of missing out: Testing relationships with negative affectivity, online social engagement, and problematic smartphone use. *Computers in Human Behavior*, *89,* 289–298. https://doi.org/10.11016/j. chb2018.08.020

Elhai, J. D., Levine, J. C., Dvorak, R. D., & Hall, B. J. (2016). Fear of missing out, need for touch, anxiety and depression are related to problematic smartphone use. *Computers in Human Behavior*, *63*, 509–516. https://doi.org/10.1016/j.chb.2016.05.079

Elhai, J. D., Yang, H., Dempsey, A. E., & Montag, C. (2020). Rumination and negative smartphone use expectancies are associated with greater levels of problematic smartphone use: A latent class analysis. *Psychiatry Research, 285*, 112845. https://doi.org/10.11016/j. psychres2020.112845

Elhai, J. D., Yang, H., Fang, J., Bai, X., & Hall, B. J. (2019). Depression and anxiety symptoms are related to problematic smartphone use severity in Chinese young adults: Fear of missing out as a mediator. *Addictive Behaviors, 57*, 0–1. https://doi.org/10.11016/j. addbeh2019.04.020

Elhai, J. D., Yang, H., McKay, D., & Asmundson, G. J. (2020). COVID-19 anxiety symptoms associated with problematic smartphone use severity in Chinese adults. *Journal of Affective Disorders*, *274*, 576–582. https://doi.org/10.1016/j.jad.2020.05.080

Elhai, J. D., Yang, H., & Montag, C. (2021). Fear of missing out (FOMO): Overview, theoretical underpinnings, and literature review on relations with severity of negative affectivity and problematic technology use. *Brazilian Journal of Psychiatry, 43*(2), 203-209. doi:10.11590/1516-44462020-0870

Elhai, J. D., Yang, H., Rozgonjuk, D., & Montag, C. (2020). Using machine learning to model problematic smartphone use severity: The significant role of fear of missing out. *Addictive behaviors*, *103*, 106261. https://doi.org/10.11016/j. addbeh2019.106261

Ellis, D. A. (2019). Are smartphones really that bad? Improving the psychological measurement of technology related behaviors. *Computers in Human Behavior*, *97*, 60-66.

Ellis, D. A., Davidson, B. I., Shaw, H., & Geyer, K. (2019). Do smartphone usage scales predict behavior? *International Journal of Human-Computer Studies*, *130*, 86–92. https://doi.org/10.1016/j.ijhcs.2019.05.004

Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The Benefits of Facebook "Friends:" Social Capital and College Students' Use of Online Social Network Sites. *Journal of Computer-Mediated Communication*, *12*(4), 1143–1168. https://doi.org/10.1111/j.1083-6101.2007.00367.x

Ellison, N. B., Steinfield, C., & Lampe, C. (2011). Connection strategies: Social capital implications of Facebook-enabled communication practices. *New Media & Society*, *13*(6), 873–892. https://doi.org/10.1177/1461444810385389

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological methods*, *23*(4), 617–634. https://doi.org/10.11037/met0000167

Epskamp, S., Waldorp, L. J., Mõttus, R., & Borsboom, D. (2017). The Gaussian graphical model in cross-sectional and time-series data, *Multivariate Behavioral Researc*h, *53*(4), 453-480, DOI: 10.11080/002731712018.1454823

Epstein, N. B., Bishop, D. S., & Levin, S. (1978). The McMaster Model of Family Functioning. *Journal of Marital and Family Therapy*, *4*(4), 19–31. https://doi.org/10.1111/j.1752-0606.1978.tb00537.x

Esen, B. K., Aktas, E., & Tuncer, I. (2013). An analysis of university students' internet use in relation to loneliness and social self-efficacy. *Procedia - Social and Behavioral Sciences*, *84*, 1504–1508. https://doi.org/10.11016/j. sbspro2013.06.780

Espinosa, J. A., Kaisler, S., Armour, F., & Money, (2019). Big data redux: New issues and challenges moving forward. Proceedings of the 52nd Hawaii International Conference on System Sciences. https://doi.org/1024251/hicss2019.131

Facebook -. (2022, January). Facebook graph API. https://developers. facebook.com/docs/graph-api/overview

Faltýnková, A., Blinka, L., ŠEvčíková, A., & Husarova, D. (2020). The associations between family-related factors and excessive internet use in adolescents. *International Journal of Environmental Research and Public Health*, *17*(5), 1754. https://doi.org/10.3390/ijerph17051754

Felisoni, D. D., & Godoi, A. S. (2018). Cell phone usage and academic performance: An experiment. *Computers & Education*, *117*, 175–187. https://doi.org/10.1016/j.compedu.2017.10.006

Feng, S., Wong, Y. K., Wong, L. Y, & Hossain, L. (2019). The Internet and Facebook Usage on Academic Distraction of College Students. *Computers & Education*, *134*, 41–49. https://doi.org/10.1016/j.compedu.2019.02.005

Fernández-Delgado, M., Cernadas, E., Barro, S., & Amorim, D. (2014). Do we need hundreds of classifiers to solve real world classification problems? *The Journal of Machine Learning Research, 15*(1), 3133–3181

Feurer M., Klein A., Eggensperger K., Springenberg J. T., Blum M., Hutter F. (2019) Auto-sklearn: Efficient and robust automated machine learning. In: Hutter F., Kotthoff L., Vanschoren J. (eds) *Automated machine learning (The Springer series on challenges in machine learning)* (1st ed. 2019 ed.). Springer. https://doi.org/10.11007/978-3-030-05318-5_6

Fineberg, N., Demetrovics, Z., Stein, D., Ioannidis, K., Potenza, M., Grünblatt, E., Brand, M., Billieux, J., Carmi, L., King, D., Grant, J., Yücel, M., Dell'Osso, B., Rumpf, H., Hall, N., Hollander, E., Goudriaan, A., Menchon, J., Zohar, J.,. . . Chamberlain, S. (2018). Manifesto for a European research network into problematic usage of the internet. *European Neuropsychopharmacology*, *28*(11), 1232–1246. https://doi.org/10.11016/j.euroneuro2018.08.004

Foresight, S. (2019, February 18). *How the internet can harm us, and what can we do about it?* Epthinktank. https://epthinktank. eu/2019/02/18/how-the-internet-can-harm-us-and-what-can-we-do-about-it/

Fioravanti, G., & Casale, S. (2020). The active and passive use of Facebook: Measurement and association with Facebook addiction. *Journal of Psychopathology, 2*. https://doi.org/10.36148/2284-0249-329

Fiorini, L., Cavallo, F., Dario, P., Eavis, A., & Caleb-Solly, P. (2017). Unsupervised machine learning for developing personalised behaviour models using activity data. *Sensors*, *17*(5), 1034. https://doi.org/10.3390/s17051034

Folkman, S., & Lazarus, R. S. (1980). An analysis of coping in a middle-aged community sample. *Journal of Health and Social Behavior, 21*(3), 219-239. https://doi.org/102307/2136617

Foygel Barber, R., & Drton, M. (2010). Extended Bayesian information criteria for Gaussian graphical models. Advances in Neural Information Processing Systems 23: 24th Annual Conference on Neural Information Processing Systems 2010, NIPS 2010.

Foygel Barber, R. F., & Drton, M. (2015). High-dimensional Ising model selection with Bayesian information criteria. *Electronic Journal of Statistics*, *9*(1), 567-607. https://doi.org/10.1214/15-EJS1012

Francis, L. J., Lewis, C. A., & Ziebertz, H. G. (2006). THE SHORT-FORM REVISED EYSENCK PERSONALITY QUESTIONNAIRE (EPQR-S): A GERMAN EDITION. *Social Behavior and Personality: An International Journal*, *34*(2), 197–204. https://doi.org/10.2224/sbp.2006.34.2.197

Fraley, C. (1998). How many clusters? Which clustering method? Answers via model-based cluster analysis. *The Computer Journal*, *41*(8), 578–588. https://doi.org/10.11093/comjnl/41.8.578

Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics (Oxford, England),* *9*(3), 432–441. https://doi.org/10.11093/biostatistics/kxm045

Fumagalli, E., Dolmatzian, M. B., & Shrum, L. J. (2021). Centennials, FOMO, and loneliness: An investigation of the impact of social networking and messaging/VoIP spps usage during the initial stage of the Coronavirus pandemic. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg2021.620739

Galeazzi, A., Franceschina, E., & Holmes, G. R. (2002). Factor analysis of social skills inventory responses of Italians and Americans. *Psychological Reports*. , *90*(4), 1115. https://doi.org/10.2466/pr0.90.4.1115-1121

Gansner, M., Nisenson, M., Carson, N., & Torous, J. (2020). A pilot study using ecological momentary assessment via smartphone application to identify adolescent problematic internet use. *Psychiatry Research, 293*, 113428. doi:10.11016/j. psychres2020.113428

Gentina, E., & Rowe, F. (2020). Effects of materialism on problematic smartphone dependency among adolescents: The role of gender and gratifications. *International Journal of Information Management*, *54*, 102134. https://doi.org/10.1016/j.ijinfomgt.2020.102134

Ghisi, M., Chiri, L. R., Marchetti, I., Sanavio, E., & Sica, C. (2010). In search of specificity: "Not just right experiences" and obsessive–compulsive symptoms in non-clinical and clinical Italian individuals. *Journal of Anxiety Disorders*, *24*(8), 879–886. https://doi.org/10.1016/j.janxdis.2010.06.011

Gibbons, F. X., & Buunk, B. P. (1999). Individual differences in social comparison: Development of a scale of social comparison orientation. *Journal of Personality and Social Psychology*, *76*(1), 129–142. https://doi.org/10.1037/0022-3514.76.1.129

Gill, P., Arlitt, M., Carlsson, N., Mahanti, A., & Williamson, C. (2011). Characterizing Organizational Use of Web-Based Services. *ACM Transactions on the Web*, *5*(4), 1–23. https://doi.org/10.1145/2019643.2019646

G Goldberg, M. E., Gorn, G. J., Peracchio, L. A., & Bamossy, G. (2003). Understanding Materialism Among Youth. *Journal of Consumer Psychology*, *13*(3), 278–288. https://doi.org/10.1207/s15327663jcp1303_09

Gómez, P., Rial., A., Braña, T., Golpe, S., & Varela, J. (2017). Screening of problematic internet use among Spanish adolescents: Prevalence and related variables. *Cyberpsychology, Behavior, and Social Networking*, *20*(4), 259-267. https://doi.org/10.11089/cyber2016.0262

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

Grasmick, H. G., Tittle, C. R., Bursik, R. J., & Arneklev, B. J. (1993). Testing the Core Empirical Implications of Gottfredson and Hirschi's General Theory of Crime. *Journal of Research in Crime and Delinquency*, *30*(1), 5–29. https://doi.org/10.1177/0022427893030001002

Greenhalgh, T., & Taylor, R. (1997). Papers that go beyond numbers (qualitative research). *BMJ (Clinical research ed.)*, *315*(7110), 740–743. https://doi.org/10.1136/bmj.315.7110.740

Griffioen, N., Rooij, M. van, Lichtwarck-Aschoff, A., & Granic, I. (2020). Toward improved methods in social media research. *Technology, Mind, and Behavior*, *1*(1). https://doi.org/10.11037/tmb0000005

Griffiths, M. (2005). A 'components' model of addiction within a biopsychosocial framework. *Journal of Substance Use*, *10*(4), 191–197. https://doi.org/10.11080/14659890500114359

Guiñazú, M. F., Cortés, V., Ibáñez, C. F., & Velásquez, J. D. (2020). Employing online social networks in precision-medicine approach using information fusion predictive model to improve substance use surveillance: A lesson from twitter and marijuana consumption. *Information Fusion, 55*, 150-163. doi:10.11016/j. inffus2019.08.006

Han, J., Kamber, M., & Pei, J. (2011). Data Mining: Concepts and Techniques (The Morgan Kaufmann Series in Data Management Systems) (3rd ed.). Morgan Kaufmann.

Hassan, S. -U., Waheed, H., Aljohani, N. R., Ali, M., Ventura, S., & Herrera, F. (2019). Virtual learning environment to predict withdrawal by leveraging deep learning. *International Journal of Intelligent Systems, 34*(8), 1935–1952.

Hao, Z., Jin, L., Lyu, R., & Rabia Akram, H. (2020). Problematic mobile phone use and altruism in Chinese undergraduate students: The mediation effects of alexithymia and empathy. *Children and Youth Services Review*, *118*, 105402. https://doi.org/10.1016/j.childyouth.2020.105402

Harris, B., McCredie, M., & Fields, S. (2020). Examining the psychometric properties of the smartphone addiction scale and its short version for use with emerging adults in the U. S. *Computers in Human Behavior Reports*, *1*, 100011. https://doi.org/10.11016/j. chbr2020.100011

Hassan, T., Alam, M. M., Wahab, A., & Hawlader, M. D. (2020). Prevalence and associated factors of internet addiction among young adults in Bangladesh. *Journal of the Egyptian Public Health Association*, *95*(1). https://doi.org/10.11186/s42506-019-0032-7

Hathcoat J. D., Meixner C., Nicholas M. C. (2018). Ontology and Epistemology. In: Liamputtong P. (eds). *Handbook of Research Methods in Health Social Sciences*. Springer, Singapore. https://doi.org/10.11007/978-981-10-2779-6_56-1

Hawi, N. S., & Samaha, M. (2017). Relationships among smartphone addiction, anxiety, and family relations. *Behaviour & Information Technology*, *36*(10), 1046–1052. https://doi.org/10.1080/0144929x.2017.1336254

Hawi, N. S., & Samaha, M. (2016). The Relations Among Social Media Addiction, Self-Esteem, and Life Satisfaction in University Students. *Social Science Computer Review*, *35*(5), 576–586. https://doi.org/10.1177/0894439316660340

Hawi, N., & Samaha, M. (2019). Identifying commonalities and differences in personality characteristics of Internet and social media addiction profiles: traits, self-esteem, and self-construal. *Behaviour and Information Technology,* *38*(2), 110–119. https://doi.org/10.11080/0144929X2018.1515984

Hebebci, M. T., & Shelley, M. (2018). Analysis of the relationship between university students' problematic internet use and loneliness. *International Journal of Assessment Tools in Education*, *5*(2), 223–234. https://doi.org/1021449/ijate.402690

Henderson, M., Selwyn, N., Finger, G., & Aston, R. (2015). Students' everyday engagement with digital technology in university: exploring patterns of use and 'usefulness.' *Journal of Higher Education Policy and Management*, *37*(3), 308–319. https://doi.org/10.1080/1360080x.2015.1034424

Heuer, H. & Breiter, A., (2018). Student success prediction and the trade-off between big data and data minimization. In: Krömker, D. & Schroeder, U. (Hrsg.), DeLFI 2018 - Die 16. E-Learning Fachtagung Informatik. Bonn: Gesellschaft für Informatik e. V. . (S219-230).

Hevey, D. (2018). Network analysis: a brief overview and tutorial. *Health Psychology and Behavioral Medicine*, *6*(1), 301–328. https://doi.org/10.11080/216428502018.1521283

Hicks SC, Liu R, Ni Y, Purdom E, Risso D (2021) mbkmeans: Fast clustering for single cell data using mini-batch *k*-means. *PLOS Computational Biology* *17*(1): e1008625. https://doi.org/10.11371/journal. pcbi.1008625

Hood, S. B. (2013). Psychological Measurement and Methodological Realism. *Erkenntnis*, *78*(4), 739–761. https://doi.org/10.1007/s10670-013-9502-z

Hou, Y, Xiong, D., Jiang, T., Song, L., & Wang, Q. (2019). Social media addiction: Its impact, mediation, and intervention. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, *13*(1). https://doi.org/10.5817/cp2019-1-4

Huang, C. (2010). Internet addiction: Stability and change. *European Journal of Psychology of Education*, *25*(3), 345–361. https://doi.org/10.11007/s10212-010-0022-9

Hughes, M. E., Waite, L. J., Hawkley, L. C., & Cacioppo, J. T. (2004). A short scale for measuring loneliness in large surveys: Results from two population-based studies. In *Research on Aging*. https://doi.org/10.11177/0164027504268574

Hunt, M. G., Marx, R., Lipson, C., & Young, J. (2018). No more FOMO: Limiting social media decreases loneliness and depression. *Journal of Social and Clinical Psychology*, *37*(10), 751–768. https://doi.org/10.11521/jscp2018.37.10.751

Insights. (n. d.). Insights. Retrieved January 7, 2022, from https://insightsapp. org/

International personality item pool. (2006). *Choice Reviews Online*, *43*(11), 43–6861. https://doi.org/10.5860/choice.43-6861

Introduction to Cisco IOS NetFlow - A Technical Overview - Cisco. (n. d.). Retrieved January 29, 2021, from https://University. cisco.com/c/en/us/products/collateral/ios-nx-os-software/ios-netflow/prod_white_paper0900aecd80406232. html

Javaeed, A., Jeelani, R., Gulab, S., & Ghauri, S. K. (2019). Relationship between internet addiction and academic performance of undergraduate medical students of Azad Kashmir. *Pakistan Journal of Medical Sciences*, *36*(2). https://doi.org/10.112669/pjms.362.1061

Jayarajah, K., Lee, Y, Misra, A., & Balan, R. K. (2015). Need accurate user behaviour? Pay attention to groups. UbiComp 2015 - Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing. https://doi.org/10.11145/27508582804289

Jiang, Q., Huang, X., & Tao, R. (2013). Internet Addiction: Cybersex. In *Principles of Addiction*. https://doi.org/10.11016/B978-0-12-398336-7.00081-4

Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: A review and recent developments. In Philosophical Transactions of the Royal Society A: *Mathematical, Physical and Engineering Sciences*. https://doi.org/10.11098/rsta2015.0202

Jolliffe, I. T. (2002). Principal Component Analysis, Second Edition. Encyclopedia of Statistics in Behavioral Science. https://doi.org/102307/1270093

Jolliffe, I. T. (2010). *Principal Component Analysis (Springer Series in Statistics)* (Softcover reprint of the original 2nd ed. 2002 ed.). Springer.

Jolliffe, I. T. (1990). Principal Component Analysis: A beginner's guide - I. Introduction and application. *Weather*, *45*(10), 375–382. https://doi.org/10.1002/j.1477-8696.1990.tb05558.x

Jones, W. H., Briggs, S. R., & Smith, T. G. (1986). Shyness: Conceptualization and measurement. *Journal of Personality and Social Psychology*, *51*(3), 629–639. https://doi.org/10.1037/0022-3514.51.3.629

Kabasakal., Z. (2015). Life satisfaction and family functions as-predictors of problematic Internet use in university students. *Computers in Human Behavior*, *53*, 294–304. https://doi.org/10.11016/j. chb2015.07.019

Kalkan, M. (2008). Dating anxiety in adolescents: Scale development and effectiveness of cognitive-behavioral group counseling. *Egitim Arastirmalari - Eurasian Journal of Educational Research 8*. 55-68.

Kanjo, E., Kuss, D. J., & Ang, C. S. (2017). NotiMind: Utilizing Responses to Smart Phone Notifications as Affective Sensors.ie*EE Access*, *5*, 22023–22035. https://doi.org/10.1109/access.2017.2755661

Kanjo, E., Ortega A. D., Anwar, A., Al S. A., William, J. (2021):CrowdTracing: Overcrowding clustering and detection system for social distancing. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.14709762. v1 *(PDF) CrowdTracing: Overcrowding clustering and detection system for social distancing*. Available from: https://www. researchgate. net/publication/353274327_CrowdTracing_Overcrowding_Clustering_andDetection_System_for_Social_Distancing [accessed Jan 18 2022].

Kannan, B., Karthik, S., Pal, G. K., & Menon, V. (2019). Gender variation in the prevalence of Internet addiction and impact of internet addiction on reaction time and heart rate variability in medical college students. *Journal of Clinical and Diagnostic Research*. https://doi.org/10.7860/jcdr/2019/40839.12753

Kardefelt-Winther, D. (2014). A conceptual and methodological critique of internet addiction research: Towards a model of compensatory internet use. *Computers in Human Behavior*, *31*, 351–354. https://doi.org/10.1016/j.chb.2013.10.059

Karsay, K., Schmuck, D., Matthes, J., & Stevic, A. (2019). Longitudinal effects of excessive smartphone use on stress and loneliness: The moderating role of self-disclosure. *Cyberpsychology, Behavior, and Social Networking, 22*(11), 706–713. https://doi.org/10.11089/cyber2019.0255

K. Kaye, L., Orben, A., A. Ellis, D., C. Hunter, S., & Houghton, S. (2020). The Conceptual and Methodological Mayhem of "Screen Time." *International Journal of Environmental Research and Public Health*, *17*(10), 3661. https://doi.org/10.3390/ijerph17103661

Kesheng, L., Yikun, N., Zihan, L. and Bin, D., (2020). Data Mining and feature analysis of college students' campus network behavior, *2020 5th IEEE International Conference on Big Data Analytics (ICBDA)*, pp.231-237, doi: 10.11109/ICBDA490402020.9101257

Kim, I., Kim, R., Kim, H., Kim, D., Han, K., Lee, P. H., Mark, G., & Lee, U. (2019). Understanding smartphone usage in college classrooms: A long-term measurement study. *Computers & Education*, *141*, 103611. https://doi.org/10.1016/j.compedu.2019.103611

Kim, J., Larose, R., & Peng, W. (2009). Loneliness as the cause and effect of problematic internet use: The relationship between internet use and psychological wellbeing. *Cyberpsychology and Behavior*, *12*(4), 451–455. https://doi.org/10.11089/cpb2008.0327

Kim, Y. J., Roh, D., Lee, S. K., Canan, F., & Potenza, M. N. (2018). Factors Statistically Predicting At-Risk/Problematic Internet Use in a Sample of Young Adolescent Boys and Girls in South Korea. *Frontiers in Psychiatry*, *9*. https://doi.org/10.3389/fpsyt2018.00351

Kırcaburun, K., Kokkinos, C. M., Demetrovics, Z., Király, O., Griffiths, M. D., & Çolak, T. S. (2018). Problematic online behaviors among adolescents and emerging adults: Associations between cyberbullying perpetration, problematic social media use, and psychosocial factors. *International Journal of Mental Health and Addiction, 17*(4), 891–908. https://doi.org/10.11007/s11469-018-9894-8

Kirchner, T. R., & Shiffman, S. (2016). Spatio-temporal determinants of mental health and wellbeing: Advances. In *geographically-explicit ecological momentary assessment (GEMA)* Springer Science and Business Media LLC. doi:10.11007/s00127-016-1277-5

Kita, E., & Luria, G. (2018). The mediating role of smartphone addiction on the relationship between personality and young drivers' smartphone use while driving. *Transportation Research. Part F, Traffic Psychology and Behaviour, 59*, 203-211. doi:10.11016/j. trf2018.09.001

Kitchin, R. (2014). Big Data, new epistemologies and paradigm shifts. *Big Data & Society*, *1*(1), 205395171452848. https://doi.org/10.1177/2053951714528481

Kittinger, R., Correia, C. J., & Irons, J. G. (2012). Relationship between facebook use and problematic internet use among college students. *Cyberpsychology, Behavior, and Social Networking*, *15*(6), 324–327. https://doi.org/10.11089/cyber2010.0410

Koç, T., & Turan, A. H. (2020). The Relationships Among Social Media Intensity, Smartphone Addiction, and Subjective Wellbeing of Turkish College Students. *Applied Research in Quality of Life*, *16*(5), 1999–2021. https://doi.org/10.1007/s11482-020-09857-8

Kohler, U., & Luniak, M. (2005). Data Inspection using Biplots. *The Stata Journal: Promoting Communications on Statistics and Stata*, *5*(2), 208–223. https://doi.org/10.1177/1536867x0500500206

Koronczai, B., Urbán, R., Kökönyei, G., Paksi, B., Papp, K., Kun, B., Arnold, P., Kállai, J., & Demetrovics, Z. (2011). Confirmation of the three-factor model of problematic internet use on off-line adolescent and adult Samples. *Cyberpsychology, Behavior, and Social Networking*, *14*(11), 657–664. https://doi.org/10.11089/cyber2010.0345

Kosinski, M., Stillwell, D., & Graepel, T. (2013). Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(15), 5802–5805. https://doi.org/10.11073/pnas.1218772110

Kotz, D., & Essien, K. (2005). Analysis of a Campus-Wide Wireless Network. *Wireless Networks*, *11*(1–2), 115–133. https://doi.org/10.1007/s11276-004-4750-0

Kroenke, K., Spitzer, R. L. and Williams, J. B. (2001) The Patient Health Questionnaire-9. *Journal of general internal medicine, 16(*9):606–613.

Kroese, F. M., de Ridder, D. T. D., Evers, C., & Adriaanse, M. A. (2014). Bedtime procrastination: introducing a new area of procrastination. *Frontiers in Psychology*, *5*. https://doi.org/10.3389/fpsyg.2014.00611

Kumar, N., Kumar, A., Mahto, S. K., Kandpal, M., Deshpande, S. N., & Tanwar, P. (2019). Prevalence of excessive internet use and its correlation with associated psychopathology in 11th and 12th grade students. *General Psychiatry*, *32*(2), e100001. https://doi.org/10.11136/gpsych-2018-100001

Kuss, D. J. (2021). Risk reduction and harm prevention in technology use. A commentary on Swanton et al. ’s (2020) ‘Problematic risk-taking involving emerging technologies: A stakeholder framework to minimize harms'. *Journal of Behavioral Addictions, 9*(4), DOI: https://doi.org/10.11556/20062020.00079.

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

Kuss, D. J., Griffiths, M. D., & Binder, J. F. (2013). Internet addiction in students: Prevalence and risk factors. *Computers in Human Behavior*, *29*(3), 959–966. https://doi.org/10.11016/j. chb2012.12.024

Kuss, D. J., Griffiths, M. D., & Pontes, H. M. (2017). Chaos and confusion in DSM-5 diagnosis of Internet Gaming Disorder: Issues, concerns, and recommendations for clarity in the field. *Journal of Behavioral Addictions*, *6*(2), 103–109. https://doi.org/10.1556/2006.5.2016.062

Kuzilek, J., Vaclavek, J., Fuglik, V. and Zdrahal, Z. (2018). Student Drop-out Modelling Using Virtual Learning Environment Behaviour Data. In: *Lifelong Technology-Enhanced Learning - 13th European Conference on Technology Enhanced Learning* (Pammer-Schindler, Victoria; Pérez-Sanagustín, Mar; Drachsler, Hendrik; Elferink, Raymond and Maren, Scheffel eds.), Lecture Notes in Computer Science, Springer, pp. 166–171. doi: https://doi.org/10.1007/978-3-319-98572-5_13

Kwon, M., Kim, D. J., Cho, H., & Yang, S. (2013). The Smartphone addiction scale: Development and validation of a short version for adolescents. *PLoS ONE*, *8*(12), e83558. https://doi.org/10.11371/journal. pone.0083558

Kwon, M., Lee, J. Y, Won, W. Y, Park, J. W., Min, J. A., Hahn, C., Gu, X., Choi, J. H., & Kim, D. J. (2013). Development and validation of a smartphone addiction scale (SAS). *PLoS ONE*, *8*(2), e56936. https://doi.org/10.11371/journal. pone.0056936

La Greca, A. M., & Stone, W. L. (1993). Social Anxiety Scale for Children-Revised: Factor Structure and Concurrent Validity. *Journal of Clinical Child Psychology*, *22*(1), 17–27. https://doi.org/10.1207/s15374424jccp2201_2

Lau, A. L. D., Cummins, R. A., & Mcpherson, W. (2005). An Investigation into the cross-cultural equivalence of the personal wellbeing index. *Social Indicators Research, 72*(3), 403–430. https://doi.org/10.11007/s11205-004-0561-z

Lazarus, R. S., & Folkman, S. (1984). *Stress, Appraisal, and Coping* (1st ed.). Springer Publishing Company.

Leary, M. R. (1983). A Brief Version of the Fear of Negative Evaluation Scale. *Personality and Social Psychology Bulletin*, *9*(3), 371–375. https://doi.org/10.1177/0146167283093007

Ledger of Harms. (2021). Retrieved from Center for Humane Technology website: https://ledger. humanetech.com

Lee, S. Y, Kim, M. S., & Lee, H. K. (2019). Prevention strategies and interventions for internet use disorders due to addictive behaviors based on an integrative conceptual model. *Current Addiction Reports*, *6*(3), 303–312. https://doi.org/10.11007/s40429-019-00265-z

Lee, P. H., Tse, A. C. Y, Wu, C. S. T., Mak, Y. W., & Lee, U. (2021). Validation of self-reported smartphone usage against objectively-measured smartphone usage in Hong Kong Chinese adolescents and young adults. *Psychiatry Investigation, 18*(2), 95-100. doi:10.30773/pi2020.0197

Leung, L. (2008). Linking Psychological Attributes to addiction and improper ue of the mobile phone among adolescents in Hong Kong. *Journal of Children and Media*, *2*(2), 93–113. https://doi.org/10.1080/17482790802078565

Leung, L. (2010). Effects of Motives for Internet Use, Aloneness, and Age Identity Gratifications on Online Social Behaviors and Social Support among Adolescents. In R. Zheng, J. Burrow-Sanchez, & C. Drew (Eds.), *Adolescent Online Social Communication and Behavior: Relationship Formation on the Internet* (pp. 120-135). IGI Global. https://doi.org/10.4018/978-1-60566-926-7.ch008

Li, B., Wu, Y, Jiang, S., & Zhai, H. (2018). WeChat addiction suppresses the impact of stressful life events on life satisfaction. *Cyberpsychology, Behavior, and Social Networking*, *21*(3), 194–198. https://doi.org/10.11089/cyber2017.0544

Li, D., Zhang, W., Li, X., Zhen, S., & Wang, Y. (2010). Stressful life events and problematic Internet use by adolescent females and males: A mediated moderation model. *Computers in Human Behavior*, *26*(5), 1199–1207. https://doi.org/10.1016/j.chb.2010.03.031

Li, G., Hou, G., Yang, D., Jian, H., & Wang, W. (2019). Relationship between anxiety, depression, sex, obesity, and internet addiction in Chinese adolescents: A short-term longitudinal study. *Addictive Behaviors*, *90*, 421–427. https://doi.org/10.11016/j. addbeh2018.12.009

Li, L., Griffiths, M. D., Niu, Z., & Mei, S. (2020). The trait-state fear of missing out scale: Validity, reliability, and measurement invariance in a Chinese sample of university students. *Journal of Affective Disorders*, *274*, 711–718. https://doi.org/10.1016/j.jad.2020.05.103

Li, Q., Dai, W., Zhong, Y, Wang, L., Dai, B., & Liu, X. (2019b). The mediating role of coping styles on impulsivity, behavioral inhibition/approach system, and internet addiction in adolescents from a gender perspective. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg2019.02402

Liao, P. C., Chen, S. K., & Lin, S. S. J. (2018). Latent profiles of stress and their relationships with depression and problematic Internet use among college freshmen. *Scandinavian Journal of Psychology*, *59*(6), 621–630. https://doi.org/10.1111/sjop.12489

Lin, X., Su, W., & Potenza, M. N. (2018). Development of an Online and Offline Integration Hypothesis for healthy internet use: Theory and preliminary evidence. *Frontiers in Psychology*, *9*, 1–11. https://doi.org/10.3389/fpsyg2018.00492

Lin, Y. H., Pan, Y. C., Lin, S. H., & Chen, S. H. (2016). Development of short-form and screening cutoff point of the Smartphone Addiction Inventory (SPAI-SF). *International Journal of Methods in Psychiatric Research*, *26*(2), e1525. https://doi.org/10.1002/mpr.1525

Liu, C., & Ma, J. (2018a). Development and validation of the Chinese social media addiction scale. *Personality and Individual Differences*, *134*, 55–59. https://doi.org/10.1016/j.paid.2018.05.046

Liu, C., & Ma, J. (2018b). Social support through online social networking sites and addiction among college students: The mediating roles of fear of missing out and problematic smartphone use. *Current Psychology*, *39*(6), 1892–1899. https://doi.org/10.1007/s12144-018-0075-5

Liu, H., Lafferty, J., Wasserman, L. (2009). The nonparanormal: Semiparametric estimation of high dimensional undirected graphs . *Journal of Machine Learning Research*, 10(80), 2295−2328. https://www.jmlr.org/papers/volume10/liu09a/liu09a.pdf

Liu, Q., Niu, G., Fan, C., & Zhou, Z. (2017). Passive use of social network site and its relationships with self-esteem and self-concept clarity: A moderated mediation analysis. *Acta Psychologica Sinica*. https://doi.org/10.3724/sp. j.10412017.00060

Liu, X., Liu, L., Yang, J., Chai, F., Wang, A., Sun, L., & Ma, D. (1997). Reliability and validity of the adolescents self-rating life events checklist. *Chinese Journal of Clinical Psychology*.

Liu, Y., & Du, J. (2015). Parameter Optimization of the SVM for Big Data. *2015 8th International Symposium on Computational Intelligence and Design (ISCID)*. https://doi.org/10.1109/iscid.2015.185

Loneliness: human nature and the need for social connection. (2008). *Choice Reviews Online*, *46*(03), 46–1765. https://doi.org/10.5860/choice.46-1765

Lopez-Fernandez, O. (2017). Short version of the smartphone addiction scale adapted to Spanish and French: Towards a cross-cultural research in problematic mobile phone use. *Addictive Behaviors*, *64*, 275–280. https://doi.org/10.11016/j. addbeh2015.11.013

Lopez-Fernandez, O., Kuss, D. J., Romo, L., Morvan, Y, Kern, L., Graziani, P., Rousseau, A., Rumpf, H. -J., Bischof, A., Gässler, A. -K., Schimmenti, A., Passanisi, A., Männikkö, N., Kääriänen, M., Demetrovics, Z., Király, O., Chóliz, M., Zacarés, J. J., Serra, E., … Billieux, J. (2017). Self-reported dependence on mobile phones in young adults: A European cross-cultural empirical survey. *Journal of Behavioral Addictions*, *6*(2), 168–177. https://doi.org/10.11556/2006.62017.020

Lopez-Fernandez, O., Williams, A. J., & Kuss, D. J. (2019). Measuring Female Gaming: Gamer Profile, Predictors, Prevalence, and Characteristics From Psychological and Gender Perspectives. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg2019.00898

Loton, Daniel (2007) Problem video game playing, self esteem and social skills: an online study. Other Degree thesis, Victoria University.

Lovibond, S. H., & Lovibond, P. F. (1995). Manual for the depression anxiety stress scales. In *Psychology Foundation of Australia*. https://doi.org/DOI: 10.11016/0005-7967(94)00075-U

Lu, X., & Yeo, K. J. (2015). Pathological internet use among Malaysia university students: Risk factors and the role of cognitive distortion. *Computers in Human Behavior*, *45*, 235–242. https://doi.org/10.11016/j. chb2014.12.021

Luk, T. T., Wang, M. P., Shen, C., Wan, A., Chau, P. H., Oliffe, J., Viswanath, K., Chan, S. S. C., & Lam, T. H. (2018). Short version of the smartphone addiction scale in Chinese adults: Psychometric properties, sociodemographic, and health behavioral correlates. Journal of Behavioral Addictions, 7(4), 1157–1165. https://doi.org/10.11556/2006.72018.105

Lyubomirsky, S., & Lepper, H. S. (1999). A measure of subjective happiness: Preliminary reliability and construct validation. *Social Indicators Research*. https://doi.org/10.11023/A:1006824100041

Machimbarrena, J., González-Cabrera, J., Ortega-Barón, J., Beranuy-Fargues, M., Álvarez-Bardón, A., & Tejero, B. (2019). Profiles of problematic internet use and its impact on adolescents' health-related quality of life. *International Journal of Environmental Research and Public Health*, *16*(20), 3877. https://doi.org/10.3390/ijerph16203877

Macur, M., Király, O., Maraz, A., Nagygyörgy, K., & Demetrovics, Z. (2016). Prevalence of problematic internet use in Slovenia. *Slovenian Journal of Public Health*, *55*(3), 202–211. https://doi.org/10.11515/sjph-2016-0026

Maier, G., Feldmann, A., Paxson, V., & Allman, M. (2009). On dominant characteristics of residential broadband internet traffic. Proceedings of the ACM SIGCOMM Internet Measurement Conference, IMC. https://doi.org/10.11145/1644893.1644904

Maimon, O., & Rokach, L. (2010). *Data Mining and Knowledge Discovery Handbook* (2nd ed. 2010 ed.). Springer.

Marciano, L., Schulz, P. J., & Camerini, A. L. (2021). How smartphone use becomes problematic: Application of the ALT-SR model to study the predicting role of personality traits. *Computers in Human Behavior*. https://doi.org/10.11016/j. chb2021.106731

Marengo, D., Poletti, I., & Settanni, M. (2020). The interplay between neuroticism, extraversion, and social media addiction in young adult facebook users: Testing the mediating role of online activity using objective data. *Addictive Behaviors, 102*, 106150. doi:10.11016/j. addbeh2019.106150

Marengo, D., Sariyska, R., Schmitt, H. S., Messner, E., Baumeister, H., Brand, M., et al. (2021). Exploring the associations between self-reported tendencies toward smartphone use disorder and objective recordings of smartphone, instant messaging, and social networking app usage: Correlational study. *Journal of Medical Internet Research, 23*(9), e27093. doi:102196/27093

Masood, A., Luqman, A., Feng, Y, & Ali, A. (2020). Adverse consequences of excessive social networking site use on academic performance: Explaining underlying mechanism from stress perspective. *Computers in Human Behavior*, 113, 106476. https://doi.org/10.11016/j. chb2020.106476

Marttila, E., Koivula, A., & Räsänen, P. (2021). Does excessive social media use decrease subjective wellbeing? A longitudinal analysis of the relationship between problematic use, loneliness and life satisfaction. *Telematics and Informatics, 59*, 101556. https://doi.org/10.11016/j. tele2020.101556

Mazzocchi, F. (2015). Could big data be the end of theory in science? *EMBO Reports*. https://doi.org/10.115252/embr201541001

McCloskey, W., Iwanicki, S., Lauterbach, D., Giammittorio, D. M., & Maxwell, K. (2015). Are Facebook “friends” helpful? Development of a Facebook-based measure of social support and examination of relationships among depression, quality of life, and social support. *Cyberpsychology, Behavior, and Social Networking*. https://doi.org/10.11089/cyber2014.0538

McDonald, J. (2008). Measuring personality constructs: The advantages and disadvantages of self-reports, informant reports and behavioural assessments. https://www. nottingham. ac. uk/sociology/documents/enquire/volume-1-issue-1-dodorico-mcdonald. pdf

Medeiros, D. S. V., Cunha Neto, H. N., Lopez, M. A., Luiz, L. C., Fernandes, N. C., Vieira, A. B., … Diogo, D. M. (2020). A survey on data analysis on large-Scale wireless networks: online stream processing, trends, and challenges*.* *Journal of Internet Services and Applications.* https://doi.org/10.11186/s13174-020-00127-2

Meerkerk, G. J., Van Den Eijnden, R. J. J. M., Vermulst, A. A., & Garretsen, H. F. L. (2009). The Compulsive Internet Use Scale (CIUS): Some psychometric properties. *Cyberpsychology and Behavior*. https://doi.org/10.11089/cpb2008.0181

Melo, C., Madariaga, L., Nussbaum, M., Heller, R., Bennett, S., Tsai, C. C., & van Braak, J. (2020). Editorial: Educational technology and addictions. *Computers and Education*. https://doi.org/10.11016/j.compedu2019.103730

Michael, W. B., & Smith, R. A. (1976). The development and preliminary validation of three forms of a self-concept measure emphasizing school-related activities. *Educational and Psychological Measurement*. https://doi.org/10.11177/001316447603600240

Moberg, F. B., & Anestis, M. D. (2015). A preliminary examination of the relationship between social networking interactions, internet use, and thwarted belongingness. *Crisis*, *36*(3), 187–193. https://doi.org/10.11027/0227-5910/a000311

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 medicine*, *6*(7), e1000097. https://doi.org/10.11371/journal. pmed.1000097

Monacis, L., De Palo, V., Griffiths, M. D., & Sinatra, M. (2017a). Exploring individual differences in online addictions: The role of identity and attachment. *International Journal of Mental Health and Addiction*. https://doi.org/10.11007/s11469-017-9768-5

Monacis, L., De Palo, V., Griffiths, M. D., & Sinatra, M. (2017b). Social networking addiction, attachment style, and validation of the Italian version of the Bergen Social Media Addiction Scale. *Journal of Behavioral Addictions*. https://doi.org/10.11556/2006.62017.023

Moos, R. H., & Moos, B. S. (1994). Family Environment Scale manual (3rd ed.). Palo Alto, CA: Consulting Psychologists Press.

Morahan-Martin, J., & Schumacher, P. (2000). Incidence and correlates of pathological internet use among college students. *Computers in Human Behavior*, *16*(1), 13–29. https://doi.org/10.11016/S0747-5632(99)00049-7

Moreno, M. A., Jelenchick, L. A., & Christakis, D. A. (2013). Problematic internet use among older adolescents: A conceptual framework. *Computers in Human Behavior, 29*(4), 1879–1887. https://doi.org/10.11016/j. chb2013.01.053

Moretta, T., Buodo, G., Demetrovics, Z., & Potenza, M. N. (2022). Tracing 20 years of research on problematic use of the internet and social media: Theoretical models, assessment tools, and an agenda for future work. *Comprehensive Psychiatry*, *112*, 152286. https://doi.org/10.11016/j.comppsych2021.152286

Munro E., Hardie J., (2019). Why we should stop talking about objectivity and subjectivity in social work, *The British Journal of Social Work*, Volume 49, Issue 2, Pages 411–427, https://doi.org/10.11093/bjsw/bcy054

Murphy, E. (2017). Responding to the needs of students with mental health difficulties in higher education: an Irish perspective. *European Journal of Special Needs Education, 32*(1), 110–124. https://doi.org/10.11080/088562572016.1254966

Nagamori, S., Mikawa, K., Goto, M., & Ogihara, T. (2019). An analytic model to represent relation between finish date of job-hunting and time-series variation of entry tendencies. *Industrial Engineering & Management Systems, 18*(3), 292–304. https://doi.org/10.7232/iems2019.18.3292

Neal., D. J., & Carey, K. B. (2005). A follow-up psychometric analysis of the self-regulation questionnaire. *Psychology of Addictive Behaviors*. https://doi.org/10.11037/0893-164X.19.4.414

Nie, Norman & Hillygus, D. Sunshine & Erbring, Lutz. (2008). Internet use, interpersonal relations, and sociability: A time diary study.110.11002/9780470774298. ch7.

Nimon, K. F., & Oswald, F. L. (2013). Understanding the results of multiple linear regression. *Organizational Research Methods, 16*(4), 650–674. https://doi.org/10.11177/1094428113493929

Nolen-Hoeksema, S., Wisco, B. E., & Lyubomirsky, S. (2008). Rethinking rumination. *Perspectives on Psychological Science*. https://doi.org/10.11111/j.1745-69242008.00088. x

Nunnally, I. (2021). Psychometric Theory (3rd ed.). MC GRAW HILL INDIA.

O'Brien, O., Sumich, D. A., Kanjo, D. E., & Kuss, D. D. (2022). WiFi at university: A better balance between education activity and distraction activity needed. *Computers and Education Open*, *3*, 100071. https://doi.org/10.11016/j. caeo2021.100071

Odac, H., & Kalkan, M. (2010). Problematic Internet use, loneliness and dating anxiety among young adult university students. *Computers and Education*, *55*(3), 1091–1097. https://doi.org/10.11016/j.compedu2010.05.006

Odaci, H., & Çelik, Ç. B. (2013). Who are problematic internet users? An investigation of the correlations between problematic internet use and shyness, loneliness, narcissism, aggression and self-perception. *Computers in Human Behavior*, *29*(6), 2382–2387. https://doi.org/10.11016/j. chb2013.05.026

Oksanen, J., Blanchet, F. G., Friendly, M., Kindt, R., Legendre, P., McGlinn, D., Minchin, P. R., O'Hara, R. B., Simpson, G. L., Solymos, P., Stevens, M. H. H., Szoecs, E., & Wagner, H. (2020). vegan: Community Ecology Package (2.5-7) [Computer software]. https://CRAN. R-project. org/package=vegan

Oldham S, Fulcher B, Parkes L, Arnatkevičiūtė A, Suo C, et al. (2019) Consistency and differences between centrality measures across distinct classes of networks. *PLOS ONE 14*(7): e0220061. https://doi.org/10.11371/journal. pone.0220061

Oluwafemi, O. O., Bibire, A. H., Mebu, V. A., Dung, P. H., & Aderibigbe, J. K. (2020). Conditional indirect effects of gender and school on internet use for academic activities and social-moral development among secondary school students in Nigeria. *Cogent Social Sciences*, *6*(1), 1748478. https://doi.org/10.11080/233118862020.1748478

Online Safety Bill (2021). Retrieved 9 December 2021, from https://assets. publishing. service. gov. uk/government/uploads/system/uploads/attachment_data/file/985033/Draft_Online_Safety_Bill_Bookmarked. pdf

Opsahl, T., Agneessens, F., & Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks, 32*(3), 245–251. https://doi.org/10.11016/j. socnet2010.03.006

Orrù, G., Monaro, M., Conversano, C., Gemignani, A., & Sartori, G. (2020). Machine learning in psychometrics and psychological research. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg2019.02970

Ostendorf, S., Wegmann, E., & Brand, M. (2020). Problematic social-networks-use in German children and adolescents—The interaction of need to belong, online self-regulative competences, and age. *International Journal of Environmental Research and Public Health*, *17*(7), 2518. https://doi.org/10.3390/ijerph17072518

Ozdemir, B., Cakir, O., & Hussain, I. (2018). Prevalence of nomophobia among university students: A comparative study of Pakistani and Turkish undergraduate students. *Eurasia Journal of Mathematics, Science and Technology Education*, *14*(4), 1519–1532. https://doi.org/1029333/ejmste/84839

Özdemir, Y, Kuzucu, Y, & Ak, Ş. (2014). Depression, loneliness and internet addiction: How important is low self-control? *Computers in Human Behavior*, *34*, 284–290. https://doi.org/10.11016/j. chb2014.02.009

Paik S. H,. Kim D. J. Smart healthcare systems and precision medicine. (2019) *Advanced Experimental Medical Biology*. ;1192:263-279. doi: 10.11007/978-981-32-9721-0_13. PMID: 31705499.

Panel for the Future of Science and Technology. (2020). Potentially negative effects of internet use. European Parliamentary Research Service. https://www. europarl. europa. eu/RegData/etudes/IDAN/2020/641540/EPRS_IDA(2020)641540_EN. pdf

Parry, D. A., Davidson, B. I., Sewall, C. J. R., Fisher, J. T., Mieczkowski, H., & Quintana, D. S. (2020, October 1). A systematic review and meta-analysis of discrepancies between logged and self-reported digital media use. https://doi.org/10.11038/s41562-021-01117-5

Peach, R. L., Yaliraki, S. N., Lefevre, D., & Barahona, M. (2019). Data-driven unsupervised clustering of online learner behaviour. *Npj Science of Learning*, *4*(1). https://doi.org/10.11038/s41539-019-0054-0

Peng, S., Zhou, B., Wang, X., Zhang, H., & Hu, X. (2020). Does high teacher autonomy support reduce smartphone use disorder in Chinese adolescents? A moderated mediation model. *Addictive Behaviors*, *105*(October 2019), 106319. https://doi.org/10.11016/j. addbeh2020.106319

Pernkopf, F., & Bouchaffra, D. (2005). Genetic-based EM algorithm for learning Gaussian mixture models.ie*EE Transactions on Pattern Analysis and Machine Intelligence*, *27*(8), 1344–1348. https://doi.org/10.11109/tpami2005.162

Petersen, W. (1965). Society and the Adolescent Self-Image. Morris Rosenberg. Princeton University Press, Princeton, N. J., 1965. xii + 326 pp. $6.50. *Science*. https://doi.org/10.11126/science.148.3671.804

Pontes H. M., Griffiths M. D. (2015). Measuring DSM-5 internet gaming disorder: Development and validation of a short psychometric scale, *Computers in Human Behavior, 45*, pp.137-143, 10.11016/j. chb2014.12.006

Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin*, *135*(2), 322–338. https://doi.org/10.11037/a0014996

Pressman, S. D., Kraft, T., & Bowlin, S. (2020). Well-being: Physical., psychological., and social. In *Encyclopedia of Behavioral Medicine*. https://doi.org/10.11007/978-3-030-39903-0_75

Price, A., & Smith, H. A. (2019). USI National Report on Student Mental Health in Third Level Education. Retrieved from www. usi.ie/wp-content/uploads/2019/08/WEB-USI-MH-report-1. pdf

Primi, C., Fioravanti, G., Casale, S., & Donati, M. A. (2021). Measuring problematic Facebook use among adolescents and young adults with the Bergen Facebook addiction scale: A psychometric analysis by applying item response theory. I*nternational Journal of Environmental Research and Public Health, 18*(6), 2979. https://doi.org/10.3390/ijerph18062979

Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Fear of missing out scale: FoMOs. *Computers in Human Behavior*, *29*, 1814–1848. https://doi.org/10.11037/t23568-000

Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. *Computers in Human Behavior, 29*(4), 1841–1848. https://doi.org/10.11016/j. chb2013.02.014

Qazi, A., Naseer, K., Qazi, J., AlSalman, Naseem, U., Yang, S., Hardaker, G., & Gumaei, A. (2020). Conventional to online education during COVID-19 pandemic: Do develop and underdeveloped nations cope alike. *Children and Youth Services Review*. https://doi.org/10.11016/j. childyouth2020.105582

Qin, L., Cheng, L., Hu, M., Liu, Q., Tong, J., Hao, W., Luo, T., & Liao, Y. (2020). Clarification of the cut-off score for nine-item internet gaming disorder scale–short form (IGDS9-SF) in a Chinese context. *Frontiers in Psychiatry, 11*. https://doi.org/10.3389/fpsyt2020.00470

R Core Team. (2020). R: A language and environment for statistical computing. R foundation for statistical computing. https://www. R-project. org/

Radford, J., & Joseph, K. (2020). Theory in, theory out: The uses of social theory in machine learning for social science. *Frontiers in Big Data*, *3*. https://doi.org/10.3389/fdata.2020.00018

Rashid, T., & Asghar, H. M. (2016). Technology use, self-directed learning, student engagement and academic performance: Examining the interrelations. *Computers in Human Behavior*, *63*, 604–612. https://doi.org/10.1016/j.chb.2016.05.084

Razaque, A., Ben Haj Frej, M., Almi'ani, M., Alotaibi, M. & Alotaibi, B. (2021). Improved Support Vector Machine Enabled Radial Basis Function and Linear Variants for Remote Sensing Image Classification. *Sensors (Basel, Switzerland), 21*(13), 4431. https://doi.org/10.3390/s21134431

Reer, F., Tang, W. Y, & Quandt, T. (2019b). Psychosocial well-being and social media engagement: The mediating roles of social comparison orientation and fear of missing out. *New Media & Society*, *21*(7), 1486–1505. https://doi.org/10.1177/1461444818823719

Reid, R. C., Garos, S., & Carpenter, B. N. (2011b). Reliability, Validity, and Psychometric Development of the Hypersexual Behavior Inventory in an Outpatient Sample of Men. *Sexual Addiction & Compulsivity*, *18*(1), 30–51. https://doi.org/10.1080/10720162.2011.555709

Robayo-Pinzon, O., Foxall, G. R., Montoya-Restrepo, L. A., & Rojas-Berrio, S. (2021). Does excessive use of smartphones and apps make us more impulsive? An approach from behavioural economics. *Heliyon, 7*(2), e06104. doi:10.11016/j. heliyon2021. e06104

Roberts, J. A., & David, M. E. (2016). My life has become a major distraction from my cell phone: Partner phubbing and relationship satisfaction among romantic partners. *Computers in Human Behavior*, *54*, 134–141. https://doi.org/10.1016/j.chb.2015.07.058

Robinaugh, D. J., Millner, A. J., & McNally, R. J. (2016). Identifying highly influential nodes in the complicated grief network. *Journal of Abnormal Psychology*, *125*(6), 747–757. https://doi.org/10.1037/abn0000181

Rodriguez-Blazquez, C., Frades-Payo, B., Forjaz, M. J., Ayala, A., Martinez-Martin, P., Fernandez-Mayoralas, G., & Rojo-Perez, F. (2010). Psychometric properties of the international wellbeing index in community-dwelling older adults. *International Psychogeriatrics, 23*(1), 161–169. https://doi.org/10.11017/s104161021000092x

Romero-Rodríguez, J. M., Aznar-Díaz, I., Marín-Marín, J. A., Soler-Costa, R., & Rodríguez-Jiménez, C. (2020b). Impact of Problematic Smartphone Use and Instagram Use Intensity on Self-Esteem with University Students from Physical Education. *International Journal of Environmental Research and Public Health*, *17*(12), 4336. https://doi.org/10.3390/ijerph17124336

Rodriguez M. Z., Comin C. H., Casanova D., Bruno O. M., Amancio D. R., et al. (2019) Clustering algorithms: A comparative approach. *PLOS ONE 14*(1): e0210236. https://doi.org/10.11371/journal. pone.0210236

Rosenberg, M. (1965). *Rosenberg Self-Esteem Scale (RSES)*. APA PsycTests. https://doi.org/10.1037/t01038-000

Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement. In *Psychological monographs*. https://doi.org/10.11037/h0092976

Rouis, S., Limayem, M., & Salehi-Sangari, E. (2017b). Impact of Facebook Usage on Students' Academic Achievement: Roles of Self-Regulation and Trust. *Electronic Journal of Research in Education Psychology*, *9*(25), 961–994. https://doi.org/10.25115/ejrep.v9i25.1465

Rozgonjuk, D., Schivinski, B., Pontes, H. M., & Montag, C. (2021). Problematic Online Behaviors Among Gamers: the Links Between Problematic Gaming, Gambling, Shopping, Pornography Use, and Social Networking. *International Journal of Mental Health and Addiction*. https://doi.org/10.11007/s11469-021-00590-3

Ruggeri, K., Garcia-Garzon, E., Maguire, I., Matz, S., & Huppert, F. A. (2020). Well-being is more than happiness and life satisfaction: a multidimensional analysis of 21 countries. *Health and Quality of Life Outcomes*, *18*(1). https://doi.org/10.11186/s12955-020-01423-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/10.11037/0022-3514.39.3.472

Russell, D. W. (1996). UCLA Loneliness Scale (Version 3): Reliability, Validity, and Factor Structure. *Journal of Personality Assessment*, *66*(1), 20–40. https://doi.org/10.1207/s15327752jpa6601_2

Ryding, F. C., & Kuss, D. J. (2020). Passive objective measures in the assessment of problematic smartphone use: A systematic review. *Addictive Behaviors Reports*, *11*, 100257. https://doi.org/10.1016/j.abrep.2020.100257

Salehan, M., & Negahban, A. (2013). Social networking on smartphones: When mobile phones become addictive. *Computers in Human Behavior*, *29*(6), 2632–2639. https://doi.org/10.1016/j.chb.2013.07.003

Sanders, G. S., Baron, R. S., & Moore, D. L. (1978b). Distraction and social comparison as mediators of social facilitation effects. *Journal of Experimental Social Psychology*, *14*(3), 291–303. https://doi.org/10.1016/0022-1031(78)90017-3

Sandra, L., Lumbangaol, F., & Matsuo, T. (2021). Machine learning algorithm to predict student's performance: A systematic literature review. *TEM Journal*, 1919–1927. https://doi.org/10.18421/tem104-56

Saxena, A., Prasad, M., Gupta, A., Bharill, N., Patel, O. P., Tiwari, A., Er, M. J., Ding, W., & Lin, C. T. (2017). A review of clustering techniques and developments. *Neurocomputing*, *267*, 664–681. https://doi.org/10.11016/j. neucom2017.06.053

Schwartz, B., Ward, A., Monterosso, J., Lyubomirsky, S., White, K., & Lehman, D. R. (2002b). Maximizing versus satisficing: Happiness is a matter of choice. *Journal of Personality and Social Psychology*, *83*(5), 1178–1197. https://doi.org/10.1037/0022-3514.83.5.1178

Sculley D. Web-Scale k-Means clustering. In: Proceedings of the 19th International Conference on World Wide Web. WWW'10. New York, NY, USA: *Association for Computing Machinery;* 2010. p.1177–1178. Available from: 10.11145/1772690.1772862.

Sela, Y, Zach, M., Amichay-Hamburger, Y, Mishali, M., & Omer, H. (2020). Family environment and problematic internet use among adolescents: The mediating roles of depression and fear of missing out. *Computers in Human Behavior, 106*, 106226. doi:10.11016/j. chb2019.106226

Servidio, R. (2021). Fear of missing out and self-esteem as mediators of the relationship between maximization and problematic smartphone use. *Current Psychology*. https://doi.org/10.11007/s12144-020-01341-8

Shakya, H. B., & Christakis, N. A. (2017). Association of Facebook use with compromised wellbeing: A longitudinal study. *American Journal of Epidemiology, 185*(3), 203-211. doi:10.11093/aje/kww189

Shane-Simpson, C., Brooks, P. J., Obeid, R., Denton, E. G., & Gillespie-Lynch, K. (2016). Associations between compulsive internet use and the autism spectrum. *Research in Autism Spectrum Disorders*, *23*, 152–165. https://doi.org/10.11016/j. rasd2015.12.005

Shek, D. T. L., & Yu, L. (2012). Internet Addiction Phenomenon in Early Adolescents in Hong Kong. *The Scientific World Journal*, *2012*, 1–9. https://doi.org/10.1100/2012/104304

Sherer, M., Maddux, J. E., Mercandante, B., Prentice-Dunn, S., Jacobs, B., & Rogers, R. W. (1982). The self-efficacy scale: construction and validation. *Psychological Reports*. https://doi.org/102466/pr0.1982.512.663

Shiffman S, Stone AA, Hufford MR. (2008). Ecological momentary assessment. *Annual Review Clinical Psychology*, *4*, 1-32. doi: 10.11146/annurev. clinpsy.3.022806.091415. PMID: 18509902.

Simó-Sanz, C., Ballestar-Tarín, M. L., & Martínez-Sabater, A. (2018). Smartphone Addiction Inventory (SPAI): Translation, adaptation and validation of the tool in Spanish adult population. *PLOS ONE*, *13*(10), e0205389. https://doi.org/10.11371/journal. pone.0205389

Singelis, T. M. (1994). The Measurement of Independent and Interdependent Self-Construals. *Personality and Social Psychology Bulletin*, *20*(5), 580–591. https://doi.org/10.1177/0146167294205014

Sirigatti, S., Stefanile, C., Giannetti, E., Iani, L., Penzo, I., & Mazzeschi, A. (2009). Assessment of factor structure of Ryff's psychological wellbeing scales in Italian adolescents. *Bollettino Di Psicologia Applicata, 56.* 30-50.

Smith, H. M., & Betz, N. E. (2000). Development and Validation of a Scale of Perceived Social Self-Efficacy. *Journal of Career Assessment*, *8*(3), 283–301. https://doi.org/10.1177/106907270000800306

Soraci, P., Ferrari, A., Barberis, N., Luvarà, G., Urso, A., del Fante, E., & Griffiths, M. D. (2020b). Psychometric Analysis and Validation of the Italian Bergen Facebook Addiction Scale. *International Journal of Mental Health and Addiction*. https://doi.org/10.1007/s11469-020-00346-5

Spada, M. M. (2014). An overview of problematic internet use. *Addictive Behaviors, 39*(1), 3-6. doi:10.11016/j. addbeh2013.09.007 [doi]

Spitzer, R. L., Kroenke, K., Williams, J. B. W., & Löwe, B. (2006). A Brief Measure for Assessing Generalized Anxiety Disorder. *Archives of Internal Medicine*, *166*(10), 1092. https://doi.org/10.1001/archinte.166.10.1092

Stead, H., & Bibby, P. A. (2017). Personality, fear of missing out and problematic internet use and their relationship to subjective wellbeing. *Computers in Human Behavior, 76*, 534–540. https://doi.org/10.11016/j. chb2017.08.016

Stopczynski, A., Sekara, V., Sapiezynski, P., Cuttone, A., Madsen, M. M., Larsen, J. E., & Lehmann, S. (2014). Measuring Large-Scale Social Networks with High Resolution. *PLoS ONE*, *9*(4), e95978. https://doi.org/10.1371/journal.pone.0095978

Stone, A. A., & Shiffman, S. (1994). Ecological Momentary Assessment (Ema) in Behavioral Medicine. *Annals of Behavioral Medicine*, *16*(3), 199–202. https://doi.org/10.1093/abm/16.3.199

Struk, A. A., Carriere, J. S. A., Cheyne, J. A., & Danckert, J. (2016). A Short Boredom Proneness Scale. *Assessment*, *24*(3), 346–359. https://doi.org/10.1177/1073191115609996

Su, W., Han, X., Jin, C., Yan, Y, & Potenza, M. N. (2019). Are males more likely to be addicted to the internet than females? A meta-analysis involving 34 global jurisdictions. *Computers in Human Behavior, 99*, 86–100. https://doi.org/10.11016/j. chb2019.04.021

Sung, Y, Nam, T. H., & Hwang, M. H. (2020). Attachment style, stressful events, and internet gaming addiction in Korean university students. *Personality and Individual Differences*, *154*, 109724. https://doi.org/10.11016/j. paid2019.109724

Syakur, M. A., Khotimah, B. K., Rochman, E. M. S., & Satoto, B. D. (2018). Integration K-Means Clustering Method and Elbow Method For Identification of The Best Customer Profile Cluster. *IOP Conference Series: Materials Science and Engineering*, *336*, 012017. https://doi.org/10.1088/1757-899x/336/1/012017

Tang, C., Wu, A., Yan, E., Ko, J., Kwon, J., Yogo, M., Gan, Y, & Koh, Y. (2018). Relative risks of internet-related addictions and mood disturbances among college students: a 7-country/region comparison. *Public Health*, *165*, 16–25. https://doi.org/10.11016/j. puhe2018.09.010

Tateno, M., Teo, A. R., Ukai, W., Kanazawa, J., Katsuki, R., Kubo, H., & Kato, T. A. (2019). Internet addiction, smartphone addiction, and Hikikomori trait in Japanese young adult: social isolation and social network. *Frontiers in Psychiatry, 10*. https://doi.org/10.3389/fpsyt2019.00455

Tesar, M. (2020). Towards a Post-Covid-19 'New Normality?': Physical and Social Distancing, the Move to Online and Higher Education. *Policy Futures in Education*, *18*(5), 556–559. https://doi.org/10.1177/1478210320935671

The International Wellbeing Group. (2013). Personal wellbeing index – adult (PWI-A) (No.5). http://www. acqol.com. au/uploads/pwi-a/pwi-a-english. pdf

Think Tank European Parliament. (2019, January). Harmful internet use Part II: Impact on culture and society. https://www. europarl. europa. eu/RegData/etudes/STUD/2019/624269/EPRS_STU(2019)624269_EN. pdf

Throuvala, M. A., Griffiths, M. D., Rennoldson, M., & Kuss, D. J. (2019). School-based Prevention for Adolescent Internet Addiction: Prevention is the Key. A Systematic Literature Review. *Current Neuropharmacology*, *17*(6), 507–525. https://doi.org/10.2174/1570159x16666180813153806

Thompson, E. R. (2007). Development and Validation of an Internationally Reliable Short-Form of the Positive and Negative Affect Schedule (PANAS). *Journal of Cross-Cultural Psychology*, *38*(2), 227–242. https://doi.org/10.1177/0022022106297301

Tian, Y, Si, Y, Meng, W., Bian, Y, Han, P., Hu, J., Wang, P., & Gao, F. (2018). Mediating Factors of the Association Between Shyness and Generalized Pathological Internet Use in Chinese University Students. *International Journal of Mental Health and Addiction*, *17*(3), 555–572. https://doi.org/10.1007/s11469-018-9979-4

Topcu, I., & Erdur-Baker, Z. (2012). Affective and cognitive empathy as mediators of gender differences in cyber and traditional bullying. *School Psychology International*, *33*(5), 550–561. https://doi.org/10.1177/0143034312446882

Trevisan, M., Giordano, D., Drago, I., Munafo, M. M., & Mellia, M. (2020). Five Years at the Edge: Watching Internet From the ISP Network.ie*EE/ACM Transactions on Networking*, *28*(2), 561–574. https://doi.org/10.1109/tnet.2020.2967588

Truzoli, R., Viganò, C., Galmozzi, P. G., & Reed, P. (2019b). Problematic internet use and study motivation in higher education. *Journal of Computer Assisted Learning*, *36*(4), 480–486. https://doi.org/10.1111/jcal.12414

Tudorel, O. I., Vintilă, M., Vlaicu, L., Bălăuță, D., Goian, C., & Rusu, A. (2018). Romanian version of the internet addiction test: psychometric properties and cross-gender invariance. *International Journal of Mental Health and Addiction*, *17*(2), 234–246. https://doi.org/10.11007/s11469-018-0014-6

Tuli, F. (2011). The basis of distinction between qualitative and quantitative research in social science: Reflection on ontological, epistemological and ethodological perspectives. *Ethiopian Journal of Education and Sciences*, *6*(1). https://doi.org/10.4314/ejesc. v6i1.65384

Vadher, S. B., Panchal, B. N., Vala, A. U., Ratnani, I. J., Vasava, K. J., Desai, R. S., & Shah, A. H. (2019). Predictors of problematic internet use in school going adolescents of Bhavnagar, India. *International Journal of Social Psychiatry*, *65*(2), 151–157. https://doi.org/10.11177/0020764019827985

Vally, Z., Laconi, S., & Kaliszewska-Czeremska, K. (2020). Problematic internet use, psychopathology, defense mechanisms, and coping strategies: a cross-sectional study from the United Arab Emirates. *Psychiatric Quarterly*, *91*(2), 587–602. https://doi.org/10.11007/s11126-020-09719-4

Van Borkulo, C. D., Borsboom, D., Epskamp, S., Blanken, T. F., Boschloo, L., Schoevers, R. A., & Waldorp, L. J. (2014). A new method for constructing networks from binary data. *Scientific Reports, 4*(1). https://doi.org/10.11038/srep05918

Van Deursen, A. J. A. M., Bolle, C. L., Hegner, S. M., & Kommers, P. A. M. (2015). Modeling habitual and addictive smartphone behavior: The role of smartphone usage types, emotional intelligence, social stress, self-regulation, age, and gender. *Computers in Human Behavior 45,* 411-420. https://doi.org/10.1016/j.chb.2014.12.039.

Yarkoni, T., & Westfall, J. (2017). Choosing Prediction Over Explanation in Psychology: Lessons from machine learning. *Perspectives on Psychological Science*, *12*(6), 1100–1122. https://doi.org/10.11177/1745691617693393

Vayre, E., & Vonthron, A. M. (2019). Identifying work-related internet's uses—at work and outside usual workplaces and hours—and their relationships with work–home interface, work engagement, and problematic internet behavior. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg2019.02118

Yeturu, K., (2020) Chapter 3 - Machine learning algorithms, applications, and practices in data science, *Handbook of Statistics, Elsevier,* Volume 43, 2020, 81-206. https://doi.org/10.1016/bs.host.2020.01.002.

Victorin, S., Åsberg Johnels, J., Bob, E., Kantzer, A., Gillberg, C., & Fernell, E. (2020). Significant gender differences according to the problematic and risky internet use screening scale among 15-year-olds in Sweden. *Acta Paediatrica,* *109*(9), 1891–1892. https://doi.org/10.11111/apa.15240

Youyou, W., Kosinski, M., & Stillwell, D. (2015). Computer-based personality judgments are more accurate than those made by humans. *Proceedings of the National Academy of Sciences*, *112*(4), 1036–1040. https://doi.org/10.11073/pnas.1418680112

Walsh, S. P., White, K. M., & McD Young, R. (2010). Needing to connect: The effect of self and others on young people's involvement with their mobile phones. *Australian Journal of Psychology*, *62*(4), 194–203. https://doi.org/10.1080/00049530903567229

Wang, W. C. (2018). Exploring the Relationship Among Free-Time Management, Leisure Boredom, and Internet Addiction in Undergraduates in Taiwan. *Psychological Reports*, *122*(5), 1651–1665. https://doi.org/10.1177/0033294118789034

Wang, R., Chen, F., Chen, Z., Li, T., Harari, G. M., Tignor, S., Zhou, X., Ben-Zeev, D., & Campbell, A. T. (2014). StudentLife: Assessing Mental Health, Academic Performance and Behavioral Trends of College Students Using Smartphones. *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 3-14. ACM.

Wang, W. C., Kao, C. H., Huan, T. C., & Wu, C. C. (2010). Free Time Management Contributes to Better Quality of Life: A Study of Undergraduate Students in Taiwan. *Journal of Happiness Studies*, *12*(4), 561–573. https://doi.org/10.1007/s10902-010-9217-7

Wartberg, L., Zieglmeier, M., & Kammerl, R. (2020). An empirical exploration of longitudinal predictors for problematic internet use and problematic gaming behavior. *Psychological Reports*, *124*(2), 543–554. https://doi.org/10.11177/0033294120913488

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology*, *54*(6), 1063–1070. https://doi.org/10.11037/0022-3514.54.6.1063

Wegmann, E., Oberst, U., Stodt, B., & Brand, M. (2017). Online-specific fear of missing out and Internet-use expectancies contribute to symptoms of Internet-communication disorder. *Addictive Behaviors Reports*, *5*, 33–42. https://doi.org/10.1016/j.abrep.2017.04.001

Weinstein, A., & Lejoyeux, M. (2010). Internet addiction or excessive internet use. *The American journal of drug and alcohol abuse*, *36*(5), 277–283. https://doi.org/10.3109/009529902010.491880

Weybright, E. H., Caldwell, L. L., Ram, N., Smith, E. A., & Wegner, L. (2015). Boredom Prone or Nothing to Do? Distinguishing Between State and Trait Leisure Boredom and Its Association with Substance Use in South African Adolescents. *Leisure Sciences*, *37*(4), 311–331. https://doi.org/10.1080/01490400.2015.1014530

Williams, G. C., & Deci, E. L. (1996). Internalization of biopsychosocial values by medical students: A test of self-determination theory. *Journal of Personality and Social Psychology*, *70*(4), 767–779. https://doi.org/10.1037/0022-3514.70.4.767

Wohn, D. Y, & Larose, R. (2014). Effects of loneliness and differential usage of Facebook on college adjustment of first-year students. *Computers and Education*, *76*, 158–167. https://doi.org/10.11016/j.compedu2014.03.018

Wright, S. L., Wright, D. A., & Jenkins-Guarnieri, M. A. (2013). Development of the Social Efficacy and Social Outcome Expectations Scale. *Measurement and Evaluation in Counseling and Development*, *46*(3), 218–231. https://doi.org/10.1177/0748175613484042

Xu, X., Wang, J., Peng, H., & Wu, R. (2019). Prediction of academic performance associated with internet usage behaviors using machine learning algorithms*. Computers and. Human Behavior, 98, 166-173.* doi:10.11016/j. chb2019.04.015

Yang, X. H., Yu, H. J., Liu, M. W., Zhang, J., Tang, B. W., Yuan, S., Gasevic, D., Paul, K., Wang, P. G., & He, Q. Q. (2019). The impact of a health education intervention on health behaviors and mental health among Chinese college students. *Journal of American College Health*, *68*(6), 587–592. https://doi.org/10.1080/07448481.2019.1583659

Yaqoob, I., Hashem, I. A. T., Gani, A., Mokhtar, S., Ahmed, E., Anuar, N. B., & Vasilakos, A. V. (2016). Big data: From beginning to future. *International Journal of Information Management*, *36*(6), 1231–1247. https://doi.org/10.1016/j.ijinfomgt.2016.07.009

Yang, Z., Asbury, K., & Griffiths, M. D. (2019). "A Cancer in the Minds of Youth?" A Qualitative Study of Problematic Smartphone Use among Undergraduate Students. *International Journal of Mental Health and Addiction*, *19*(4), 934–946. https://doi.org/10.1007/s11469-019-00204-z

Ye, Y, & Lin, L. (2015). Examining relations between locus of control, loneliness, subjective wellbeing, and preference for online social interaction. *Psychological Reports*, *116*(1), 164–175. https://doi.org/102466/07.09. PR0.116k14w3

Yee, N. (2006a). Motivations for Play in Online Games. *CyberPsychology & Behavior*, *9*(6), 772–775. https://doi.org/10.1089/cpb.2006.9.772

Yee, N. (2006b). The Psychology of Massively Multi-User Online Role-Playing Games: Motivations, Emotional Investment, Relationships and Problematic Usage. In: Schroeder, R., Axelsson, AS. (eds) *Avatars at Work and Play. Computer Supported Cooperative Work,* vol 34. Springer, Dordrecht. https://doi.org/10.1007/1-4020-3898-4_9

Yildirim, C., & Correia, A. P. (2015). Exploring the dimensions of nomophobia: Development and validation of a self-reported questionnaire. *Computers in Human Behavior*, *49*, 130–137. https://doi.org/10.1016/j.chb.2015.02.059

Young, K. S. (1996). Psychology of computer use: XL. Addictive use of the Internet - A case that breaks the stereotype. *Psychological Reports s,* *79*(3), 899–902. https://doi.org/102466/pr0.1996.79.3.899

Young, K. S. (1998). Internet Addiction: The Emergence of a New Clinical Disorder. *CyberPsychology & Behavior*, *1*(3), 237–244. https://doi.org/10.1089/cpb.1998.1.237

Young, K. S., & Brand, M. (2017). Merging Theoretical Models and Therapy Approaches in the Context of Internet Gaming Disorder: A Personal Perspective. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.01853

Yu, L., Recker, M., Chen, S., Zhao, N., & Yang, Q. (2018). The moderating effect of geographic area on the relationship between age, gender, and information and communication technology literacy and problematic internet use. *Cyberpsychology, Behavior, and Social Networking*, *21*(6), 367–373. https://doi.org/10.11089/cyber2017.0503

Zhang, Y., Ding, Q., & Wang, Z. (2021). Why parental phubbing is at risk for adolescent mobile phone addiction: A serial mediating model. *Children and Youth Services Review*, *121*, 105873. https://doi.org/10.1016/j.childyouth.2020.105873

Zhang, M. X., & Wu, A. M. (2020). Effects of smartphone addiction on sleep quality among Chinese university students: The mediating role of self-regulation and bedtime procrastination. *Addictive Behaviors*, *111*, 106552. https://doi.org/10.1016/j.addbeh.2020.106552

Zheng, Y, Yang, X., Zhou, R., Niu, G., Liu, Q., & Zhou, Z. (2020b). Upward social comparison and state anxiety as mediators between passive social network site usage and online compulsive buying among women. *Addictive Behaviors*, *111*, 106569. https://doi.org/10.1016/j.addbeh.2020.106569

Zhong, J., Zheng, Y, Huang, X., Mo, D., Gong, J., Li, M., & Huang, J. (2021b). Study of the Influencing Factors of Cyberbullying Among Chinese College Students Incorporated With Digital Citizenship: From the Perspective of Individual Students. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.621418

Zhou M., Ma M., Zhang Y, SuiA K., Pei D. & Moscibroda T.2016. EDUM: classroom education measurements via large-scale WiFi networks. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (*UbiComp '16*). Association for Computing Machinery, New York, NY, USA, 316–327. DOI:https://doi.org/10.11145/2971648.

Zhu, Y. Q., Chen, L. Y, Chen, H. G., & Chern, C. C. (2011b). How does Internet information seeking help academic performance? – The moderating and mediating roles of academic self-efficacy. *Computers & Education*, *57*(4), 2476–2484. https://doi.org/10.1016/j.compedu.2011.07.006

Appendices

Appendix A

Contribution of First author

Contribution of first author (Oonagh O'Brien) to each of the literature reviews:

- Initiation of review
- Development of ideas for focus of the review
- Search for and collection of literature for the review
- Analysis of literature
- Draft review preparation and updates based on multiple iterations of co-author feedback
- All authors reviewed and approved the final literature reviews

Contribution of first author (Oonagh O'Brien) to empirical chapters 4 and 6

- Study conception and design
- Development of key ideas with co-authors
- Data collection, cleaning , analysis and interpretation
- Draft manuscript preparation and updates based on multiple iterations of co-author feedback
- All authors reviewed and approved the final empirical chapters

Contribution of first author (Oonagh O'Brien) to empirical chapter 5

- Study conception and design
- Development of key ideas with co-authors
- Development of online survey
- Participant recruitment
- Data collection, cleaning , analysis and interpretation
- Draft manuscript preparation and updates based on multiple iterations of co-author feedback
- All authors reviewed and approved the final empirical chapters

Appendix B

University WiFi Network Demographics of Users

2018/2019	Student	Staff Headcount
Male Full-time	5036	573
Female Full-time	3428	574
Male Part-time	2733	
Female Part-time	1386	
Apprentice in part-time	1088	

* Guests may also use the WiFi network

Appendix C

University Activity by User Session for University Academic Year 2018/2019

Month	University Activity
September'18	Semester 1 begins 12th, Week 1-3
October '18	Bank holiday 29th Oct, Week 4-7
November '18	Week 7 – Week 11
December '18	Week 12,13, 14-21 exams- University closed 22nd Dec
January '19	5,7,8 Exams. Semester 2 begins Jan 28th, Week 1
February'19	Open Week 2-5
March '19	Open Bank Holiday18th, Week 6-9
April '19	2 weeks Easter, Week 10,11
May '19	Week 12, 13 Exams 11-24th May

Appendix D

Percentage Male and Female Results Above Cut-off in Psychometric Tests

.	*Male*			*Female*				
Psychometric Test	N	N Above Cut-off	%Above Cut-off	N	N Above Cut-off	% Above Cut-off	Cut-off	Valid Range
SAS-SV	362	169	47	469	284	61	33 female, 31 male => potentially addictive smartphone usage	6 to 60
PIUQ-SF-9	341	80	23	449	123	27	>=22 => potential problematic general internet usage	9 to 45
IGDS9-SF	331	3	1	435	1	0	>=32 => potential internet gaming disorder	9 to 45
BSMAS	326	25	8	442	91	21	>=19, potentially addicted social media usage	5 to 30
PPCS-18	289	3	1	396	0	0	>=76 => potentially problematic internet pornography consumption	5 to 50
FOMO	322	N/A	N/A	432	N/A	N/A	N/A	0 to 100
PWI	362	220	61	469	267	57	< 50 => suggests wellbeing is less than normal	20 to 80
UCLA	308	204	66	428	305	71	>= 43 indicator of moderate or high degree of loneliness	18 to 126

Appendix E

Classified Websites

Primary Domain	Hosted Sites	Classifications	flows
heanet.ie		cloud and technology	5621874137
google.com		search	2174952534
facebook.com		social media	874595546
amazon.com		shopping	694626286
apple.com		Apple	493527063
microsoft.com		cloud and technology	380185765
akamai.com		cloud and technology	377188104
fastly.com		cloud and technology	169430825
amazon.com	hcee.ie www.tum.ie citsu.ie www. cut.ie www. cit.ie	education	55912633
edu.ie		education	52032369
verizonbusiness.com		cloud and technology	43574715
centurylink.com		cloud and technology	31700098
cloudflare.com		cloud and technology	30631902
verizondigitalmedia.com		cloud and technology	28984676
google.com	chekian.com	search	27737001
google.com	lenium1. cf	search	27142364
blackboard.com		education	24460872
verisign.com		cloud and technology	23483033
dropboxinc.com	391ii.com www. hdqrza.com93338v.cc www. freejidi. tk6j6. top	education	22285154
icann. org		cloud and technology	22023919
xandr.com		advertising	21982783
root-servers. net.	tandemfliegen.at	cloud and technology	21342958
mcafee.com		cloud and technology	19975001
twitter.com		social media	19167770
verizondigitalmedia.com	cognipace.com ltwh7. tkcm8ro.tkd6h53.Tkbro sciencequarterly.com	other	18041317
google.com	41.cn onionflix.cc newmax.infoftempurl.com itempurl.com	social media	16876148
microsoft.com	caricert. cw	cloud and technology	16354119
whatsapp.com		social media	16128230
microsoft.com	pepperhost.de www. creativepixel.dk falconcomp.com www.wsrd. nlpearlandgasket.com	cloud and technology	15242719
none		other	15212133
yahoo-inc.com		search	14787855
dropboxinc.com		education	13793260
google.com	cukieuphumy.com icarion.com aatpc. uschristfreedomforhaiti. Org conhantaotranvan.com	education	13604573
criteo.com		advertising	13267983
microsoft.com	bing.com msftconnecttest.com bing.	search	12655834

	netpassport.net interoperabilitybridges.com		
google.com	pulkkinen. io	search	12501333
t-systems.com		cloud and technology	11957075
netflix.com		streaming	10209915
integralads.com		advertising	10198024
alibaba-inc.com		shopping	9998246
microsoft.com	galuna.com sdrv.ms826b1. tk1drv.ms kundbheiraten.de	cloud and technology	9816562
hetzner. de		cloud and technology	9801196
avast.com		cloud and technology	9610178
linkedin.com		education	9165702
vmware.com		cloud and technology	9100452
tencent.com		social media	9030506
google.com	mtqnia.com dns.Google durangomuseoa.Eu ssecure-auth.designx0522.com	other	8977329
ans. net		cloud and technology	8924025
leaseweb.com		cloud and technology	8397066
dropbox.com		education	8248668
bogon		other	8109977
spotify.com		streaming	8065920
three.ie		other	7860809
digitalocean.com		cloud and technology	7612563
eir.ie		other	7510295
openx.com		advertising	7419686
inap.com		cloud and technology	7367467
newrelic.com		cloud and technology	6944903
packet.com		cloud and technology	6426470
stackpath.com	musescore.com netdna-ssl.com timesofisrael.com memuplay.com lyricsmode.com	education	6285200
mopub.com	mopub.com	advertising	6269473
microsoft.com	msftconnecttest. xyz	cloud and technology	6206210
google.com	ynot01.com	search	6177407
microsoft.com	University.thelettero.com kettelhoit.se www.intrinsic. gg www. ghally.com ttkonsortium.com	education	6046840
google.com	vaeslucas.nl	search	5889081
pubmatic.com		advertising	5764552
ovh. net		cloud and technology	4986044
adobe.com		education	4909273
microsoft.com	stepnordic.com portcheck. net	cloud and technology	4893438
youtube.com		streaming	4633742
king.com		gaming	4576518
google.com	ak0. twclipperton.org	search	4429295
paddypowerbetfair.com		gaming	4348832
google.com	ibtekarmedia.com	search	4264765
linode.com		cloud and technology	4239632
worldstream.com		cloud and technology	4013514

kaspersky.com		cloud and technology	3959073
verizonmedia.com		streaming	3693363
google.com	starwarsrp.co.uk	gaming	3656768
stackpath.com	ultimateguitar.com musescore.com timesofisrael.com memuplay.comdavar1. co. il	education	3641368
rackspace.com		cloud and technology	3511622
opendns.com	mtqnia.com dreamshops.in talkitupglobal.com michiganpaving.net jackberben. net	other	3505669
automattic.com		cloud and technology	3500288
alibabagroup.com		shopping	3444048
twitter.com	itoen-haiku.jp7style.xyzjflabo.org	social media	3336349
twitter.com	cpress.co rankmaker.net 47jnl.tk strapyoung. worktwiaso-bee.com	social media	3320496
microsoft.com	sahs.at	education	3306024
stackpath.com		cloud and technology	3243374
twitter.com	39finder.pw tweeter.workjonas-polls.online twitterprojector.com	social media	3230957
twitter.com	buckget.us	social media	3031347
microsoft.com	abraccio.co.uk	education	2917626
ntt.com		cloud and technology	2779508
microsoft.com	williscaregroup.ie	education	2742853
google.com	tdala.se	search	2732529
valve. net		gaming	2648073
microsoft.com	px-investor.cz	education	2636303
aib.ie		other	2628545
microsoft.com	mkolegija.it	education	2617774
stackpath.com	cavalierhospitals.com	other	2358069
conversantmedia.com		advertising	2345567
servercentral.com		cloud and technology	2313749
google.com	activtrainer.com	education	2220772
bt.com		other	2194432
root-dns-server. net	University.rollhq.co.nz baughanlaw.com www.rollhq.nz	cloud and technology	2176839
nasa. gov	yesmkr.comhsecservices.com	education	2172326
mail. mil	perdolik.dev	other	2168235
umd. edu		education	2167450
isi. edu	allabouttheword.com kort.co	education	2161539
telegram. org		social media	2130348
zscaler.com		cloud and technology	2059768
mediamath.com		advertising	2038913
isc. org	aakarsolutions.com	education	1927242
psinet. hn	zzzcn.info www.xn--kenstorkkken-2jb.com	cloud and technology	1921853
mopub.com	mopub.commopubtrk.com	advertising	1915466
ibm.com		education	1837643

microsoft.com	msn.comm sn.netmicrosoft-msn.org msncdn.com zorfq.tk	social media	1789784
worldstream. nl		cloud and technology	1641749
cloudflare.com	strattic.ionextgen-global.com authrock.com cryosinternational.com steamboatmagazine.com	cloud and technology	1573108
amobee.com		advertising	1568378
comscore.com		advertising	1540785
limelight.com		cloud and technology	1507538
fastly.com	chengfeilong.com nuxse.com ending.workgtranchedone.com liujilu.com	education	1280756
worldstream. nl	gcadvert.com worldfamous.metrustburn.com	advertising	1129100
fastly.com	tv.dkcharlie.dk tv2local.dk knaek-cancer.dk tvtider.dk	streaming	1125851
koumar. net		other	1116491
akamai.com	popcap.com	gaming	1113917
google.com	danielsuppes.me	education	1084075
cloudflare.com	moenico.com 886946.com www.fuck163. arthdbigtitsporn.com wobo.online	streaming	964908
salesforce.com		cloud and technology	862964
google.com	aitaleabiamoglobal.com flyfishingireland.ie	other	826854
netactuate.com		cloud and technology	820018
cogentco.com		cloud and technology	787762
doubleverify.com		advertising	723178
stackpath.com	hwcdn.netbestgamesvault.com cyberslut2069.com ntrsttl.com israelnationalnews.com	gaming	655808
privax.com		other	650172
quantcast.com		advertising	644827
ans. net	ehypo.sknordeakindlustus. ee4tecture.ch allthingslive. fichorvatskoubytovanie.sk	shopping	631695
microsoft.com	fesselndes.de rushwan.net	education	604078
fastly.com	xn--lebensqualittsmarken-mzb.de domol.de best-view.de rossmann-logistik.de rossmann-produkttester.de	shopping	600004
f5.com		cloud and technology	593866
hetg.ie	sjcautosltd.com	shopping	564109
centurylink.com	etsi.pwduatepeinsaat.com kolayparataktikleri.cf clairemurthwaite.com brentamartin.com	other	513371
amazon.com	diamond.poker	gaming	503406
google.com	unact-union.ru falappi.itwinplaystation5.ga wikibia.comfortnitelive. tk	gaming	489979
rte.ie		streaming	441133

bitdefender. ro		cloud and technology	408734
rocketfuel.com		advertising	407456
edgenetworkservices.com		other	407406
digitalplanet.ie	grantsonline.ie	education	378070
cdnetworks.com		cloud and technology	357125
adjust.com		advertising	354416
google.com	ffestudio.commesuk.com kissmotorcycletours.com shamrockscamogie.com moonlightagency. in	other	349768
windscribe.com		other	348628
spotx. tv		advertising	346256
fb.com		social media	310653
telecity.com		cloud and technology	276051
m247.com		cloud and technology	269754
jump. net. uk		cloud and technology	262948
godaddy.com		cloud and technology	254118
aptum.com		cloud and technology	254012
amazon.com	exotik.com	shopping	185020
rutracker. org		streaming	179606
ucc.ie		education	171330
chinaunicom. cn		cloud and technology	170743
cloudflare.com	clairesaccessories. infoclaires. esclairesstores.com. phclaires. declairesclub.com	shopping	166865
ebayinc.com		shopping	166856
omc. co. il		cloud and technology	160726
serveryou.com		cloud and technology	155467
eoreality. net		gaming	155326
compuweb.com	onlysonos.org onlysonos. Mobi onlysonos.com onlysonos.info onlysonos. co	shopping	147103
nforce.com		cloud and technology	145696
amazon.com	estigator.com	education	141771
cisco.com		cloud and technology	141524
twitter.com	futureducktwitter.co.uk fairward.chxn--btrw6b.org xn--wgv71a483g.org immofree.com	social media	134730
microsoft.com	queensu.ca jiosaavn.comyouth4work.co masp. netmcalistersdeli.com	education	130070
twitter.com	twitter.comarwuu.tk xn--lha. cct3witter.comtvipe.tk	social media	128628
twitch. tv		streaming	128050
vianw. pt	khleeg.comlefdomain.com cb-msp-02.com checktime.info shopstoregamesesss.com	cloud and technology	126197
nih. gov	coronarymicrovasculardysfunction.com spilanthesacmella.com	education	126132

	saveanchorage.net pubchem. netshafranibdreprint.com		
microsoft.com	university.internetanalyzer.n et internetanalyzer.net asg-worldwide.com	cloud and technology	124043
amazon.com		other	120869
hernlabs. se		other	105806
aliyun.com		cloud and technology	98897
chinamobile.com		other	77788
fastly.com	xn�lebensqualittsmarken-mzb.de domol.de best-view.de rossmann-logistik.de rossmann-produkttester.de	shopping	53417
verizon.com		streaming	51884

Appendix F

Classifications Used for Websites and Explanation and Examples of the Classification (Content Taxonomy - IAB Tech Lab, n. d.).

Classification	Explanation
advertising	Domains associated with marketing or advertising e. g., Mopub.com
Apple	4 percent of overall network activity was to Apple, predominantly data backup, then Apple tv, Apple music or software downloads.
streaming	Domains for television, movie streaming or music streaming such as spotify.com, youtube.com, or rte.ie
education	Domains for which the primary purpose is for education or is used in education in University such as wikemedia.com or dropbox. inc
gaming	Websites that are associated with video games or betting such paddypower.com or king.com
cloud and technology	Cloud services, software companies, network security services. This classification includes Internet service and technology related activities that occur in the background when accessing a domain, such as technology to enable a safer Internet, application delivery and networking technology that optimizes the delivery of network-based applications. Examples are heanet.ie
search	This classification includes websites that are used for internet searches, e. g., Google.com
shopping	Websites for which the primary purpose is shopping such as Amazon.com, Ebayinc.com, exotik.com Alibaba-inc.com
social media	Websites used for social interaction and communication, Twitter.com, facebook.com, telegram. org
other	Websites that do not naturally sit in any of the other categories, e. g., AitaleabiamoGlobal.com, aib.ie

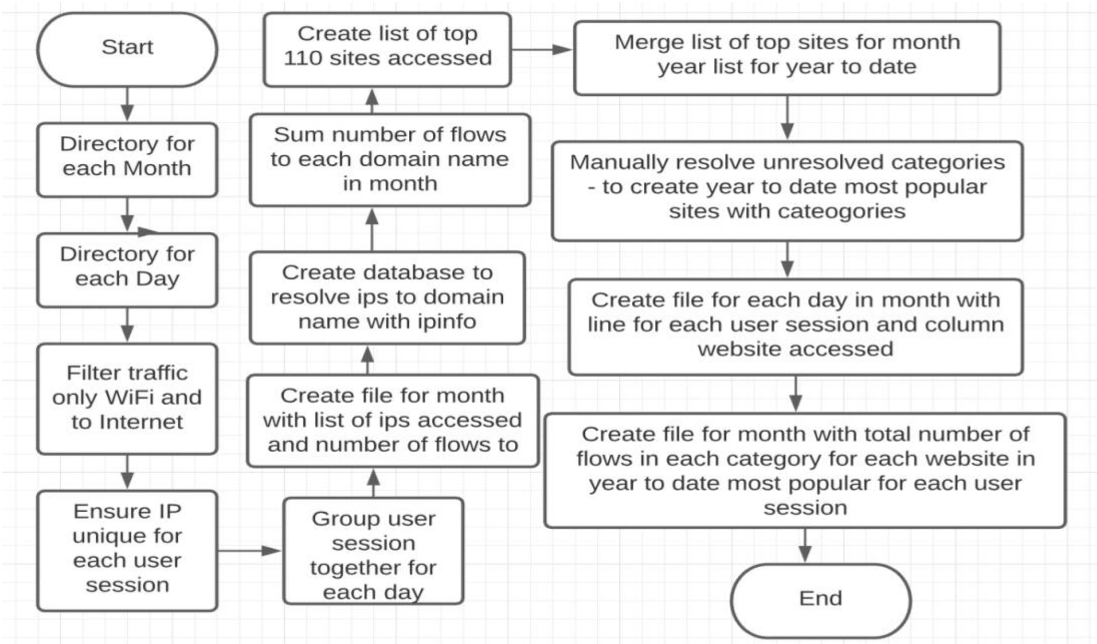
Appendix G

Samples of User Sessions, Each Details the Number of Flows in Each Category of Activity for a User.

User Id	cloud and technology	search	social media	shopping	education	streaming	advertising	other	gaming
1	5188	1565	613	404	426	0	422	43	10
2	2536	742	294	188	185	0	150	21	5
3	2371	1242	392	200	4	12	0	0	14
4	1175	436	118	74	2	6	0	0	6
5	10898	3793	1653	1127	483	71	234	172	47
6	5423	1674	580	469	183	33	94	68	21
7	23151	2987	1090	915	944	212	115	0	23
8	10218	1061	336	284	323	71	46	0	6
9	9171	3323	1048	1163	327	44	74	41	72
10	4504	1145	296	361	115	18	23	11	26

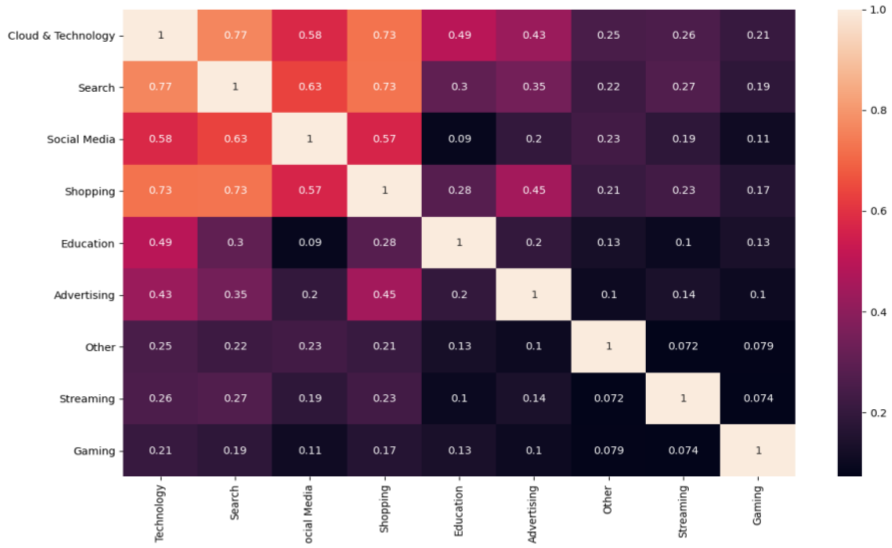
Appendix H

High level Representation of Cleaning and Filtering Netflow Data to Create User Profiles of Activity Each Day.



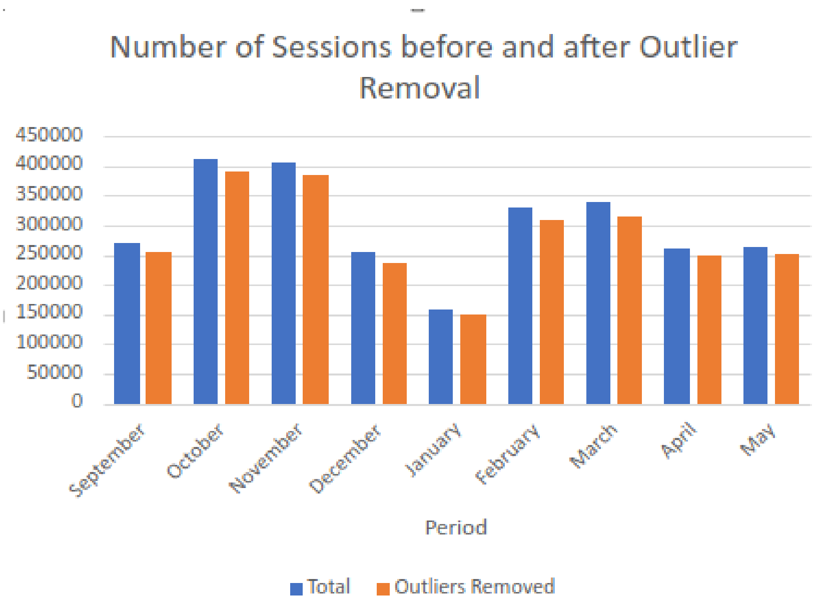
Appendix I

Heat Map of Correlations Internet Activity for the Academic Year 2018/19



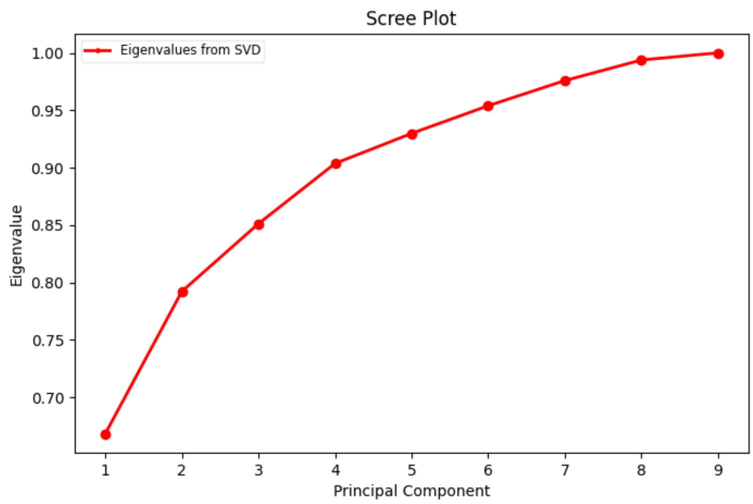
Appendix J

Sessions and Outliers for Each Month.



Appendix K

Elbow Graph of Cumulative Principal Component Variance.



Appendix L

Principal Component Analysis of User Sessions

Figure L1.

Principal Component Loadings for Principal Component 1 - 'Distraction' and Principal Component 2 - 'Not social media' Based on User sessions for the Academic Year.

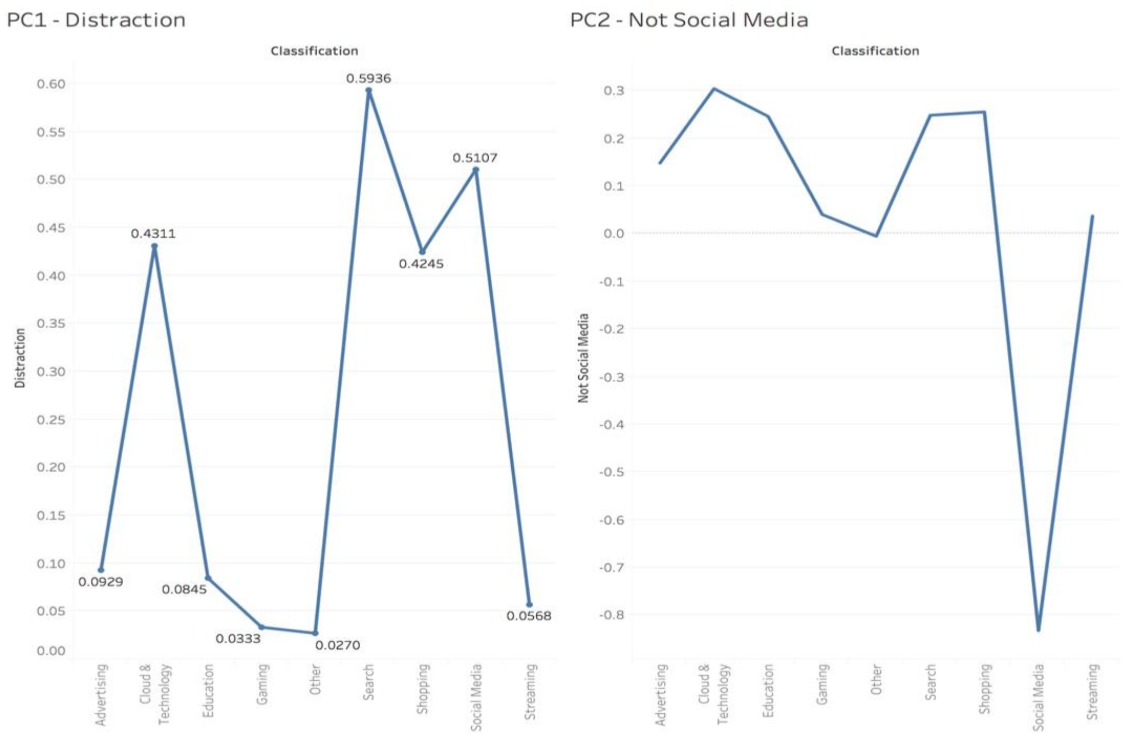
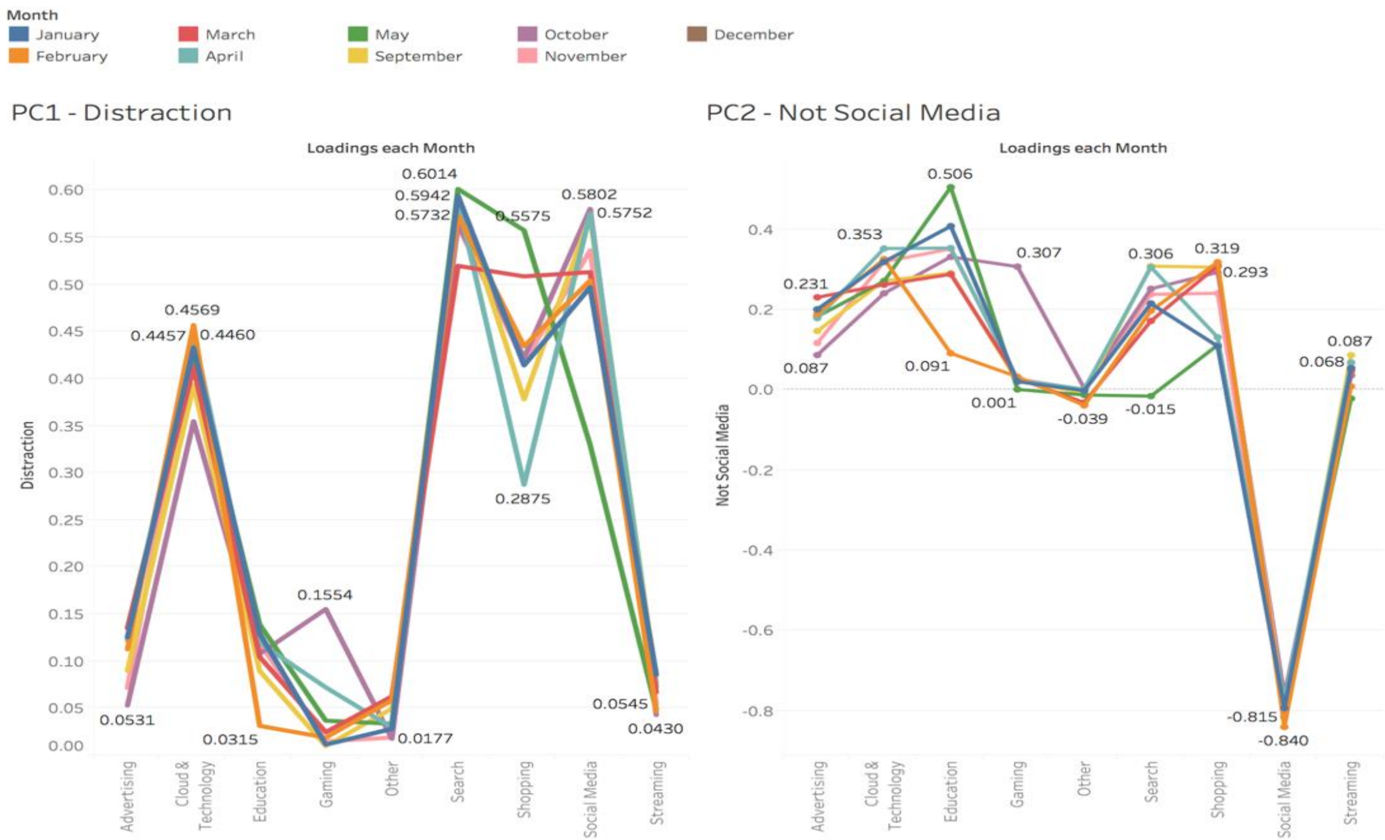


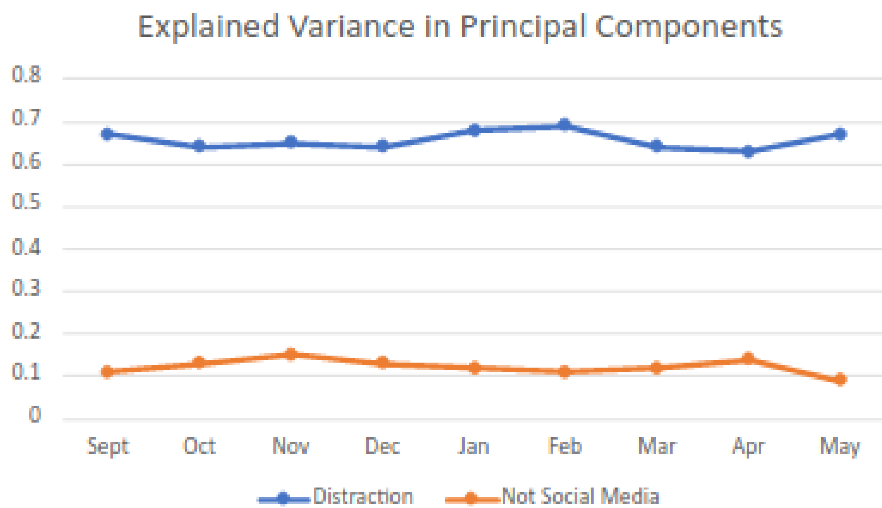
Figure L2.

Principal Component Loadings for Principal Component 1 - 'Distraction' and Principal Compontent 2 - 'Not social Media' based on User Sessions for Each Month.



Appendix M

Explained Variance for Each Principal Component for the Academic Year and for Each Month.



Appendix N

User Sessions and Activity

Figure N1.

Number of User Sessions Active in Each Classification Semester 1 2018/2019.

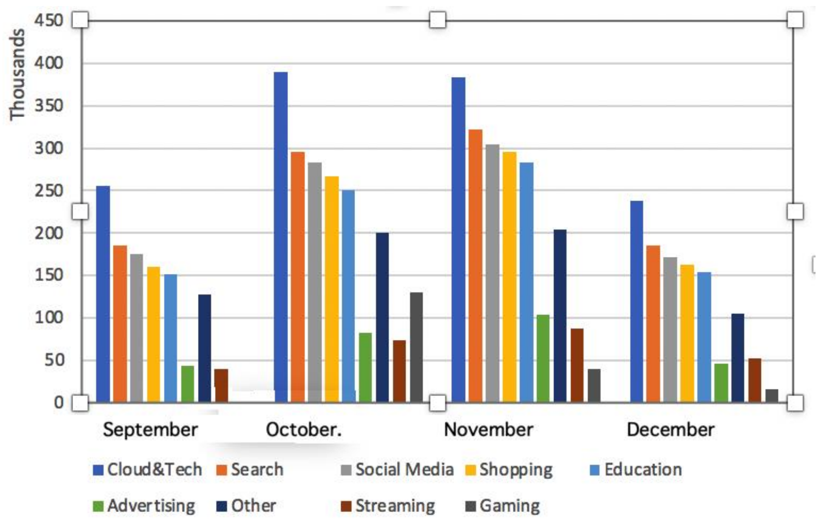


Figure N2.

Number of User Sessions Active in Each Classification Semester 2 2018/2019.

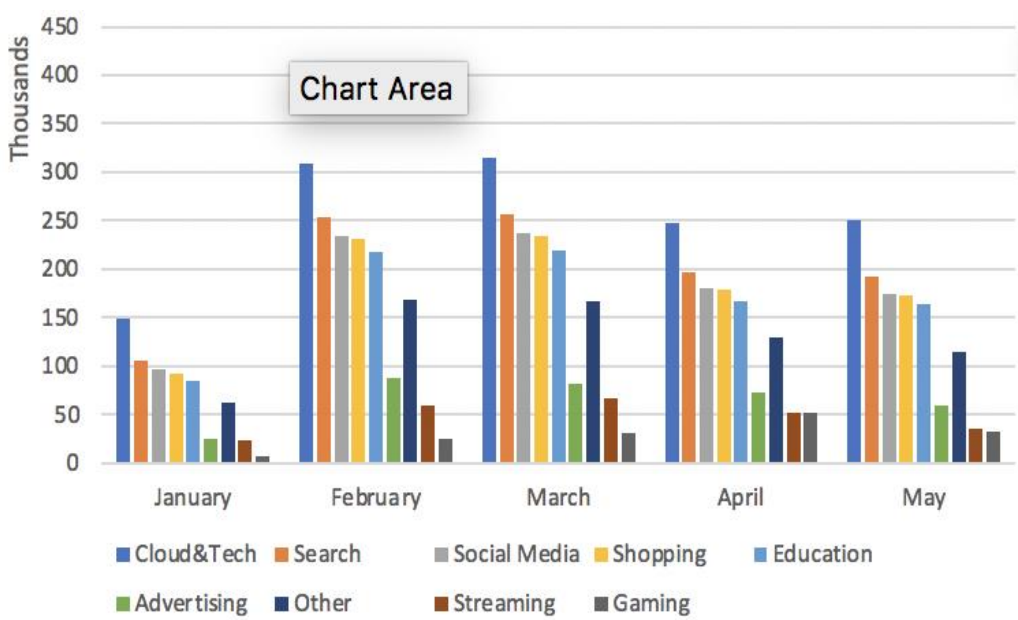


Figure N3.

Mean Activity in Each Classification where there was User Activity for Semester 1 2018/2019.

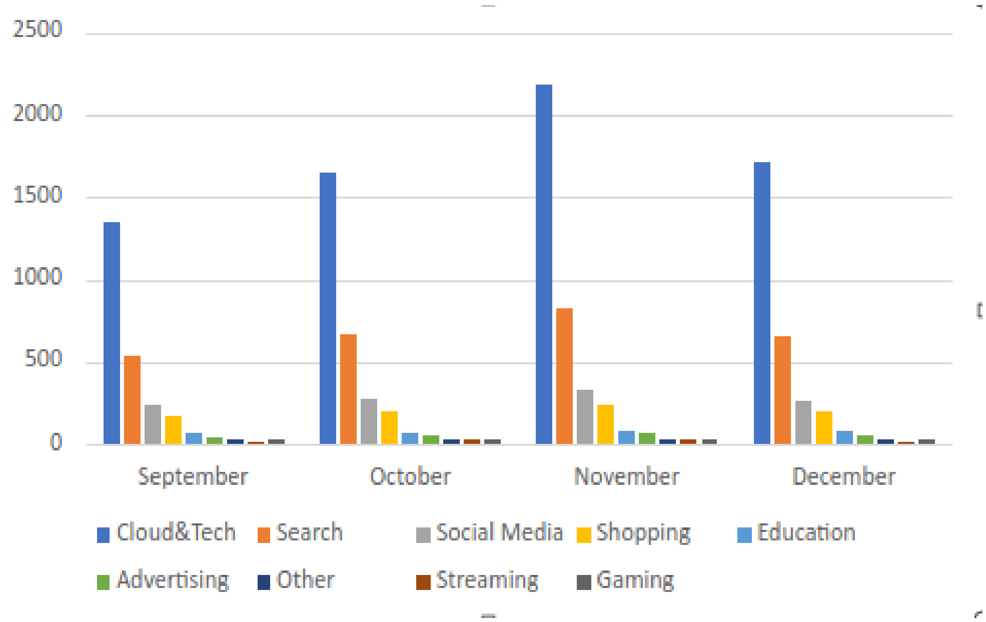
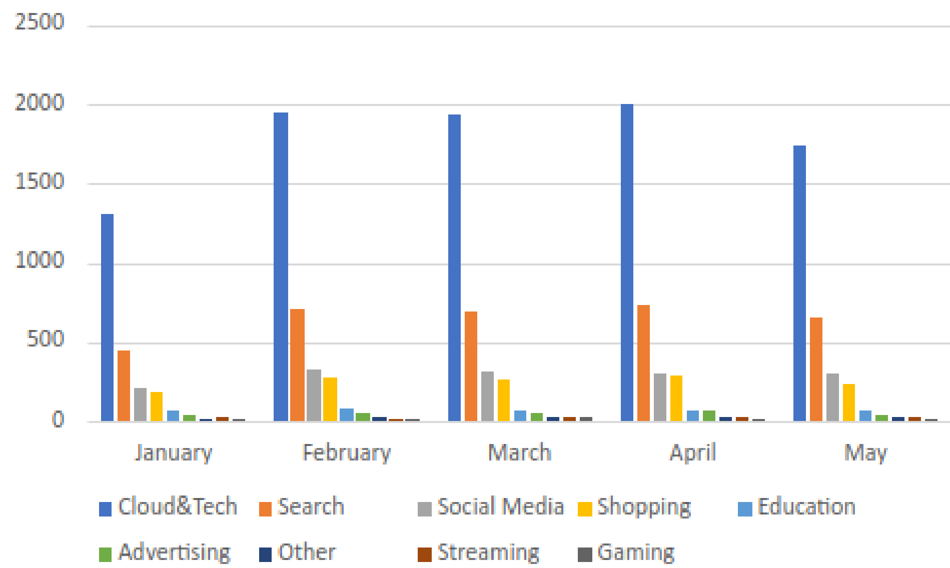


Figure N4.

Mean Activity in Each Classification Where there was User Activity for Semester 2 2018/2019.



Appendix O

Top Sites Accessed in Each Classification for Academic Year 2018/2019

Site Name	Classification	Percentage of Total Activity
heanet.ie	cloud and technology	47.37
microsoft.com	cloud and technology	32
akamai.com	cloud and technology	3.18
apple.com	Apple	4.16
google.com	search	19.09
yahoo-inc.com	search	0.12
microsoft.com	search (bing.com)	0.11
facebook.com	social media	7.37
twitter.com	social media	028
Google.com (onionflix.com)	social media (onionflix.com)	0.14
amazon.com	shopping	5.85
alibaba-inc.com	shopping	0.08
alibabagroup.com	shopping	0.03
Amazon.com (cit.ie)	education (cit.ie)	0.47
edu.ie	education	0.44
blackboard.com	education	021
xandr.com	advertising	0.19
criteo.com	advertising	0.11
integralads.com	advertising	0.09
verizondigitalmedia.com	other	0.15
none	other	0.13
google.com	other	0.08
netflix.com	streaming	0.09
spotify.com	streaming	0.07
youtube.com	streaming	0.04
king.com	gaming	0.04
paddypowerbetfair.com	gaming	0.04
google.com	gaming (starwarsrp. co. uk)	0.03

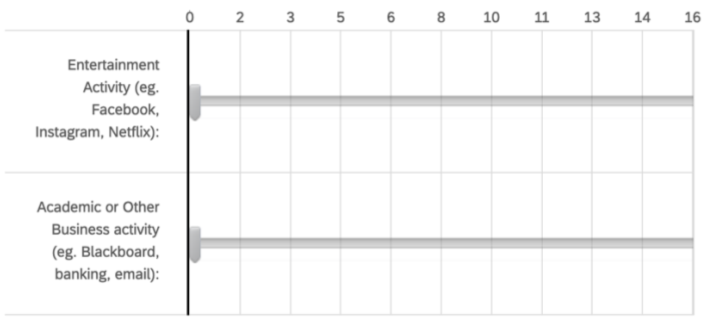
Appendix P

General Questions on Internet Use

Q. Internet Application Checklist - Please estimate the percentage of time of your overall internet time you have spent on the following online activities over the past month, e. g. A student response might be :- academic activities 20%, social media 25%, email 15%, online shopping 20% ,news sites 20% - total 100%Note :- the total is automatically calculated you do not need to provide a value

- Academic work ☐
- Email ☐
- Youtube ☐
- Facebook, Instagram, WhatsApp ☐
- Twitter ☐
- Netflix ☐
- Adult entertainment sites (eg. pornography or explicit sexual content) ☐
- Online Auctions (eg. Ebay) ☐
- Online Gambling (eg. Paddy Power) ☐
- Online Gaming (eg. League of Legends, Fortnite) ☐
- Online Shopping (eg. Amazon) ☐
- Online Dating (eg. Tindr, Grindr) ☐
- News Sites ☐
- Stock Trading ☐
- Surfing the Internet ☐
- Chat room ☐
- Other ☐

Q. Please estimate the number of hours you spend daily on …



Q. Do you think your internet activities are beneficial to your physical health

Q. Do you think your internet activities are beneficial to your mental health

Answered on a 5 point Likert scale from Definitely Yes to Definitely not

Appendix Q

WiFi at University: A Better Balance between Education Activity and Distraction Activity Needed.

https://www.sciencedirect.com/science/article/pii/S2666557321000422