An Exploration of Internet Use and Subjective Wellbeing Across 42 Societies: Implications for Human Development

A thesis presented in partial fulfilment of the requirements
for the degree of

Master of Arts
In
Psychology

At Massey University, Albany,
New Zealand.

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2025

Abstract

Since the internet became a household utility, there has been concern surrounding the potential negative association between using the internet and wellbeing. However, less attention has been given to specific types of internet use and their relationships to subjective wellbeing. Furthermore, evidence is largely concentrated in western, educated, industrialized, rich and democratic societies. This cross-sectional study aims to investigate how the type of internet use relates to different components of subjective wellbeing in 42 countries from 10 global regions. In addition, it aims to test Human Development Index (HDI) as an explanatory moderator of country-level differences in these relationships. The sample consisted of 24,009 participants (M_{age} = 36.53, SD_{age} = 12.3, 50% female) from the Harris Panel, a global panel curated by the international polling firm Nielsen. Analyses were carried out using descriptive correlations and multilevel modelling. Aggregate-level correlational analysis revealed complex relationships where internet use was paradoxically associated positively to life satisfaction, depression and anxiety. Region-level correlation analysis showed that time online and entertainment correlations with life satisfaction varied across regions, but correlations with depression and anxiety symptoms were consistently positive. Moreover, sharing news and information, and connecting socially correlations were consistently positive with life satisfaction, but more variable with depression and anxiety. Multilevel models showed that time online and life satisfaction were negatively associated at high-HDI levels and non-significant at low-HDI. Relationships between time online and entertainment, and depression and anxiety were significant, positive and stronger in high-HDI contexts compared to low-HDI. There were inverse relationships with sharing news and information, connecting socially and depression symptoms which were positive in high-HDI contexts and negative in low-HDI. Results underscore that the strongest contrasts across HDI settings lie in the associations with depression and anxiety, rather than in overall life satisfaction. This highlights the importance of considering broader societal level factors when investigating the relationship between internet use on subjective wellbeing.

Acknowledgements

I would like to extend my gratitude to three scholars of Massey University. First and foremost, I would like to thank the late Professor James Liu. I would not have started this journey without him. His enthusiasm for research was infectious and helped shape the vision for this project. To Evan Valdes for taking on the role of supervisor, for whose patience and dedication to excellence guided me through the complexities of research and authorship. This was a major support in guiding me to finish this project and persevere through the challenges along the way. Lastly, to Dr Matt Williams for his highly valued and balanced oversight.

Last but not least, I would like to extend more than gratitude to my extremely understanding and encouraging partner Livia. You were at my side every step of the way, enduring late nights and constant schedule changes, experiencing every high and every low, and never letting me lose sight. You made the impossible feel possible.

Table of Contents

List of Figures

List of Tables

1. Introduction

The internet has become a central platform for communication, information access, and social engagement in the modern world. Researchers have expressed concern for the role of internet use and its potential associations with subjective wellbeing since it arrived in households in the early 90s (Capraro et al., 2025; Kraut et al., 1998). Like other technologies, the fear was that it would steal away time and interfere with human activities that support subjective wellbeing (Kraut, 1998). However, this narrative is contested by researchers who argue that the internet has the capacity to positively contribute to subjective wellbeing by facilitating human connection (Dienlin et al., 2017).

The current debate regarding the link between internet use and subjective wellbeing has focused on methodological concerns, quality of data, and external validity. Broadly, existing evidence reveals small inconsistent associations between internet use and various indicators of subjective wellbeing. However, most recent research has focused on adolescents, young adults, and social media use, with comparatively less attention paid to other types of internet use in the general population (Cunningham et al., 2021; Huang, 2010; Liu et al., 2019; Santos et al., 2023; Vuorre & Przybylski, 2024). Furthermore, many samples within this literature are from Western Educated Industrialized Rich and Democratic societies (WEIRD; Henrich et al., 2010; Vuorre & Przybylski, 2023a). This suggests that the existing literature offers a limited perspective, as findings from WEIRD samples may not generalize globally. Internet use is increasing globally; more research is needed using global samples outside of the developed world. Therefore, the aim of this thesis is to investigate how different types of internet use are associated with both positive and negative components of subjective wellbeing (i.e., life satisfaction, depression, and anxiety) in the general population, and whether these relationships vary depending on a country’s level of human development.

Firstly, chapter 1 starts by outlining the key concepts of internet use, subjective wellbeing and the Human Development Index (HDI)[1]. It then discusses the current debate, highlighting the global interest in studying internet use and subjective wellbeing as well as describing the current state of the literature on the relationship between internet use and subjective wellbeing. This is followed by subsequent sections that include a theoretical and empirical discussion of; specific internet uses and their links to subjective wellbeing; and cross-cultural evidence of this relationship and the potential moderating effect of Human Development using country-level HDI. The chapter ends with a description of present study and research questions. Subsequent chapters entail the methods, results and the discussion chapters.

[1] Information and HDI data can be found at https://hdr.undp.org/data-center/human-development-index#/indicies/HDI

Internet Use

The internet has become a critical component of modern society, facilitating the exchange of information, transactions, and interactions between people and technology (Weinberg, 2014). Globally, the internet serves various purposes. Among adults under age 64, the most popular uses include finding information (62.4%), staying in touch with family and friends (59.6%), and entertainment such as watching videos, movies, pornography and playing games (53.3%) (Statista, 2024).

Internet penetration, which measures the percentage of the population with access to the internet, globally stands at 67.9% (Petrosyan, 2025), with people reported to spend an average of 6.5 hours online daily (Pelchen, 2024). Access and usage vary significantly between regions, with developed nations like the U.S. leading in connectivity with 90% of Americans using the internet daily, and 41% report being constantly connected (Poushter et al., 2024). Though developed regions such as Scandinavia, Western Europe and the Anglosphere have higher internet penetration, rates are increasing in developing nations (Warf, 2017). As a globally pervasive tools of daily life in communication, information access, and leisure, the internet continues to warrant critical examination for its link with human behaviour and wellbeing.

Subjective Wellbeing

Subjective wellbeing is the self-assessment of one’s own life broadly incorporating components of thought, feelings and overall experience (Diener et al., 1999). Subjective wellbeing has two components: a cognitive element which relates to thoughts and cognitions about one’s life, and an affective element that relates to both the positive and negative emotional experience of a person in their day-to-day (Diener et al., 1999). For the purpose of this study, we focus on three key subdomains of subjective wellbeing: life satisfaction to represent the cognitive element, and depressive and anxiety symptoms to represent the affective component.

Life satisfaction

Life satisfaction is one of the cognitive components of subjective wellbeing, reflecting individuals' evaluative judgments about the overall quality of their lives (Pavot & Diener, 1993). Life satisfaction is linked to enduring aspects of daily life and is less sensitive to small fluctuations compared to mood and affect (Pavot & Diener, 2008). Higher life satisfaction in adults has been linked to better physical, and mental health as well as linking to higher prevalence of health-related behaviours such as sleep (Kim et al., 2021). Common predictors of life satisfaction are big things like marriage, household income, standards of living, positive and negative experiences, marriage, social support, freedom and safety (Jarden et al., 2022; Pavot & Diener, 1993, 2008). So, if internet use is going to contribute towards life satisfaction, then I would argue that it is through supporting some of these bigger predictors of life satisfaction. Given the ubiquity of internet use in daily life, understanding the extent to which it relates to life satisfaction is important for understanding potential positive correlates of internet use.

Depressive and Anxiety Symptoms

Depressive symptoms are characterised by low mood, irritability, loss of pleasure, physical changes in weight, appetite, sleep, cognitive impairment, lack of focus, fatigue, low energy and also cognitions such as negative thoughts and attitude towards the self or world (American Psychiatric Association, 2013).[2] Anxiety symptoms are characterized by cognitions such as excessive worry and negative self-thoughts. Other physical and somatic

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[2] Life satisfaction is generally framed as the cognitive component of subjective wellbeing. However, this note is to acknowledge that while depression and anxiety are framed as the affective components of subjective wellbeing they both entail some cognitions within their potential symptoms.

symptoms such as Symptoms such as fatigue, difficulty concentrating, irritability, tension, stress and worry Fatigue, stomach pains, muscle tightness, chest pain, dizziness (American Psychiatric Association, 2013; Haug et al., 2004).

Depression and anxiety symptoms are commonly screened concepts in reflecting general wellbeing in everyday life (Kroenke et al., 2010). Experiencing symptoms of depression or anxiety is normal. However, experiencing symptoms in excess or prolonged periods may be signs of a disorder which is a serious health concern. Global prevalence of depressive disorders is estimated at 3.6% and 3.7% for anxiety disorders (Dattani et al., 2025). Given their high prevalence, studying depressive and anxiety symptoms in the context of everyday activities such as internet use is essential for understanding correlates developing early interventions and promoting mental health.

Internet Use and Subjective Wellbeing

Ongoing debate

The relationship between internet use and subjective wellbeing remains a contested area of research, with scholars divided over the strength, direction, and implications of associations (Capraro et al., 2025). Over the past decade, the debate over the impact of internet use on subjective wellbeing has intensified, particularly as social media has entered public discourse as a potential explanation for rising rates of mental health issues among adolescents (Lukianoff & Haidt, 2018). Among scholars, prominent researchers Jonothan Haidt and Jean Twenge sit on one side emphasizing theoretical effects of internet use on subjective wellbeing and mental health. On the other hand, scholars such as Andrew Przybylski, Amy Orben, Candice Odgers, Jeff Hancock, Matthew Jané and Christopher Ferguson provide a more cautious perspective by drawing attention to evidence that challenges the prevailing narrative. The following sections will outline these stances, beginning with Haidt, followed by Przybylski and the other perspectives before discussing and reviewing relevant literature for the relationship between internet use and subjective wellbeing.

The Mental Health Crisis

Haidt and colleagues propose a two-part theory which claims to explain a mental health crisis that Haidt believes began to surface between 2010-2012 in the US and other Western regions (Blomqvist et al., 2019; Botha et al., 2023; Twenge et al., 2018, 2022; Twenge & Campbell, 2019). According to Haidt, this period marks a sharp rise in mental distress, for which he identifies features of social media as contributors (Twenge et al., 2018, 2022; Twenge & Campbell, 2019). Multiple sources show that depression, anxiety, stress, self-harm and suicide rates in US teenagers have been increasing since the late 2000s (Curtin, 2020; Daly, 2022; Keyes et al., 2019; Wilson & Dumornay, 2022). Furthermore, using data from the National Survey on Drug Use and Health, a national survey of more than 165,000 US adolescents between the age of 12 and 17, from 2009 to 2019 rates of major depression increased from 8.1% to 15.8% (Daly, 2022). Using hierarchical age-period-cohort models, Keyes et al. (2019) analysed yearly survey data from the Monitoring the Future survey (N = 512,283) finding that depressive symptoms decreased between 1991 and 2011 and then increased from 2011 through to 2018 in young people aged between 13 and 18 (Keyes et al., 2019). Furthermore, cohort differences at the age of 18 showed that 19.1% of the 1997-2001 cohort, had high depressive symptoms, which was much higher than the previous 1992-1996 cohort at just over 10% (Keyes et al., 2024). Curtin (2020) reported that the National Center for Health Statistics showed that following a period of stability between from 2000-2007, suicide prevalence in adolescents rose by more than 50% between 2007 and 2018, which is an increase of 3.9 adolescents per 100,000 persons over this time period (Curtin, 2020).[3] While research data shows that youth mental has declined throughout the period of the late 2000s and the past decade, evidence of a sharp increase in 2010-2012 as proposed by Haidt is debatable. The evidence suggests more of gradual escalation rather than a distinct increase that can be pinpointed to a time point between 2010 to 2012 when social media adopted certain features. This raises questions as to the ability of attributing rising mental distress concerns to developments in social media and risks oversimplifying a complex and potentially multifaceted social problem (Odgers & Jensen, 2020).

Nevertheless, part one of Haidt's theory posits that children are now spending their developmental years on social media which is impacting their natural development (Lukianoff & Haidt, 2018). Rather than spending time outside playing and learning, their time is spent inside on social media, thereby inhibiting emotional growth and resilience (Lukianoff & Haidt, 2018). Foundationally, Haidt proposes that during the 90s growing concerns for child safety contributed to overprotective parenting resulting in children no longer spending as much time outside playing alone, and without adult supervision. As a result, they missed learning opportunities in navigating various problems through play and interaction with peers (Lukianoff & Haidt, 2018). According to Lukianoff & Haidt (2018), this sets a foundation for a shift in social norms around childhood development throughout the 2000s which leads into the significance of social media.

The second part of Haidt's theory resides within the evolution of social media, mobile phone technology and mental health. Though social media has been around since the mid-nineties, Haidt specifically argues that apps like Instagram and Facebook, and certain features such as the front facing camera in smartphones, and the 'like' button in social media

[3] Though this is an alarming statistic and any increase in suicide should be taken seriously, these are comparatively lower than adult populations (CDC, 2023).

platforms, coincide with the deterioration seen in youth mental health (Allen & Haidt, 2020; Twenge et al., 2022). Haidt argues that these features encourage an unhealthy relationship with the online world as these features contribute to negative experiences such as greater screentime, social comparisons and body image concerns (Twenge et al., 2022). These technological shifts represent fundamental changes in the social environment of young people which Haidt believes have profound implications for their mental health.

An Alternative Narrative

In contrast to Haidt's narrative, Ferguson (2025) and Orben & Przybylski (2019) argue that blaming social media for the problems faced by youth today is the latest moral panic. Moral panic is underpinned by the idea that new media are often subjected to a sense of panic which is where one group, in this case researchers and parents, express strong concerns over the behaviours or lifestyle of another group, while focusing primarily on the harms of said behaviours (Bowman, 2015). This is not to suggest that internet use will turn out not to play some kind of role, but to remain more cautious in the face of contradictory evidence (Ferguson, 2025; Orben & Przybylski, 2019). Furthermore, this raises the question of whether internet use can be placed in the same category as previous moral panics. In light of globalisation and the internet's extensive reach, the online environment arguably represents a more complex and far-reaching coverage than earlier shifts in the social world.

There are a few key features that makes the internet more complex than previous sources of moral panic. Firstly, the internet is far reaching. Fads and movements might capture subsets of individuals; however, consider that Facebook alone has over 3 billion users connecting monthly worldwide (Dixon, 2023). As such, the internet is more inclusive, essentially capturing a wider population.

Secondly, the internet makes many activities easily available and instantaneous; for example, news media, video content, pornography, gaming, public chat forums and reddit discussions, online communities, social networking and so on. This means internet users can get instant gratification with less effort compared to a time when the internet was not a household utility.

Third, the internet contains complex application designs that use algorithms to show content that most aligns with a person's beliefs and interests, such that online platforms show content that is likely to be more interesting and therefore more captivating to the individual (Van Bavel et al., 2021). In other words, certain online environments are designed to keep users engaged.

Essentially, the internet environment and available applications make using the internet a complex behaviour with the potential of managing and engaging with multiple streams of information through different platforms to achieve different goals (Hancock et al., 2022). So, where concerns about video games (and other such activities) pertained to people playing video games, using the internet entails more than just one activity and so impacts more people. For these reasons, enhancing our understanding of the way the online environment relates to human wellbeing is paramount and requires careful study and consideration to ensure safe and informed use.

Insights from the broader research

To this point, the broad debate outlines a contrasting narrative theorizing the damaging effects of internet use to the more cautious perspective that considers the explanation of a moral panic. In light of the debate, research investigating the correlates of internet use and subjective wellbeing are mixed. There is a body of work that finds that higher internet use is associated with greater life satisfaction and fewer symptoms of depression and anxiety (e.g. Bessière et al., 2010; Cotten et al., 2012; Dienlin et al., 2017; Labrague, 2014; Liu et al., 2019; Nie et al., 2016; Oh et al., 2014; Pénard et al., 2013; Quintana et al., 2018; Vuorre & Przybylski, 2023a; Yan et al., 2023). Others report the opposite, associating internet use with lower life satisfaction and heightened depressive and anxious symptoms (e.g. Huang, 2010; Liu et al., 2019; McDool et al., 2020; Orben & Przybylski, 2019; Twenge et al., 2018; Twenge & Campbell, 2019). Meanwhile, several studies detect non-significant or no association at all (Choi et al., 2012; Ferguson, 2025; Heffer et al., 2019; Labrague, 2014; Nie et al., 2016; Vuorre & Przybylski, 2023b).

Even so, meta-analyses quantify the broader trend that underpins the described mixed findings. In their meta-analysis, Huang, (2017) found that time spent online was associated with a small but statistically significant negative relationship with a combined measure of subjective wellbeing (k = 63, r = -.07). More recently, Cunningham et al. (2021) carried out a meta-analysis of 62 studies with a concentrated focus on depression and observed a small and significant association between time spent online and depression symptoms (r = 0.11). Though results from these meta-analyses point to a tendency towards a negative relationship within the literature of internet use and subjective wellbeing, these analyses focused primarily on social networking, while relying on samples of young adults. Further, while the focus on time is reflective of the general literature this is limited in the sense that it does not specify what users were doing with their time online (Liu et al., 2019). This leaves room to extend research and include a wider sample base using more widespread forms of internet use.

Experimental research

A large body of research in this area is cross-sectional design. Methodologically, these lack inferential capabilities in determining whether spending time online or using the internet has causal effect on outcomes such as life satisfaction, depression and anxiety. Establishing cause and effect would result in greater explanatory power, providing more conclusive evidence to support or challenge Haidt's causal claims and be better equipped to inform rigorous policy and clinical practice. However, experimental research examining the causal relationship between internet use and subjective wellbeing has also produced mixed results.

The following paragraphs review some research to highlight the challenge of manipulating internet use in experimental research.

Individual studies have attempted to isolate the effects of internet use, particularly Facebook, on wellbeing by employing abstinence or restriction paradigms. For instance, Allcott et al. (2020) conducted a randomised controlled trial in which US adults were incentivized to deactivate their Facebook accounts for four weeks. The experimental group received a payment of $102 with an additional $5 per completed survey and $15 total completion payment. Results indicated a very small but statistically significant effect on subjective wellbeing ($d = 0.09$). While the study featured strong controls to ensure participants remained logged out, selection bias is a concern as the sample was drawn from individuals already expressing a desire to quit Facebook.

Similarly, abstaining from Facebook in Denmark was found to improve life satisfaction and affective wellbeing (Tromholt, 2016). However, because no compliance monitoring was implemented, it remains uncertain whether the observed benefits were due to full abstinence or partial reductions of Facebook use. Another study by Mosquera et al. (2020), in which Facebook and Facebook Messenger use was restricted among US university students for one week, reported reduced depressive symptoms, but found no significant effects with life satisfaction, happiness, or worry.

Shifting away from periods of total abstinence, German adults who reduced their daily Facebook use by 30 minutes over a two-week period showed improvements in both life satisfaction and depressive symptoms (Brailovskaia et al., 2023). Despite relying on self-reported compliance, the results suggest that even small behavioural changes can meaningfully affect wellbeing. Alternatively, rather than abstaining, Yuen et al., (2019) instructed participants to use Facebook for 20 minutes, finding that, in comparison to general web browsing, positive affect decreased but there was no significant change in negative affect. This finding indicates that certain types of internet activity may inhibit positive emotional experiences without necessarily increasing negative emotions.

In contrast to the prevailing narrative of harm, Przybylski et al. (2021) conducted a cross-national study in the United Kingdom, United States, and Hong Kong, where students abstained from social media for one day. Surprisingly, the UK and Hong Kong participants reported reduced satisfaction with their day, and Hong Kong students showed a small but significant increase in negative affect after controlling for age and gender. Within the context of 1-4 weeks, one day might be considered very short, and part of a different category. Further, these findings may reflect withdrawal effects rather than long-term impacts. Nevertheless, these findings highlight the consideration of both time frame and cultural context when interpreting results.

More recently, Ferguson (2025) reviewed 27 experimental studies in a meta-analysis, concluding that the non-significant effect size of (d = .088) between social media use and mental wellbeing did not differ statistically from zero. The author further settled that current experimental evidence does not yet robustly support a causal link between internet use and subjective wellbeing. As with cross-sectional research there was significant heterogeneity across the studies included in this meta-analysis. Additionally, it is important to note that conclusions from this meta-analysis are being publicly contested and debated (Rausch & Haidt, 2024; Stein, 2024). [4]

Collectively, these studies reveal a nuanced picture. Though experimental methods can suggest causal links between internet use and subjective wellbeing, isolating one form of social media (usually Facebook) leaves open the potential of spending more time on other

[4] Haidt and colleagues have criticized this evidence in a series of blog posts which questions the integrity of the data, highlights statistical errors, and methodological decisions (Rausch & Haidt, 2024; Stein, 2024). However, Matthew Jane has re-analysed the data making the changes relating to the identified errors (Jané, 2024a), as well as including previously overlooked research (Jané, 2024b). Both Matthew Jane's re-analyses show little to no change to the outcome of results. In all cases, these are not peer-reviewed literature however they are relevant to the broader debate.

forms of social media or internet use such as Instagram, Snapchat, YouTube and Reddit. Furthermore, variation in participant compliance and expectancy effects may influence outcomes, reinforcing the importance of interpreting findings with caution. In addition, as Ferguson (2025) points out that a collective problem within experimental research on social media and wellbeing is hypothesis guessing. Though, arguably this is a problem for all types of research in this topic area (Odgers & Jensen, 2020). Public discourse increasingly frames internet use as harmful which means participants may anticipate researchers' expectations; potentially influencing responses and undermining the integrity of findings (Ferguson, 2025; Odgers & Jensen, 2020).

Key considerations

Two key themes emerge from the literature that warrant attention. The most prominent issue is the mixed and inconsistent results, which is likely due to several factors. Firstly, internet use occurs within a dynamic environment that changes rapidly both through program designs, applications and the way people use them. Therefore, scholars are faced with the challenge of aligning current research with a rapidly changing environment. As such, internet use can and has been conceptualised and operationalised in many ways (Bekalu et al., 2023; Cunningham et al., 2021; Ivie et al., 2020). While this provides rich detail that may be needed for theory building and formulation, it also contributes to a fragmented knowledge base making synthesis complex.

Second, data collection methods also poses a significant problem as the most commonly used method of capturing internet use is via self-report measures which users tend not to be accurate meaning high measurement variance between studies (Scharkow, 2016). However, objective measures of internet use are also faced with reliability issues given the number of programs, applications and devices people use to interact online, as well as owning multiple devices. The heterogeneity of measures is not necessarily a downside thing in relating to the bigger picture as this is necessary in understanding internet use and subjective wellbeing from a broad range of contexts however, in the meantime, it makes drawing concrete conclusions more difficult (Capraro et al., 2025). Lastly, small effect sizes in the relationship between internet use and subjective wellbeing mean that small sample sizes from early research may not have had the statistical power to detect small effects (Twenge & Campbell, 2019). Therefore, the use of larger samples is preferrable to mitigate this problem.

Given the mixed findings, low quality research and lack of clear causal evidence within many researchers are reluctant to draw concrete conclusions regarding internet use and subjective wellbeing (Capraro et al., 2025; Ferguson, 2025; Foulkes & Andrews, 2023; Odgers & Jensen, 2020; Orben, 2020; Orben & Przybylski, 2019).

The second key theme depicts an imbalance in the literature that predominantly emphasizes the harms of internet use while giving less attention to potential benefits (Allen & Haidt, 2020; Bekalu et al., 2023; Pénard et al., 2013). This is evident in a literature that links internet use to negative exposure to psychological and physical health factors such as depression, anxiety (Keles et al., 2020), poor body image (H.-R. Lee et al., 2014), poor sleep (Alonzo et al., 2021), behavioural addiction (Bachnio et al., 2019) and social comparison (Papadopoulos & Cleveland, 2023). Internet use is also linked with triggering negative emotional responses such as fear of missing out (Baker & Algorta, 2016), concerning exposure to distressing content and practices such as cyberbullying (Moore et al., 2017), and broader sociopolitical issues such as political polarization, misinformation and hate speech (Van Bavel et al., 2021). With respect to the necessity in understanding all aspects of a ubiquitous social phenomena, an imbalance could mean producing a negatively biased literature and runs the risk of framing typical behaviour as disordered (Parry et al., 2022). This highlights a need to contribute to the growing literature that investigates associations with both positive psychological outcomes, such as life satisfaction, and negative psychological outcomes such as depression and anxiety.

The debate and current state of the literature highlights the complexity of the relationship between internet use and subjective wellbeing. Haidt's rhetoric suggests that there is some certainty towards cause and effect. However, without clearer causal evidence it is possible this relationship is spurious. The challenges faced by this research area suggest that a more nuanced understanding is required in order to build a knowledge base that can identify mechanisms, situations and circumstances where internet use may be harmful or beneficial (Allen & Haidt, 2020; Kushlev, 2018; Parry et al., 2022). By narrowing the focus to specific areas of internet use and accounting for individual differences through demographic, behavioural, or moderating and mediating factors, research can move toward a more balanced account of the relationship between internet use and subjective wellbeing (Cunningham et al., 2021; Liu et al., 2019; Parry et al., 2022). A key step in this direction is to move beyond broad measures of social media and internet use and examine how distinct types of internet use relate to subjective wellbeing. Furthermore, analysing these associations across diverse national contexts can help identify whether patterns of internet use are more consistently linked to wellbeing outcomes, and may also reveal populations in which these associations are most distinct.

Type of Activity

Although research has returned general mixed associations between internet use and subjective wellbeing, these findings often lack detail regarding specific types of online activity (Cunningham et al., 2021; Huang, 2017). Much of the existing literature focuses on broad measures of internet use such as total screen time or time spent on specific platforms (e.g., Facebook, Instagram), rather than categorising and analysing the nature of internet use itself (Parry et al., 2022; Pénard et al., 2013). This represents a gap in the current literature as the mixed outcomes potentially implies that all types of internet use may not be equal in their association's subjective wellbeing (Lam et al., 2020; Szabo, 2021). While the idea of linking internet use and sub-components of subjective wellbeing has been explored to some extent in older adult populations (Lam et al., 2020; Szabo et al., 2019), this presents an opportunity to investigate specific ways of engaging online in the general population. The following section details internet use for entertainment, sharing news and information, connecting socially and communicating with family and friends and discusses research in relation to why these uses might relate individually to subdomains of subjective wellbeing.

The first part of this section outlines why different types of online activity may relate differently to subdomains of subjective wellbeing. Firstly, uses and gratifications theory posits that people are motivated to use digital media to fill psychological and social needs (Katz et al., 1973). This covers a broad range of motivations ranging from engaging in activities such as surveillance, entertainment, to seeking human experiences such as distraction, emotional release and so on (Dolan et al., 2016; Katz et al., 1973). Secondly, using the internet for entertainment, sharing news and information, connecting socially and communicating with family and friends embody human behaviours and activities that differ in their qualitative attributes. Therefore, it stands to reason that they may differ in their ability to meet psychological needs, and their associations with psychological outcomes.

Secondly, subjective wellbeing is a multi-dimensional construct containing cognitive and affective elements that include both positive and negative sides of wellbeing (Pavot & Diener, 1993, 2008). Dissecting these elements further, life satisfaction can be seen as an indication of wellbeing, whereas depression and anxiety symptoms are indications of illbeing (Agteren & Iasiello, 2020). Furthermore, illbeing and wellbeing are separate constructs that can coexist such that it is possible for someone to perceive themselves to have a good life while feeling emotionally unwell and vice versa (Headey et al., 1984; Morrison et al., 2023).

For example, consider the life of a career professional who is experiencing the stress and anxiety, and general uncertainty about their future career progression, yet they are performing well in their current role, financially stable and experience meaningful social and professional relationships. Viewing their situation solely on the basis of their negative emotions may skew the bigger picture and ignores pertinent contextual information. Therefore, it stands to reason that some ways of engaging online may associate to specific constructs within subjective wellbeing in different ways.

Entertainment is about seeking pleasure, relaxation or other forms of hedonic satisfaction as a detachment from work and other life pressures (McManus et al., 2011) (McManus et al., 2011; Tutar & Turhan, 2023). In other words, entertainment can be supportive in regulating human emotions (Newman et al., 2014). However, entertainment is also linked to avoiding negative emotions or other personal responsibilities and therefore has the potential to associate negatively with subjective wellbeing (Beutel et al., 2011). The internet offers easy access to a broad range of entertaining activities including watching videos, playing games, pornography, and engaging with hobbies. However, online applications and games are designed to keep the user engaged for prolonged amounts of time making controlled use of entertainment more difficult (Montag et al., 2019). As such, using the internet for specific forms of entertainment use has been associated with both positive and negative wellbeing outcomes (Awaworyi Churchill & Farrell, 2018; Gallistl & Nimrod, 2020; Goh et al., 2019). However, using the internet for entertainment and aimless browsing are more commonly linked to over-use which has stronger links to negative subjective wellbeing outcomes (Bowman et al., 2022; Kircaburun et al., 2020). Thus, while entertainment may offer opportunities for relaxation and enjoyment, its potential to foster overuse and avoidance behaviours complicates its overall relationship with subjective wellbeing.

Nevertheless, research investigating entertainment related internet use as a broad construct has been conducted in adult and older adult populations. For instance, Mohan & Lyons (2022) reported inconclusive results linking entertainment and gaming to quality of life in a large social dataset. Similarly, Erickson & Johnson (2011) found no significant relationship between entertainment use and both life satisfaction and depression, and a longitudinal study by Lam et al., (2020) similarly reported no effect of entertainment on life satisfaction or depression in older adults. However, research using samples of adults have returned more conclusive findings. For instance, Nie et al., (2016) found negative associations between entertainment and life satisfaction in adults aged 20 to 60. On the other hand, Bezinović et al., (2015) found a positive correlation between depressive symptoms and a combined measure of communication and entertainment in Croatian young adults. These findings suggest that the relationship of entertainment use in the general population shows clearer associations with poorer wellbeing compared to inconclusive results among older adults. These findings suggest that using the internet for entertainment may negatively associate to subjective wellbeing in the general population.

Sharing news and information is a complex construct as it entails the act of sharing news but also implies the process of news consumption. Sharing news is a reciprocal process generally with motives of information seeking, altruism and gaining social approval (Habes et al., 2021; Kümpel et al., 2015; C. S. Lee & Ma, 2012). People who share news online tend to see themselves as opinion leaders (Kümpel et al., 2015). Therefore, sharing news and information is as an active and informative type of internet use which may meet cognitive and affective needs through offering competency, surveillance, and social connections within the community.

However, news content is more often than not distressing, and exposure to negative or alarming content has been more consistently associated with heightened anxiety, worry, and stress (Garfin et al., 2020; Johnson & Davey, 1997; Kelly & Sharot, 2024). Furthermore, online news that contains negative language tend to disseminate more readily than news containing neutral language (Watson et al., 2024). This highlights the popularity of negatively themed news content. Additionally, simply reading the headlines online was enough to evoke more intensive negative emotions in comparison to positive or neutral emotion states of 306 Greek participants (Mousoulidou et al., 2024). Taken together, while greater engagement in news consumption might increase exposure to negative content and emotions, the act of sharing news itself may simultaneously align with more positive outcomes, such as life satisfaction.

Using the internet for social purposes provides the opportunity to meet social needs and maintain and facilitate social relationships which can theoretically be supportive of subjective wellbeing (Argyle, 2002; Lieberman & Schroeder, 2020). Positive social connection is a key predictor of life satisfaction (Martino et al., 2017). However, connecting socially online contains some inherent differences from socializing and maintaining relationships in person. There is a lack of verbal cues as most online communications are via written text, increased anonymity, more opportunity to form new relationships and maintain weak tie relationships, and information spreads at higher rates (Lieberman & Schroeder, 2020). These differences highlight both advantages and disadvantages of connecting socially online. For instance, anonymity supports users with social anxiety to interact with others while experiencing fewer anxious cognitions (Hutchins et al., 2021). On the contrary, anonymity and more interaction with weak ties increases the possibility of coming across aggressive behaviour which may undermine the experience of socialising online (Kim et al., 2023). Additionally, while spending more time socializing online can displace offline social connections, according to Kroencke et al., (2023) socializing online is better than not socializing at all. In their study, they found that while a combination of socialising face to face and online was associated with higher wellbeing than just socialising online, only socializing online was still more favourable than no social interaction.

Other research on connecting socially online suggests that it depends on how users interact with others while using online social tools. For instance, actively connecting with others, especially when the communication is personal and meaningful, has been linked to lower depressive symptoms and increased life satisfaction (Burke & Kraut, 2016; Escobar-Viera et al., 2018). Notably, Bessière et al. (2010) found that communicating with family and friends online predicted a small but significant reduction in depressive symptoms over 6 to 8 months. Similarly, Dienlin et al. (2017) reported that social networking site communication predicted a small increase in life satisfaction. Furthermore, Lam et al. (2020) supported these findings, reporting that internet use for general communication was linked to lower depression and higher life satisfaction in older adults. These findings suggest that connecting socially online may positively associate with subjective wellbeing under specific circumstances.

Together, this literature indicates that the purpose and context of internet use may be crucial in understanding its relationship to subjective wellbeing. While targeted social connection and communication appears to relate to positive outcomes, particularly when directed toward known others, entertainment and news use demonstrate more mixed or adverse associations. As the purpose of internet use appears to have some importance, it is imperative to include these investigations in an inclusive study of global samples. As previously highlighted, there are potential moderating and mediating factors when considering these individual relationships. This section emphasizes that there are particular nuances within each type of internet use and their potential pathways to life satisfaction, depression and anxiety that need to be teased out to increase the explanatory power that links these relationships. One factor that has been systematically overlooked is group-level differences across countries. Cross-cultural research is both useful and necessary for building stronger theories of how internet use relates to different forms of subjective wellbeing. This raises the important question regarding what using the internet for different purposes means across nations.

A cross-cultural perspective

Despite vested interest in the relationship between internet use and subjective wellbeing, existing research remains concentrated in Western, Educated, Industrialized, Rich, and Democratic (WEIRD) societies (Henrich et al., 2010). Studies from countries such as the United States, the United Kingdom, Canada, and parts of Europe have provided valuable insights, but their findings may not generalise to more culturally and economically diverse populations (Elliot et al., 2014; Erickson & Johnson, 2011; Heo et al., 2015; Hofer, 2019; Lam et al., 2020; Lelkes, 2013; Mohan & Lyons, 2024; Orben & Przybylski, 2019; Pénard et al., 2013; Szabo et al., 2019; Twenge et al., 2021). Furthermore, recent reviews continue to highlight the underrepresentation of non-WEIRD contexts in this literature and call for greater inclusion of global perspectives (Baloğlu et al., 2020; Meier & Reinecke, 2021). While some cross-cultural work is emerging (e.g. Jun & Kim, 2016; Nie et al., 2016; Papadopoulos & Cleveland, 2023; Vuorre & Przybylski, 2023a), the literature base still reflects the experiences of digitally connected populations in developed nations. Addressing this gap is essential for building a more inclusive and globally valid evidence base but also comes with the responsibility of considering meaningful differences that may exist across global contexts.

Theoretically, the relationship between internet use and subjective wellbeing may differ across cultural and socioeconomic contexts as countries are separated not only by geography but also by concepts such as political systems, laws, values, and social norms. Culture can be understood as the shared behaviours, beliefs, and attitudes that develop within a social and historical environment (Hofstede et al., 2010). At the country-level, these cultural norms are further shaped by institutions, history, and government, all of which may influence how individuals connect and engage in society, and by proxy, online. This provides consideration of essential context and meaning to the connection and tools and potential outcomes offered by the internet. However, though countries vary in countless respects, they also exhibit systematic similarities that justify their classification into broader groups which is useful for analysis and comparison (Romano et al., 2021).

At a deeper level, drawing on the Inglehart & Baker's (2000) theory of cultural values, this theory suggests that there are systematic similarities that underpin rich and poor societies. The core idea of this theory is that as societies progress socioeconomically, they shift from survival values (economic and physical security, order and conformity) to self-expression values (autonomy, creativity, tolerance) (Inglehart & Baker, 2000). As economic and physical security concerns are met through socioeconomic development, individual choice and freedoms take greater precedence (Inglehart & Oyserman, 2004). In other words, economic progression is linked to values of self-expression and individual freedoms which may also influence the way internet use is approached, framed and valued. As internet use is closely tied to human connections, these values may under pin potential differences across the relationship between internet use and subjective wellbeing across rich and poor countries.

In addition, Human Development Index (HDI) is a way of describing a country based on indexes of health, education and national income (United Nations Development Programme, 2025). Essentially, HDI describes an overall quality of life based on the broad socioeconomic environment of a country in relation to the potential longevity, education and economic security which contribute to shaping and describing the sociopolitical context. As higher indexes indicate higher levels of any of the three indicators this suggests that the socioeconomic environment may be similar at similar levels of HDI. Therefore, HDI may serve as a measurable proxy of the broader socioeconomic environment in assessing potential differences of the relationship and subjective wellbeing across global contexts.

Global research

The following section will outline and discuss relevant research in relation to internet use and subjective wellbeing in a global context. Although global research on internet use and subjective wellbeing is limited, some research has observed a relationship between internet use and subjective wellbeing across a large number of countries. For instance, Ganju et al. (2016) found that adoption and use of information and communication technologies was positively related to subjective wellbeing across 160 countries. In a more detailed study, across 164 countries, having access to and using the internet was predictive of life satisfaction, and daily positive and negative life experiences along with other components of general wellbeing: social life satisfaction, social support, community wellbeing, physical wellbeing and social wellbeing (Vuorre & Przybylski, 2024). As a secondary database was used, positive and negative life experiences were the option most closely related to the affective components of subjective wellbeing. Lastly, in a longitudinal study with a 72 country sample, Vuorre & Przybylski (2022) found that internet use predicted life satisfaction and positive psychological wellbeing outcomes between 2008 and 2019. As such, Vuorre & Przybylski (2023a) argue that globally, internet use is related to positive outcomes of health and wellbeing across global contexts.

Alternatively, other global research has noted that geographical location and socioeconomic development may highlight differences in outcomes of internet use and subjective wellbeing. In their meta-analysis, Hancock et al. (2022) found that North America and Asia showed positive associations between social media use and wellbeing; however, in Europe this relationship was negative. Additionally, when using segregated measures of wellbeing, North America and Europe had higher levels of depression and also social wellbeing (Hancock et al., 2022).

In a more detailed country comparison of mobile phone use, Panova et al. (2020) showed that specific internet uses varied across cultures. For instance, in the US mobile internet use was related to higher depression and anxiety, conversely usage was related to lower depression in Spain and Colombia. Though this research focused primarily on mobile phone internet use, it shows that outcomes can differ across different global contexts and across different types of internet use.

Furthermore, researching using data from the Gallup World Poll showed a positive relationship between internet use and wellbeing but noted that effects were strongest in poorer regions and some relationships were negligible in more affluent countries (Graham & Nikolova, 2013). Similarly, in comparing mobile and regular internet connections, mobile use was related to greater perceptions of personal wealth and life satisfaction in poorer nations (Bartikowski et al., 2018). These examples allude to differences between rich and poor countries which suggests that outcomes could vary on the basis of a country's human development.

Overall, the global research reviewed provides valuable contributions and is suggestive that internet use and subjective wellbeing could vary based on HDI. However, the reviewed literature predominantly distinguishes between being an internet user or not with some research specific to social media and mobile phone use. As such, information about how the internet is used is not explicit, meaning that no clear inferences can be made about the relationship between specific online behaviours and subjective wellbeing. As such, more work is needed to explore the possible differences highlighted in the literature. Given the preliminary variation observed in the studies reviewed, it is proposed that a country's Human Development Index is worth investigating as a potential moderator of the relationship between different types of internet use (e.g., time online, entertainment, sharing news and information, connecting socially and communicating with family and friends) and subjective wellbeing indicators (e.g., depression, anxiety, and life satisfaction).

The Current Study

The aim of present research is to investigate how the type of online activity may relate to different components of subjective wellbeing and whether these associations vary as a function of human development. Given the mixed results of the literature and limited cross-cultural research, this study opted to employ a descriptive analysis to first describe the relationship across 42 countries and look for potential patterns of variation using region-level contexts. To contribute to balancing a literature that is overwhelmed by enquiry of negative relationships and effects, this research aims to investigate both positive and negative attributes of subjective wellbeing.

As this research is in part data driven and exploratory in nature, the preceding research questions are used to explore topic of internet use and subjective wellbeing. [5]

Research Questions:

Question 1

How does the type of online activity (e.g., time online, entertainment, sharing news and information, connecting socially, and communicating with family and friends) relate to subjective wellbeing (e.g., life satisfaction, depression and anxiety?

Question 2

Does the relationship between internet use (e.g., time online, entertainment, sharing news and information, connecting socially and communicating with family and friends) and

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[5] Appendix G outlines the data driven decisions that were made throughout the process of carrying out the present research. In addition, Appendix H shows table H.12 and H.13 which contain the multilevel analysis results for secondary country-level moderators that were tested as part of the exploratory process. These moderators were not used as part of the primary analysis.

subjective wellbeing (e.g., life satisfaction, depression, anxiety) vary across regional contexts?

Question 3

Does a country's level of human development (i.e., Human Development Index) moderate the relationship between internet use (e.g., time online, entertainment, sharing news and information, connecting socially and communicating with family and friends) and subjective wellbeing (e.g., life satisfaction, depression, anxiety)? How does this relationship differ for countries high in HDI versus low in HDI?

Confounding variables

Confounding variables are factors that can have an effect on both the dependent and independent variables (Wysocki et al., 2022). It is important to consider statistical controls in order to reduce the influence of third variables that may introduce bias into the target relationships (Memon, 2024; Wysocki et al., 2022). This allows the effect of the predictor to be observed without noise or interference from other variables that may also be predictors themselves (Memon, 2024; Wysocki et al., 2022). This increases precision as without considering statistical control, this runs the risk of misinterpreting the observed associations and reduces the clarity of relationship between variables (Memon, 2024; Wysocki et al., 2022). This is imperative as it allows the analysis to isolate each of the type of internet use as predictors in their relationships with life satisfaction, depression and anxiety. Choices should be carefully justified so as not to inadvertently introduce bias (Wysocki, 2022). Furthermore, the focus of the present research is not generational or gender differences regarding the relationship between internet use and subjective wellbeing. Thus, age and gender were diligently selected as two plausible confounding variables of the relationship between internet use and subjective wellbeing. The following paragraphs outlines rationales for including these variables as statistical controls.

Age: Age effects relating to internet use have been identified in numerous studies (Blachnio et al., 2015; Boulianne & Shehata, 2022; Koc & Gulyagci, 2013; Seabrook et al., 2016). Specifically, being younger is a predictor of more frequent internet use (Koc & Gulyagci, 2013). Older generations were less likely consume online news and post comments compared to younger cohorts (Boulianne & Shehata, 2022). Age has also been found to affect subjective wellbeing. For instance, a UK study found that from age 40 to age 70 there was a steady increase in life satisfaction (Baird et al., 2010). Age was also found to be a significant predictor as depression and anxiety reduced throughout adult life (Henderson et al., 1998; Jorm, 2000). Therefore, it is plausible that age may be a confounding variable and potentially influence types of internet use and the subcomponents of subjective wellbeing.

Gender: Gender has also been of interest and gender difference on internet use are apparent especially how they use it. For instance being male is a significant predictor of more frequent internet use (Koc & Gulyagci, 2013). Furthermore, males are more likely to use the internet for entertainment purposes, whereas females use social media more frequently (Bünning et al., 2023). Gender also impacts life satisfaction, depression and anxiety. Globally, females report higher levels of life satisfaction compared to men (Joshanloo & Jovanović, 2020). However, females are at a much greater risk of developing depression and anxiety in from early adulthood to middle age (Faravelli et al., 2013). As such, gender is a plausible confounding variable that may influence types of internet use and the subcomponents of subjective wellbeing.

2. Method

Design

This study used a cross-sectional design. The present research was carried out using a secondary database from a much larger project investigating the broader influence of internet use on humans. A cross-sectional survey allowed an efficient method of collecting data from a large sample size of 24,009. As the relationship between internet use and subjective wellbeing has been relatively underexplored in a number of the sample countries, a descriptive analysis was deemed useful to identify where a relationship may be present, and to generate data to support future research of potential causal inferences.

Participants and Procedure

As an existing data source was used, the sample size was determined prior to the conceptualization of this study. The rationale for the sample size via power analysis and specific details on the sampling process can be found in (Romano et al., 2021). Romano et al. (2021) recruited 24,009 participants from 42 nations (M_{age}= 36.5 years, SD_{age} = 12.3; 50% female, Argentina, Australia, Bolivia, Brazil, Canada, China, Columbia, Egypt, Finland, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Italy, Japan, Kenya, Mexico, Malaysia, Morocco, Netherlands, New Zealand, Nigeria, Pakistan, Panama, Peru, Philippines, Poland, Portugal, Russia, Serbia, Singapore, South Africa, South Korea, Spain, Sweden, Taiwan, Turkey, Venezuela, United Kingdom, and United States) making up 10 global regions. Each country contained between 427 to 1126 participants (an average of 571.6 per country). See Table A.1 in Appendix A for demographics per country and a breakdown of global regions.

Participants were recruited through the Harris Panel, a global panel curated by the international polling firm Nielsen that encompasses > 10 million individuals. Participants were invited by email or were given access to the survey link through the local panel provider portal, where surveys were completed from Dec 6, 2018, to Jan 24, 2019. Surveys were given in the dominant language of each country, except for three African countries by the recommendations of local collaborators, where it was advised that English would be most appropriate. Non-English translations of the survey were performed by a coalition of different researchers through the committee method (Brislin, 1980) or back-translation (Behling & Law, 2000).

Exclusions

The only exclusion was applied to age, as the survey was intended for persons 18 years and older, any participants who did not specify their age, or specified an age under 18, were excluded from the data analysis. The original data collected had 24,009 participants. After age exclusions, this was reduced to 23,859.

Measures[6]

Time online

Time online was measured by asking participants "how many waking hours a day would you say you are online (e.g. connected to the internet)?" Participants could select "almost all the time" or free type how many waking hours per day[7]. For analysis, "Almost all the time" was coded as 24 hours[8].

Type of internet use

The first three items were prefaced with the prompt, "how frequently do you use the internet for the following?" Responses to the following questions were given using a 7-point scale using 1 (Never), 2 (Rarely - monthly or less), 3 (Somewhat Rarely - weekly or less), 4

[6] Relevant items were selected for the purposes of the present research from a subset of items that were originally collected by Romano et al. (2021).
[7] As this survey item was free text, participants used inconsistent formats to indicate time spent online estimation. Therefore, Appendix I describes a set of rules that were followed to systematically code the inputs into whole numbers.
[8] A rationale for this decision can be found in appendix J

(Occasionally - daily or less), 5 (Somewhat Frequently - a few times a day), 6 (Frequently - several times a day), or 7 (All the time).

Entertainment. "Entertainment (e.g. games, TV Shows, movies, following celebrities, etc.)."

Sharing news and information. "Share news and information with others."

Social internet use. "Connect socially to others."

Communicational internet use. This item was a separate survey question from the items above. Participants were asked, "in general, how often do you do the following? Use the internet (email, video calls, or messaging, SMS etc) to stay in touch with family and friends." Responses were given using a 7-point scale ranging from 1 (Never) to 7 (All the time).

Life Satisfaction

Life satisfaction was measured with the following two questions from the Satisfaction With Life Scale (SWLS) (Diener et al., 1985). "All things considered, how satisfied are you these days with your life as a whole?" and "All things considered, how satisfied are you these days with your standard of living?" Participants responded using a 7-point scale ranging from 1 (Completely dissatisfied) to 7 (Completely satisfied). The SWLS is a 5-item scale however, smaller versions have been shown to produce similar results (Cheung & Lucas, 2014). In the present study, a mean score was calculated per participant to give a life satisfaction score with high internal consistency ($\alpha = .85$). Higher scores indicated higher levels of life satisfaction.

Depression symptoms

Depression symptoms were measured using the Patient Health Questionnaire - 8 (PHQ-8), a short diagnostic or research tool used for identifying depression which can be self-administered (Kroenke et al., 2001, 2009). PHQ-8 is derived from PHQ-9 and excludes a question about suicidal ideation. The PHQ-8 and 9 have high reliability (Cronbach alpha ranges from 0.82 to 0.89) (Alpizar et al., 2018; Kroenke et al., 2001; Pressler et al., 2011). The PHQ-8 is commonly used globally with good cross-cultural reliability and has been validated in multiple locations such as Europe, Latin America and Asia (Alpizar et al., 2018; Arias De La Torre et al., 2023; Xiong et al., 2015). It contains questions such as "how often during the past 2 weeks were you bothered by little interest or pleasure in doing things" and "how often during the past 2 weeks were you bothered by feeling down depressed or hopeless." Responses ranged from 1 (Not at all) to 4 (Nearly every day). In the present study, a total sum for each participant gave a score of depressive symptoms with high internal consistency ($\alpha = .89$). Scores range from 8 to 32. Higher scores indicate greater symptoms of depression.

Anxiety symptoms

Anxiety symptoms were measured using the Generalized Anxiety Disorder – 7 (GAD-7) scale. GAD-7 is a 7-item questionnaire suitable for use as a research or diagnostic tool in identifying anxiety (Löwe et al., 2008; Spitzer et al., 2006). It has high reliability ($\alpha = .92$) and is validated and used globally (Löwe et al., 2008; Spitzer et al., 2006; Tong et al., 2016; Villarreal-Zegarra et al., 2024). Questions included "how often during the past 2 weeks were you bothered by feeling nervous, anxious or on edge" and "how often during the past 2 weeks were you bothered by worrying too much about different things." Responses ranged from 1 (Not at all) to 4 (Nearly every day). In this study, a total sum for each participant gave an anxiety symptoms score with high reliability ($\alpha = .90$). Scores range from 7 to 28 where higher scores indicate greater anxiety symptoms.

Human Development Index

Human Development Index (HDI) was used as a country-level moderator. HDI is a country rating between 0 (low human development) to 1 (high human development), combining indexes of health, education and economic growth. HDI data was sourced from the United Nations database from the same year as data collection in 2018 (United Nations Development Programme, 2025)[9]. In the present sample, HDI scores ranged from 0.532 to 0.939 of which 18 countries were below the mean (0.80).

Demographic variables

Age was measured by asking participants "What is your age?" Responses were captured using a numerical text field. Gender was assessed by asking "what is your gender?" with two available responses (1 = male, 2 = female).

Data Analysis

Correlational analyses and descriptive statistics were performed using SPSS version 29.0.1.0 (171) for windows. Moderation analyses were carried out in RStudio 2023.12.0+369 "Ocean Storm" Release for windows (R Core Team, 2022).

Research Question 1 and 2.

Correlation analyses were carried out to test questions 1 and 2. These were run at the aggregate, region and country level.

The analysis includes input variables of time online, entertainment, sharing news and information, connecting socially and communicating with family and friends. Each predictor variable was analysed separately with their respective correlations to life satisfaction, depression and anxiety. Each predictor and its relationship with the three wellbeing indicators

[9] https://hdr.undp.org/data-center/human-development-index#/indicies/HDI

are reported separately by aggregate and region level. Country level correlation analyses were performed. However, these were reported in results and can be found in indexes B through F.

Research Question 3. Moderation Analysis

Multilevel models were used to test question 3 with participants nested within 42 countries (i.e., groups). Directly observed predictor, moderating, and outcome variables are analysed, controlling for age and gender in each model. The intercepts and slopes for age and gender were allowed to freely vary in all models. Our approach examines individual variables within each country and how country-level features moderate these relationships. Cases were excluded that did not have valid data for all variables for a given analysis.

Prior to performing multilevel models, both individual and country-level predictors were grand-mean centred. Appropriate centring of individual-level predictors is crucial for the interpretation of the results (Gelman & Hill, 2006). Furthermore, there are additional considerations when centring country-level predictors (Enders & Tofighi, 2007). As our research questions are focused on cross-cultural (level 2) differences with regard to individual (level 1) measures of internet use and subjective wellbeing, grand-mean centring was more appropriate than group-mean centring to ensure a regression slope with a combination of level 1 and level 2 associations for X and Y (Enders & Tofighi, 2007).

Explanatory Multilevel Analyses

Multilevel linear regressions to investigate research question 3 were performed using the lme4 package (Bates et al., 2015). Models are shown in tables 9, 10 and 11. All tables presented use the following Greek notation: level-one residual variance (error variance) denoted with σ^2, level-two residual variance (variance of random intercepts) with τ_{00}, random slope variance (between slope group variance across slopes) with τ_{11}, and slope intercept correlation with ρ_{01} (Raudenbush & Bryk, 2002). Multilevel modelers recommend not ignoring the hierarchical structure within data by using OLS regressions even when intraclass correlation coefficients (ICC) for independent variables are low, as this would severely bias the estimates (Gelman & Hill, 2007). Each model individually contains one type of internet use as a predictor as well as the interaction with HDI, age and gender. This step was taken in order to isolate each predictor for exploratory purposes (Gelman & Hill, 2007).

Data Accessibility

The data used for the analysis of the present study is available on request. Data can be accessed by contacting Evan Valdes at Massey University E.Valdes@massey.ac.nz. The R Markdown file which contains the multilevel model code can be viewed at the following address: https://osf.io/vmqk3/?view_only=4c0ee42ec93d4378a7a8ad4e087e2d85

3. Results

Descriptive Statistics

Mean statistics for life satisfaction, depression and anxiety scores by region are shown in table 1. Mean life satisfaction scores ranged from 4.31 (SD = 1.37) in Confucian Asia to 4.83 (SD = 1.46) in South Asia. Mean depression scores ranged from 14.56 (5.02) in Confucian Asia to 16.49 (SD = 5.96) in Northern Africa. Mean anxiety scores ranged from 12.94 (SD = 5.33) in Scandinavia to 15.19 (SD = 5.32) in Northern Africa.

Table 1

Descriptive Statistics for Subjective Wellbeing Scores

Region	Life Satisfaction M (SD)	Depression M (SD)	Anxiety M (SD)
Scandinavia	4.65 (1.39)	14.88 (5.99)	12.94 (5.33)
Anglosphere	4.61 (1.41)	15.49 (6.45)	13.89 (6.01)
Western Europe	4.57 (1.40)	14.75 (5.58)	13.75 (5.17)
Confucian Asia	4.31 (1.37)	14.56 (5.02)	13.25 (4.64)
Eastern Europe	4.36 (1.43)	14.97 (5.50)	13.46 (5.12)
South-East Asia	4.62 (1.34)	15.05 (5.48)	13.49 (4.94)
Latin America	4.66 (1.50)	15.60 (5.50)	14.60 (4.87)
South Asia	4.83 (1.46)	15.49 (5.83)	14.01 (5.17)
Northern Africa	4.33 (1.56)	16.49 (5.96)	15.19 (5.32)
Sub-Saharan Africa	4.18 (1.39)	14.94 (5.51)	13.97 (5.27)

Note. Life satisfaction scores range from 1 to 7. Depression scores range from 8 to 32. Anxiety scores range from 7 to 28.

Mean statistics for the internet use variables are shown in table 2. Time online ranged from 15.35 (SD = 8.81) hours per day in Northern Africa to 16.99 (8.65) hours per day in Latin America. Frequency of internet use for entertainment scores ranged from 4.24 (SD = 1.62) in Western Europe to 4.99 (SD = 1.58) in Latin America. Frequency of internet use for News and information scores ranged from 3.61 (SD = 1.52) in Scandinavia to 4.99 (SD =

1.62) in Sub-Saharan Africa. Frequency of internet use for connecting socially scores ranged from 4.45 (SD = 1.65) in Western Europe to 5.59 (SD = 1.44) in Sub-Saharan Africa. Lastly, frequency of internet use for communicating with family and friends scores ranged from 4.27 (SD = 1.59) in Confucian Asia to 5.29 (SD = 1.55) in Sub-Saharan Africa.

Table 2

Descriptive Statistics for Measures Of Internet Use

Region	TO M (SD)	E Scores M (SD)	SN Scores M (SD)	CS Scores M (SD)	C Scores M (SD)
Scandinavia	14.89 (9.47)	4.40 (1.47)	3.61 (1.52)	4.73 (1.49)	4.32 (1.39)
Anglosphere	13.89 (9.47)	4.31 (1.68)	3.76 (1.67)	4.50 (1.71)	4.43 (1.56)
Western Europe	13.73 (9.55)	4.24 (1.62)	4.01 (1.55)	4.45 (1.65)	4.63 (1.51)
Confucian Asia	16.33 (9.31)	4.43 (1.59)	4.06 (1.51)	4.64 (1.61)	4.27 (1.59)
Eastern Europe	13.75 (9.32)	4.76 (1.62)	4.47 (1.69)	4.58 (1.71)	5.03 (1.54)
South-East Asia	16.92 (8.75)	4.96 (1.53)	4.58 (1.53)	5.25 (1.47)	4.57 (1.80)
Latin America	16.99 (8.65)	4.99 (1.58)	4.70 (1.62)	5.39 (1.48)	5.22 (1.59)
South Asia	15.67 (8.96)	4.82 (1.59)	4.70 (1.44)	5.20 (1.45)	5.02 (1.46)
Northern Africa	15.35 (8.81)	4.70 (1.64)	4.58 (1.62)	5.12 (1.54)	4.71 (1.57)
Sub-Saharan Africa	15.59 (8.78)	4.96 (1.66)	4.99 (1.62)	5.59 (1.44)	5.29 (1.55)

Note. The internet use scores are not a breakdown of the time online. Hence the sum if all specific internet use scores do not amalgamate to the amount of time spent online. TO = Time online(hours per day), E = Entertainment, SN = Sharing news and information, CS = connecting socially, C = Communicating with family and friends.

Bivariate correlations

Intercorrelations for the 10 variables used in correlation analyses and multilevel models are shown in table 3.[10] Looking at the subjective wellbeing indicators, life satisfaction

[10] The aggregate level (total sample without region or country grouping applied) correlations between the variables of interest (internet use and subjective wellbeing) are described under research question 1 and therefore they are not described in this section.

was negatively correlated with both depression and anxiety. Depression and anxiety were highly positively correlated. Regarding intercorrelations of internet use, all measures of internet use were positively correlated with weak to moderate coefficients. This suggests there is some overlap between these measures. Age and gender are included as controls but are not the focus of this study. Being younger was associated with more time online and higher use of all types of internet use. Being younger was marginally associated with lower life satisfaction. Younger participants also had higher levels of anxiety and depression. There were small correlations for gender, specifically with anxiety, depression and communicational internet use.

Research Question 1: Aggregate-level analysis:

How does the type of online activity (e.g., time online, entertainment, sharing news and information, connecting socially, and communicating with family and friends) relate to subjective wellbeing (e.g., life satisfaction, depression and anxiety)?

The correlation between time online and life satisfaction was small negative and statistically significant, whereas there were small significant positive relationships with depression and anxiety. Frequency of internet use for entertainment, sharing news and information, and connecting socially all showed small and significant positive relationships with life satisfaction, depression and anxiety. Frequency of communicating with family and friends returned a small significant positive relationship with life satisfaction and anxiety, but no significant relationship with depression.

Table 3

Bivariate Correlation Matrix

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Life Satisfaction	1									
2. Depression	-.38**	1								
3. Anxiety	-.35**	.80**	1							
4. Time Online	-.04**	.16**	.15**	1						
5. Entertainment	.05**	.11**	.12**	.21**	1					
6. Sharing News	.11**	.03**	.08**	.17**	.37**	1				
7. Connect Socially	.11**	.05**	.08**	.21**	.32**	.50**	1			
8. Communication	.15**	.01	.06**	.14**	.31**	.38**	.36**	1		
9. Age	.04**	-.19**	-.19**	-.22**	-.28**	-.13**	-.20**	-.14**	1	
10. Gender	-.03**	.08**	.11**	.03**	-.01*	-.01	.02**	.05**	-.03**	1

Note. $^{*} = p < 0.05$, $^{**} = p < 0.01$

Research Question 2: Region-Level Analysis

Does the relationship between internet use (e.g., time online, entertainment, sharing news and information, connecting socially and communicating with family and friends) and subjective wellbeing (e.g., life satisfaction, depression, anxiety) vary across regional contexts?

Due to the large number of correlations, the results for this research question are not reproduced in text but are referred to in their respective tables. These results have been summarised to describe patterns of variation across regions in the relationships between the different measures of internet use and sub-components of subjective wellbeing.

Time online. The correlational results for the relationship between time online and indicators of subjective wellbeing at the region level are presented in table 2. The Anglosphere, Europe, and North Africa showed consistent evidence of small statistically significant negative relationships between time online and life satisfaction, whereas the remaining regions returned non-statistically significant results. As such, the relationship between time online and life satisfaction varied across regions. On the other hand, there was a clear and consistent positive relationship between time online and depression and anxiety across all regions. Nine out of ten regions showed a small but significant positive relationship with depression and anxiety.

Table 4

Region Correlations for Time Online and Indicators of Subjective Wellbeing

Region	Life Satisfaction	Depression	Anxiety
Scandinavia	-.07*	.24**	.24**
Anglosphere	-.08**	.23**	.22**
West Europe	-.09**	.18**	.17**
Confucian Asia	-.02	.15**	.12**
East Europe	-.04*	.17**	.16**
South-East Asia	-.03	.13**	.13**
Latin America	-.01	.14**	.13**
North Africa	-.07*	.17**	.19**
Sub-Saharan Africa	.02	.01	.02
South Asia	-.01	.10**	.11**

Note. Regions are in descending order of average HDI.

* = $p < 0.05$, ** = $p < 0.01$

Entertainment. The region-level correlational results for the relationship between frequency of using the internet for entertainment and subjective wellbeing are shown in table 3. Six out of ten regions showed a small statistically significant positive relationship between frequency of entertainment-internet use and life satisfaction. The Anglosphere stood out as the only western region with a significant and positive correlation, though this was very small. The relationship with depression and anxiety was evident and consistently positive and statistically significant across all regions except for Sub-Saharan Africa.

Table 5

Region Correlations for Entertainment and Indicators of Subjective Wellbeing

Region	Life Satisfaction	Depression	Anxiety
Scandinavia	-.02	.22**	.23**
Anglo	.04*	.12**	.13**
Western Europe	-.01	.16**	.17**
Confucian Asia	.09**	.10**	.11**
Eastern Europe	.03	.11**	.10**
South-East Asia	.09**	.12**	.13**
Latin America	.05**	.07**	.07**
North Africa	.05	.09**	.09**
Sub-Saharan Africa	.06*	.04	.07*
South Asia	.08**	.08**	.09**

Note. Regions are in descending order of average HDI.

** = $p < 0.05$, ** = $p < 0.01$*

Sharing news and information. Table 6 presents the region level correlational results for the relationship between frequency of sharing news and information with the subjective wellbeing indicators. Across all regions, except Scandinavia, there was a consistent small positive and significant relationship between frequency of sharing news and information and life satisfaction.

Alternatively, the relationships between frequency of sharing news and information and the negative wellbeing indicators varied in statistical significance and direction across regions. More specifically, a small significant positive relationship was present in Scandinavia, Anglosphere, and West and East Europe. Alternatively, in Confucian Asia there was no significant relationship with depression and a small positive relationship with anxiety.

In contrast to other regions, Latin America and Sub-Saharan Africa returned a small negative and significant relationship between frequency of sharing news and information and depression.

Table 6

Region Correlations for Sharing News and Information and Indicators of Subjective Wellbeing

Region	Life Satisfaction	Depression	Anxiety
Scandinavia	.01	.13**	.17**
Anglo	.11**	.08**	.11**
Western Europe	.05**	.08**	.11**
Confucian Asia	.20**	.01	.04*
Eastern Europe	.05**	.07**	.12**
South-East Asia	.20**	-.01	.04
Latin America	.15**	-.05**	.01
North Africa	.09**	.01	.05
Sub-Saharan Africa	.07**	-.06*	-.01
South Asia	.19**	.01	.03

Note. Regions are in descending order of average HDI.

* = $p < 0.05$, ** = $p < 0.01$

Connecting socially. Table 7 shows the region level correlational results for the relationship between frequency of connecting socially and the indicators of subjective wellbeing. In most cases there was a small and significant positive relationship between connecting socially and life satisfaction. The exceptions were Scandinavia and Sub-Saharan Africa. Overall, the relationship between frequency of connecting socially and life satisfaction was consistently positive and significant across all regions. However, there was variability in the magnitude of relationships in West and East Europe which were notably smaller compared to the correlations in other regions.

Relationships in Scandinavia, Europe and the Anglosphere were significant positive relationships between frequency of connecting socially and the negative indicators of subjective wellbeing. In the remaining six regions, the correlations were non-statistically significant. Therefore, the relationship between connecting socially and depression and anxiety showed clear differences across regional contexts.

Table 7

Region Correlations for Connect Socially and Indicators of Subjective Wellbeing

Region	Life Satisfaction	Depression	Anxiety
Scandinavia	.06	$.10^{**}$	$.11^{**}$
Anglo	$.10^{**}$	$.10^{**}$	$.13^{**}$
West Europe	$.04^{**}$	$.08^{**}$	$.09^{**}$
Confucian Asia	$.17^{**}$	.01	.02
East Europe	$.04^{*}$	$.09^{**}$	$.12^{**}$
South-East Asia	$.20^{**}$	.01	.03
Latin America	$.10^{**}$	-.01	.02
North Africa	$.13^{**}$	.03	.05
Sub-Saharan Africa	.04	-.02	.04
South Asia	$.22^{**}$	-.02	.02

Note. Regions are in descending order of average HDI.

$^{*} = p < 0.05$, $^{**} = p < 0.01$

Communicating with family and friends. Table 8 presents the region level correlational results describing the relationship between frequency of communicating with family and friends and the subjective wellbeing indicators. Relationships with life satisfaction were significant and positive in all regions though there was variation in strength across regional contexts. For instance, the relationship for Confucian Asia was notably larger than other regions, whereas correlations observed in Sub-Saharan Africa and West Europe were notably smaller.

On the other hand, in Scandinavia, Anglosphere, West Europe and South-East Asia there were small significant and positive relationships between frequency of communicating with family and friends with depression and anxiety. Correlations between depression and anxiety were non-significant in Confucian Asia, East Europe and Sub-Saharan Africa. The relationships in North Africa and South Asia were small significant positive with anxiety but non-significant with depression. Lastly, Latin America was the only region where a significant negative relationship with both depression and anxiety was observed. Therefore, there were complex variation patterns across regions for the frequency of communicating with family and friends and the negative subjective wellbeing indicators.

Table 8

Region Correlations for Communicating with Family and Friends and Indicators of Subjective Wellbeing

Region	Life Satisfaction	Depression	Anxiety
Scandinavia	.10**	.08*	.09**
Anglo	.12**	.07**	.09**
West Europe	.07**	.05**	.09**
Confucian Asia	.25**	-.01	.01
East Europe	.16**	-.03	0.03
South-East Asia	.17**	.08**	.11**
Latin America	.17**	-.08**	-.03*
North Africa	.12**	-.03	.06*
Sub-Saharan Africa	.06*	-.04	.03
South Asia	.19**	-.01	.05*

Note. Regions are in descending order of average HDI.

* = $p < 0.05$, ** = $p < 0.01$

Country-level Analysis

Country-level correlations are shown in appendix B to F. As the regional analyses was used as the primary method of the data analysis for research question 2, the country-level correlations are not described here. These are provided for richer detail to dive deeper into specific country-level differences of the countries within the described regions.

Research question 3: Moderation Analysis

Does a country's level of human development (i.e., Human Development Index) moderate the relationship between internet use (e.g., time online, entertainment, sharing news and information, connecting socially and communicating with family and friends) and subjective wellbeing (e.g., life satisfaction, depression, anxiety)? How does this relationship differ for countries high in HDI versus low in HDI?

Testing the moderation effects of Human Development Index (HDI) on the relationship between different internet uses and subjective wellbeing was conducted using multilevel models to obtain main and interaction effects. Based on identified significant interaction effects of HDI on the relationships between types of internet use and indicators of subjective wellbeing in the multilevel models, these relationships were further probed to examine the marginal effects of HDI. Simple slopes were used to further examine the interactions using values, as suggested by Aiken and West (1991), one standard deviation (SD) above and one below the mean HDI, to indicate high-HDI (+1 SD) and low-HDI (-1 SD).

Life Satisfaction

Table 9 presents multilevel models where the outcome variable of each model was life satisfaction and the predictors for each model were the frequency of the given type of internet use, HDI and their interaction, controlling for age and gender. Intercepts and slopes were permitted to vary randomly across countries. The main effects revealed that time online negatively predicted life satisfaction (B = -.05, *CI* [-.07, -.02], p < .001). In contrast, frequency of internet use for; entertainment (B = .08, *CI* [.06, .11], p < .001), sharing news and information (B = .18, *CI* [.15, .21], p < .001), connecting socially (b = .17, CI [.14, .20], p < .001) and communicating with family and friends (B = .23, *CI* [.20, .26], p = < .001) positively predicted life satisfaction scores.

The interaction effect between time online and HDI as a predictor of life satisfaction was statistically significant (B = -.04, *CI* [-.06, -.01], p = .004). However, all other interaction between the remaining types of internet use and HDI as predictors of life satisfaction were not statistically significant.

Table 9

Multilevel Models of the Associations Between Each Internet Use and Life Satisfaction, and Their Interactions With HDI

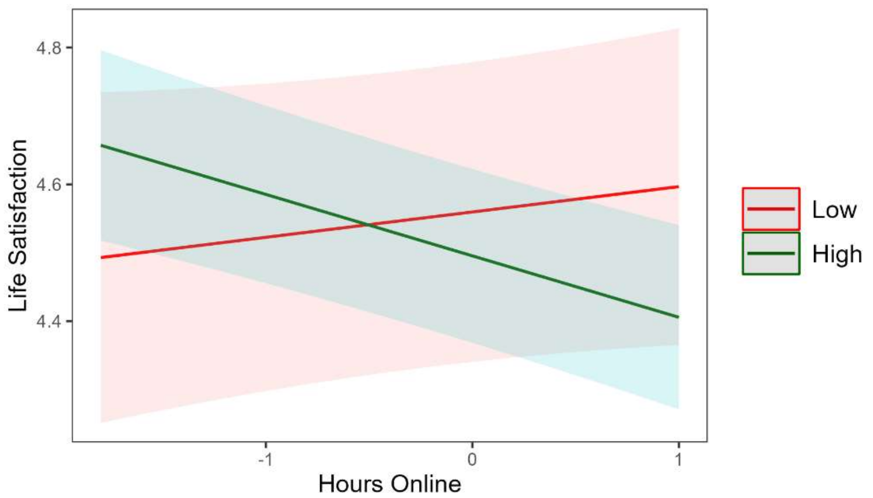
Predictors	Life Satisfaction (TO) *Estimates [CI]*	Life Satisfaction (E) *Estimates [CI]*	Life Satisfaction (SN) *Estimates [CI]*	Life Satisfaction (CS) *Estimates [CI]*	Life Satisfaction (C) *Estimates [CI]*
(Intercept)	4.44 (p <.001) [4.32 – 4.55]	4.33 (p <.001) [4.21 – 4.44]	4.37 (p <.001) [4.26 – 4.49]	4.34 (p <.001) [4.23 – 4.45]	4.37 (p <.001) [4.26 – 4.48]
TO	-.05 (p <.001) [-.07 – -.02]				
E		.08 (p <.001) [.06 – .11]			
SN			.18 (p <.001) [.15 – .21]		
CS				.17 (p <.001) [.14 – .20]	
C					.23 (p <.001) [.20 – .26]
HDI	-.02 (p =.675) [-.10 – .07]	-.01 (p =.786) [-.09 – .07]	.02 (p =.563) [-.06 – .11]	.02 (p =.674) [-.06 – .10]	.01 (p =.839) [-.07 – .09]
age	.00 (p <.001) [.00 – .01]	.01 (p <.001) [.01 – .01]	.01 (p <.001) [.00 – .01]	.01 (p <.001) [.01 – .01]	.01 (p <.001) [.01 – .01]
Gender	-.07 (p <.001) [-.10 – -.03]	-.06 (p <.001) [-.10 – -.02]	-.07 (p <.001) [-.10 – -.03]	-.07 (p <.001) [-.11 – -.03]	-.08 (p <.001) [-.12 – -.05]
TO:HDI	-.04 (p =.004) [-.06 – -.01]				
E:HDI		-.02 (p =.116) [-.04 – .00]			
SN:HDI			-.03 (p =.058) [-.06 – .00]		
CS:HDI				-.03 (p =.056) [-.06 – .00]	
C:HDI					0 (p =.96) [-.03 – .03]
Random Effects					
σ^2	1.99	1.99	1.96	1.97	1.95
τ_{00}	0.07 Country	0.07 Country	0.07 Country	0.06 Country	0.07 Country
τ_{11}	0.00 Country.TO	0.00 Country.E	0.01 Country.SN	0.01 Country.CS	0.00 Country.C
ρ_{01}	0.12 Country	0.14 Country	0.26 Country	0.37 Country	0.26 Country
ICC	0.03	0.03	0.04	0.03	0.03
N	42 Country	42 Country	42 Country	42 Country	42 Country
Obs	23197	23798	23801	23824	23816
Marg. R^2 / Cond. R^2	0.005 / 0.040	0.006 / 0.040	0.018 / 0.053	0.016 / 0.050	0.027 / 0.061

Note. TO = Time online, E = Entertainment, SN = Sharing news and information, CS = Connecting socially, C = Communicating with family and friends.

Based on these findings, we probed the interaction to examine the marginal effects of HDI for the time online-life satisfaction relationship. Countries with a low HDI showed a non-significant coefficient *(B = -.01, SE = .02, t = -.68, 95% CI [-.05, .02], p = .501).* However, in countries with a higher HDI the coefficient was negative and statistically significant *(B = -.08, SE = .02, t = -4.90, 95% CI [-.12, -.05], p <.001).* See simple slopes in figure 1.

Figure 1

Interaction Plot Depicting HDI Levels of the Time Online–Life Satisfaction Relationship



Note. The red line indicates low-HDI countries, and the green line indicates high-HDI. The levels of HDI are one standard deviation below and above the mean of the sample countries.

Depression

Table 10 presents multilevel models where the outcome variable of each model was depression and the predictors for each model were the frequency of the given type of internet use, HDI and their interaction, controlling for age and gender. Intercepts and slopes were permitted to vary randomly across countries. The main effects showed that time online (b = .65, *CI* [.56, .73], $p < .001$) and entertainment frequency (b = .37, *CI* [.28, .45], $p < .001$) positively and significantly predicted depression scores. More frequent sharing news and information (b = .05, *CI* [-.06, .15], p = 0.379) and connecting socially (b = .03, *CI* [-.06, .12], p = .544) did not significantly predict depression scores. Lastly, more frequent communicating with family and friends negatively predicted depression scores (b = -.12, *CI* [-.22, -.03], p = .012).

The interaction effect of HDI was significant for time online *(b = .15, 95% CI [.07 - .24], p = .001),* entertainment *(B = .12, 95% CI [.03 - .20], p =.006)*, sharing news (*B* = .22, *95% CI* [.11 - .33], p <.001), and connecting socially *(B = .16, 95% CI [.07 - .25], p = .001).* However, the interaction between communicating with family and friends and HDI as a predictor of depression symptoms was not statistically significant.

Table 10

Multilevel Models of the Associations Between Each Internet Use and Depression Symptoms, and Their Interactions With HDI

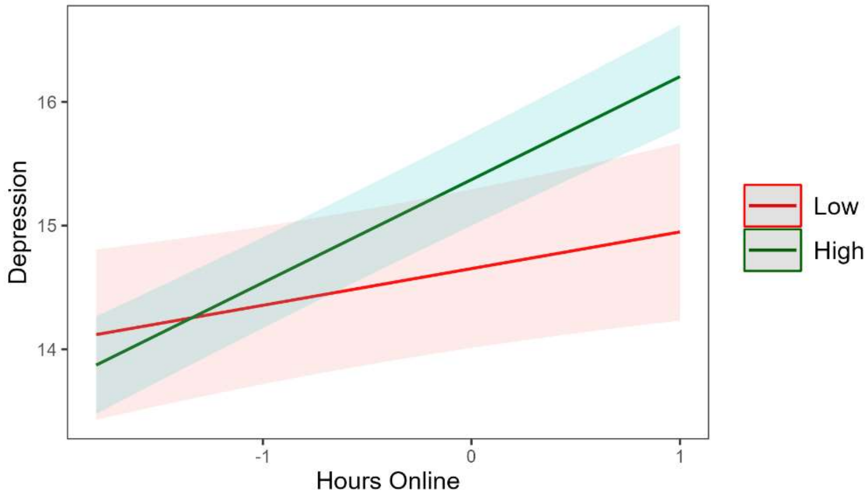
Predictors	Depression (TO) *Estimates [CI]*	Depression (E) *Estimates [CI]*	Depression (SN) *Estimates [CI]*	Depression (CS) *Estimates [CI]*	Depression (C) *Estimates [CI]*
(Intercept)	16.81 (p <.001) [16.41 – 17.21]	16.91 (p<.001) [16.51 – 17.31]	17.23 (p <.001) [16.83 – 17.62]	17.23 (p <.001) [16.83 – 17.62]	17.25 (p <0.001) [16.86 – 17.65]
TO	.65 (p<.001) [.56 – .73]				
E		.37 (p <.001) [.28 – .45]			
SN			.05 (p =.379) [-.06 – .15]		
CS				.03 (p =.544) [-.06 – .12]	
C					-.12 (p =.012) [-.22 – -.03]
HDI	.2 (p =.108) [-.04 – .45]	0.23 (p =.07) [-0.02 – 0.47]	.21 (p =.096) [-.04 – .45]	.19 (p =.129) [-.05 – .43]	.18 (p =.147) [-.06 – .43]
age	-.08 (p<.001) [-.08 – -.07]	-0.08 (p<.001) [-0.09 – -0.07]	-.09 (p<.001) [-0.09 – -.08]	-.09 (p <.001) [-.09 – -.08]	-.09 (p <.001) [-.09 – -.08]
Gender	.73 (p <.001) [.59 – .87]	0.77 (p <.001) [0.63 – 0.91]	.76 (p <.001) [.62 – .90]	.74 (p <.001) [.60 – .88]	.76 (p <.001) [.62 – .90]
TO:HDI	.15 (p =.001) [.07 – 0.24]				
E:HDI		0.12 [.03 – .20]			
SN:HDI			.22 (p <.001) [0.11 – 0.33]		
CS:HDI				.16 [p =.001) [.07 – 0.25]	
C:HDI					0.1 (p =.051) [-.00 – 0.20]
Random Effects					
σ^2	29.51	29.88	29.94	29.99	29.98
τ_{00}	0.57 Country	0.56 Country	0.55 Country	0.55 Country	0.57 Country
τ_{11}	0.02 Country.TO	0.02 Country.E	0.06 Country.SN	0.02 Country.CS	0.04 Country.C
ρ_{01}	0.45 Country	-0.02 Country	0.23 Country	0.35 Country	0.05 Country
ICC	0.02	0.02	0.02	0.02	0.02
N	42 Country	42 Country	42 Country	42 Country	42 Country
Obs	23194	23792	23796	23820	23810
Marg. R^2 / Cond. R^2	0.054 / 0.072	0.044 / 0.062	0.041 / 0.060	0.040 / 0.058	0.040 / 0.059

Note. TO = Time online, E = Entertainment, SN = Sharing news and information, CS = connecting socially, C = communicating with family and friends, LS = Life satisfaction

We probed each significant interaction to examine the marginal effects of HDI on the internet uses and their relationships with depression. For time online and depression, the effect was positive and significant in both low *(B = .50, SE = .06, t = 8.09, 95% CI [.38, .63], p <.001)* and high (B = .80, SE = .06, t = 13.61, 95% CI [.69, .92], p <.001) HDI countries (see figure 2 for simple slopes). Similarly, results for the entertainment-depression relationship which showed a positive and significant coefficient for low *(B = .25, SE = .06, t = 3.98, 95% CI [.13, .37], p <.001)* and high *(B = .49, SE = .06, t = 7.99, 95% CI [.37, .61], p <.001)* HDI countries (see figure 3 for simple slopes). The coefficient for sharing news as a predictor of depression in low-HDI countries was negative and statistically significant (B = -.17, SE = .08, t = -2.21, 95% CI [-.33, -.02], p = .03). Conversely, in high-HDI countries the coefficient was positive and statistically significant (B = .27, SE = .07, t = 3.60, 95% CI [.12, .41], p = .001) (see figure 4 for simple slopes). Lastly, contrasting results were also present between frequency of connecting socially and depression. In lower HDI countries the coefficient was negative but marginally non-significant (B = -.13, SE = .07, t = -1.95, 95% CI [-.26, .00], p = .058), whereas the coefficient of high-HDI countries was positive and statistically significant (B = .16, SE = .06, t = 3.04, 95% CI [.07, .31], p = .004) (see figure 5 for simple slopes).

Figure 2

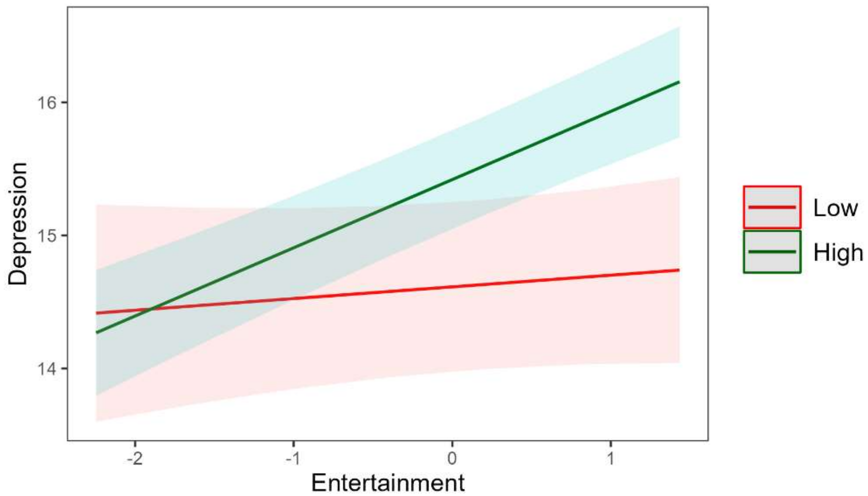
Interaction Plot Depicting HDI Levels of the Time Online-Depression Relationship



Note. *The red line indicates low-HDI countries, and the green line indicates high-HDI. The levels of HDI are one standard deviation below and above the mean of the sample countries.*

Figure 3

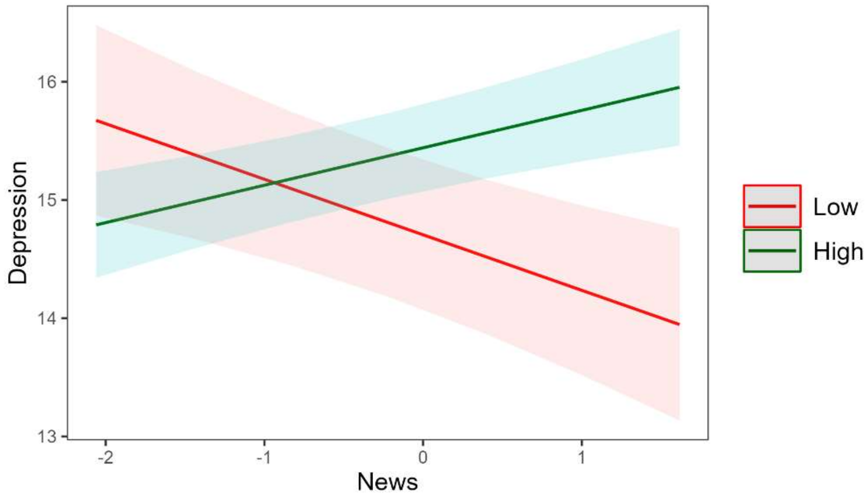
Interaction Plot Depicting HDI Levels of the Entertainment-Depression Relationship



Note. *The red line indicates low-HDI countries, and the green line indicates high-HDI. The levels of HDI are one standard deviation below and above the mean of the sample countries.*

Figure 4

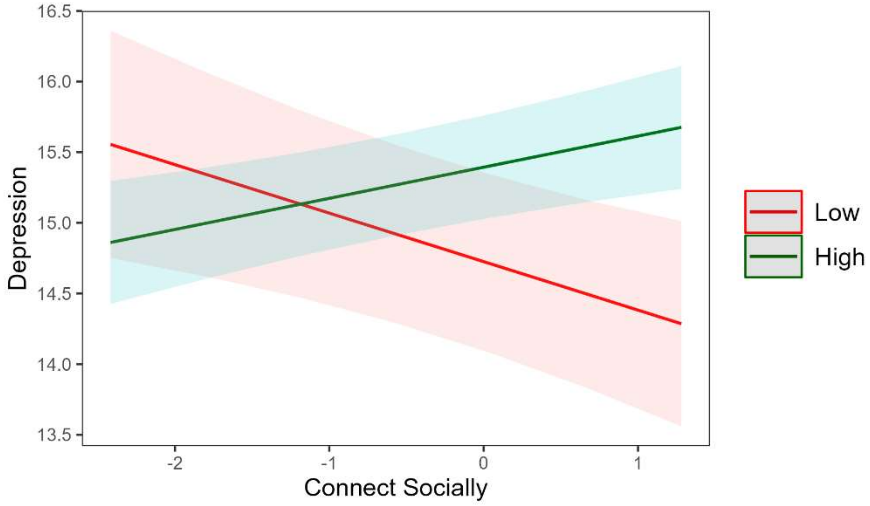
Interaction Plot Depicting HDI Levels of the Sharing News-Depression Relationship



Note. The red line indicates low-HDI countries, and the green line indicates high-HDI. The levels of HDI are one standard deviation below and above the mean of the sample countries.

Figure 5

Interaction Plot Depicting HDI Levels of the Connecting Socially-Depression Relationship



Note. The red line indicates low-HDI countries, and the green line indicates high-HDI. The levels of HDI are one standard deviation below and above the mean of the sample countries.

Anxiety

Table 11 presents multilevel models where the outcome variable of each model was anxiety and the predictors for each model were the frequency of the given type of internet use, HDI and their interaction, controlling for age and gender. Intercepts and slopes were permitted to vary randomly across countries. The main effects showed that time online (b = 0.56, *CI* [0.48, 0.65], $p < .001$), entertainment ($b = .39$, *CI* [.31, .47], $p < .001$), sharing news and information ($b = .28$, *CI* [.18, .37], $p < .001$), connecting socially ($b = .19$, *CI* [.11, .26], $p < .001$) and communicating with family and friends ($b = .10$, *CI* [.01, .19], $p = .03$) positively and significantly predicted anxiety scores.

The interaction effects between the following internet uses and HDI as predictors of anxiety symptoms were statistically significant; time online (*B = .12, 95% CI [.03, .20], p = .008*), entertainment (*B = .10, 95% CI [.02, .18], p = .015*), and sharing news (*B = .16, 95% CI [.06, .25] p = .001*). The interaction effects between connecting socially and communicating with family and friends and HDI as predictors of anxiety symptoms were not statistically significant.

Table 11

Multilevel Models of the Association Between Internet Use and Anxiety Symptoms, and Their Interactions with HDI

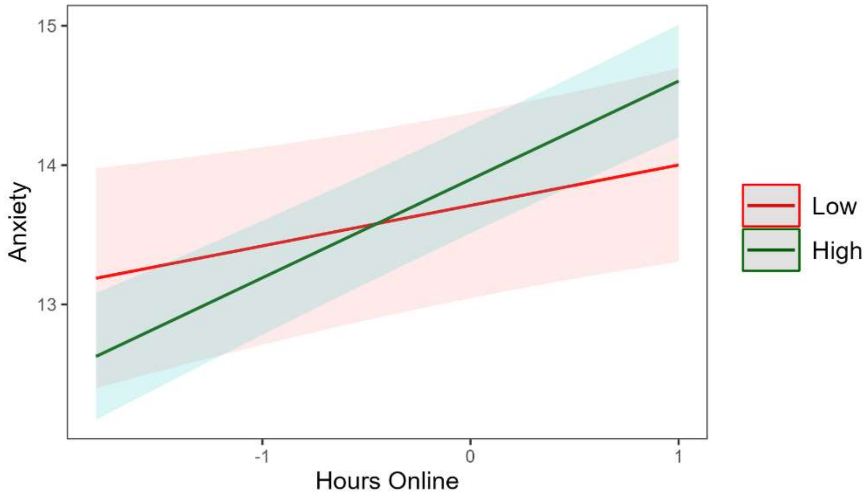
Predictors	Anxiety (TO) *Estimates [CI]*	Anxiety (E) *Estimates [CI]*	Anxiety (SN) *Estimates [CI]*	Anxiety (CS) *Estimates [CI]*	Anxiety (C) *Estimates [CI]*
(Intercept)	14.72 (p <.001) [14.33 – 15.11]	14.72 (p <.001) [14.33 – 15.10]	15.02 (p <.001) [14.64 – 15.40]	15.00 (p <.001) [14.62 – 15.38]	15.04 (p<.001) [14.66 – 15.42]
TO	.56 (p <.001) [.48 – .65]				
E		.39 (p <.001) [.31 – .47]			
SN			.28 (p <.001) [.18 – .37]		
CS				.19 (p <.001) [.11 – .26]	
C					.10 (p =.03 [.01 – .19]
HDI	.05 (p =.688) [-.20 – .31]	.08 (p =.554) [-.17 – .33]	.11 (p =.396) [-.14 – .35]	.08 (p =.559) [-.18 – .33]	.06 (p =.662) [-.20 – .31]
age	-.07 (p <.001) [-.07 – -.06]	-.07 (p <.001) [-.07 – -.06]	-.07 (p <.001) [-.08 – -.07]	-.07 (p <.001) [-.08 – -.07]	-.07 (p <.001) [-.08 – -.07]
Gender	.99 (p <.001) [.87 – 1.12]	1.04 (p <.001) [.92 – 1.17]	1.03 (p <.001) [.90 – 1.16]	1.01 (p <.001) [.88 – 1.14]	1.01 (p <.001) [.88 – 1.14]
TO:HDI	0.12** (p =.008) [.03 – .20]				
E:HDI		.10 (p =.015) [.02 – .18]			
SN:HDI			.16 (p =.001) [.06 – .25]		
CS:HDI				.07 (p =.07) [-.01 – .15]	
C:HDI					.02 (p =.653) [-.07 – .11]
Random Effects					
σ^2	24.47	24.69	24.72	24.79	24.81
τ_{00}	0.63 Country	0.60 Country	0.58 Country	0.61 Country	0.62 Country
τ_{11}	0.03 Country.TO	0.02 Country.E	0.04 Country.SN	0.01 Country.CS	0.03 Country.C
ρ_{01}	-0.03 Country	-0.31 Country	-0.06 Country	0.15 Country	-0.15 Country
ICC	0.03	0.02	0.02	0.02	0.03
N	42 Country	42 Country	42 Country	42 Country	42 Country
Obs	23197	23797	23801	23824	23815
Marg R^2 / Cond R^2	0.055 / 0.080	0.048 / 0.072	0.047 / 0.070	0.044 / 0.067	0.043 / 0.067

Note. TO = Time online, E = Entertainment, SN = Sharing news and information, CS = connecting socially, C = communicating with family and friends, LS = Life satisfaction

We probed each significant interaction to examine the marginal effects of HDI on the relationships between internet use and anxiety. For time online and anxiety, the coefficients were positive and statistically significant for lower *($B = .45$, $SE = .06$, $t = 7.19$, 95% CI [.33, .57], $p <.001$)* and higher *($B = .68$, $SE = .06$, $t = 11.51$, 95% CI [.57,.80], $p <.001$)* HDI countries (see figure 6 for simple slopes). The coefficient for entertainment and anxiety was positive and statistically significant for lower *($B = .29$, $SE = .06$, $t = 4.79$, 95% CI [.17, .41], $p <.001$)* and higher *($B = .49$, $SE = .06$, $t = 8.38$, 95% CI [.38, .60], $p <.001$)* HDI countries (see figure 7 for simple slopes). Lastly, for news and anxiety, in countries with a low-HDI the coefficient was positive but non-significant *($B = .12$, $SE = .07$, $t = 1.73$, 95% CI [-.02, .25], $p = .09$)*. The coefficient for high-HDI countries was positive and statistically significant *($B = .43$, $SE = .07$, $t = 6.63$, 95% CI [.30, .56], $p <.001$)* (see figure 8 for simple slopes).

Figure 6

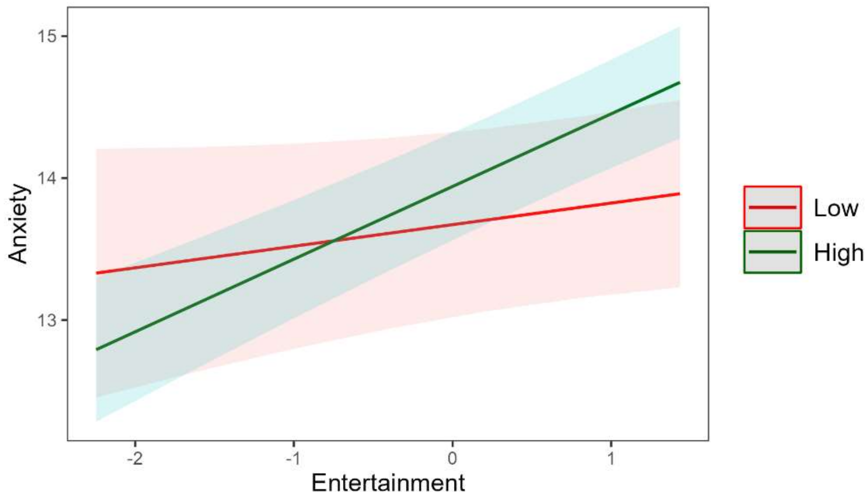
Interaction Plot Depicting HDI Levels of the Time Online-Anxiety Relationship



Note. The red line indicates low-HDI countries, and the green line indicates high-HDI. The levels of HDI are one standard deviation below and above the mean of the sample countries.

Figure 7

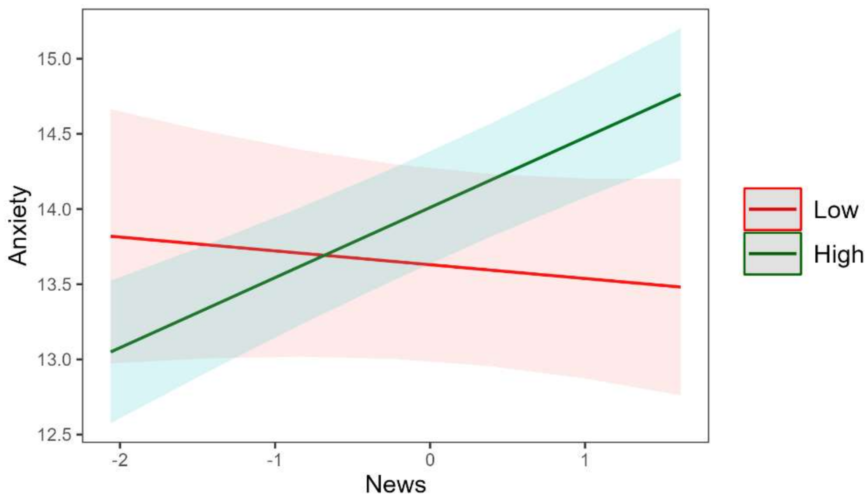
Interaction Plot Depicting HDI Levels of the Entertainment-Anxiety Relationship.



Note. The red line indicates low-HDI countries, and the green line indicates high-HDI. The levels of HDI are one standard deviation below and above the mean of the sample countries.

Figure 8

Interaction Plot Depicting HDI Levels of the Sharing News-Anxiety Relationship



Note. The red line indicates low-HDI countries, and the green line indicates high-HDI. The levels of HDI are one standard deviation below and above the mean of the sample countries.

4. Discussion

The purpose of the present research was to investigate the relationship between different types of internet use and positive and negative components of subjective wellbeing (i.e., life satisfaction, depression, and anxiety) and examine how these relationships vary across a global context. Then it sought to explain this variation by exploring HDI as a country-level moderator of these relationships. The investigation included five different predictors: time online, using the internet for entertainment, sharing news and information, connecting socially and communicating with family and friends and their associations to life satisfaction, depression symptoms and anxiety symptoms.

The present study extends the literature by examining specific types of internet use beyond time spent online and platform-based engagement, while also considering both positive and negative components of subjective wellbeing. It further addresses limitations in existing research by drawing on cross-cultural data, including populations beyond the typical WEIRD, adolescent and young adult samples.

Correlational evidence

Research Question 1*: How does the type of online activity (e.g., time online, entertainment, sharing news and information, connecting socially, and communicating with family and friends) relate to subjective wellbeing (e.g., life satisfaction, depression and anxiety)?*

Interestingly, through correlational analysis the present research finds that adults who spend more time online throughout the day may also have lower life satisfaction. However, the negative association between time online and life satisfaction was very small (r = -.04**). Huang's (2017) meta-analysis, which included primarily western samples found a similarly small correlation though this was not a statistically significant result (r = -.03, CI [-.11,.05], k

= 8). In addition a small negative non-significant relationship was also found with hedonic well-being (r = -.03, k = 176) (Hancock et al., 2022). Both of these studies are social media focused, and the present research uses more granular time-use data. Given the discourse around the potential damaging effects of internet use on general wellbeing, it is surprising that the negative effect size of the present research was so small. This potentially speaks to the heterogeneity of outcomes as the present research utilised a large sample of global citizens (N = 23,859).

In addition, spending more time online was also positively related to depressive and anxiety symptoms. With regards to time online, the present results align with the general literature which shows that more time online is weakly associated with higher depression and anxiety scores. This aligns with research from US and UK contexts, which found that heavier internet use was related to lower levels of wellbeing and higher depressive symptoms in adolescents and young adults (Twenge et al., 2018; Twenge & Campbell, 2019). Additionally, two meta-analyses returned a comparatively small negative correlations with depression symptoms (r = 0.11) (Cunningham et al., 2021; Huang, 2017). Furthermore, the relationship with anxiety is also consistent with the findings from Hancock et al. (2022), though this meta-analysis related to general social media use rather than time-use ($k = 48, r = .13, p < .01$). Whereas earlier studies have largely concentrated on social media, the present research takes a broader perspective on internet use. Therefore, the present findings indicate that overall time spent online is negatively associated with depression and anxiety in the general population.

Moving beyond time online, correlation analysis revealed that each type of internet use was related both to higher life satisfaction as well as higher scores of depression and anxiety symptoms, suggesting a paradox of simultaneous associations.

These results highlight the dual nature of internet use, demonstrating associations with both adaptive (e.g., life satisfaction) and maladaptive (e.g., depression, anxiety) associations. This paradox may suggest that different mechanisms could underlie the associations of life satisfaction compared to depression and anxiety. Life satisfaction, depression and anxiety symptoms are independent constructs which arguable do not exist on a continuum (Das et al., 2020). Where life satisfaction is an indicator of wellbeing, depression and anxiety are indicators of illbeing. So, these might provide avenues for meeting certain needs that appeal to life satisfaction, i.e. overall evaluations of life, but come with costs of increases emotional stress in terms of depression and anxiety. As the present research cannot make causal inferences, future research could look more deeply into underlying mechanisms of both positive and negative outcomes of subjective wellbeing.

In considering another alternative explanation, it is entirely possible that data collection were subject to participant response biases by participants (Westland, 2022). The total survey consisted of 25 items, though some contained multiple questions. For example, the combined PHQ-8 and GAD-7 scales which were used in the present research require participants to respond to a total of 15 statements. Responder fatigue or central tendency bias may have introduced measurement error int the internet use measures of the present study (Westland, 2022).

In summary, the relationship between different types of internet use and subjective wellbeing appears to be is complex with associations to both positive and negative component of subjective wellbeing.

Research Question 2: *Does the relationship between internet use (e.g., time online, entertainment, sharing news and information, connecting socially and communicating with family and friends) and subjective wellbeing (e.g., life satisfaction, depression, anxiety) vary across regional contexts?*

The second aim of the present research was to explore whether internet use and subjective wellbeing varied across global regions. The regional contexts used to answer this question grouped countries based on shared history, politics and values which was based off data from the world values survey (Inglehart & Baker, 2000; Romano et al., 2021).

Life satisfaction

Spending more time online was negatively associated with life satisfaction in Scandinavia, the Anglosphere, and Western Europe, but no such relationship emerged in Confucian Asia, South-East Asia, or Latin America. A similar pattern appeared for entertainment-related use. In Scandinavia, Western Europe, and Eastern Europe, no significant relationship with life satisfaction was observed, whereas in Confucian Asia, South-East Asia, and Latin America, entertainment use was positively associated with life satisfaction. Importantly, across both sets of analyses, the results for Confucian Asia, South-East Asia, and Latin America were consistent. Taken together, these findings highlight a distinction between WEIRD and non-WEIRD regions, suggesting that cultural value differences may be worth investigating for future research.

For the remaining types of internet use, sharing news and information, connecting socially and communicating with family and friends where life satisfaction associations with life satisfaction were positive in almost all regions.

Depression and anxiety

Depression and anxiety showed less regional variation in relation to time spent online and frequency of entertainment use, with higher symptom levels observed across all regions. Alternatively, regional variation emerged for the predictors of sharing news and information, connecting socially, and communicating with family and friends. Specifically, these forms of internet use were positively associated with depression and anxiety in Western regions, but not in other parts of the world. These results align with observations made in Hancock et al.'s (2022) metanalysis which found that social media use North America and Europe was associated with higher depression, but also social wellbeing. Furthermore, the observed patterns may reflect cultural values in communication and style of social engagement. Compared to more collectivistic societies, western societies place emphasis on creating new connections and place less emphasis on maintaining close relationships unlike more family-oriented cultures (Rosen et al., 2010).

The present research does not align with a meta-analysis that did not find cultural variation on the basis of Eastern and Western countries. In a meta-analysis of 93 studies from 23 countries that results Liu et al., (2019) employed a West-East dichotomy to test culture as a moderator between internet use and psychological wellbeing, and returned non-significant results (Liu et al., 2019). However, Sri Lanka, Philippines and India were included in the Western country group (Liu et al., 2019). Moreover, their measure of psychological wellbeing included other constructs stress loneliness and self-esteem (Liu et al., 2019).

Nevertheless, results from the present research highlight a potential intersection between cultural values and online behaviour. Because time online and entertainment are forms of passive internet use (Ozimek et al., 2023; Valkenburg, 2022), they are often linked with negative wellbeing outcomes (Valkenburg, 2022). Interestingly, this association was observed in Western regions but not in Eastern regions (i.e. Confucian Asia and South-East Asia) or collectivistic cultures (i.e. Latin America).

Further supporting this notion, sharing news and information, connecting socially, and communicating with family and friends align conceptually with active or engaged internet use. Across all regions, including Western contexts, these types of internet use were positively associated with life satisfaction. This suggests a promising avenue for future research to test the active-passive internet use model in non-Western cultural regions.

HDI as a Moderator

Question 3*: Does a country's level of human development (i.e., Human Development Index) moderate the relationship between internet use (e.g., time online, entertainment, sharing news and information, connecting socially and communicating with family and friends) and subjective wellbeing (e.g., life satisfaction, depression, anxiety)? How does this relationship differ for countries high in HDI versus low in HDI?*

The final aim of the present research was to examine whether HDI would explain the variation in the relationships between different types of internet use and subdomains of subjective wellbeing across countries. Multilevel interaction models were used to test the interaction of HDI in these relationships, therefore the inferences in this discussion are statistical. Recent global research has suggested that internet use is positively associated with psychological wellbeing across a broad range of global contexts (Vuorre & Przybylski, 2024). Other research has indicated that relationships between internet use and wellbeing may differ across affluent and non-affluent countries (Bartikowski et al., 2018; Graham & Nikolova, 2013; Hancock et al., 2022). Accordingly, this research explored variations at high and low levels of HDI (a country-level index measuring standard of living through constructs of health, education and country wealth).

Findings summary

Multilevel models and simple slopes analysis revealed the following findings. More time spent online was linked to lower life satisfaction in high-HDI countries, whereas in low-HDI countries the relationship was non-significant (see figure 1). In contrast, time online showed a stronger association with higher depression (see figure 2) and anxiety (see figure 5) scores in high-HDI contexts than in low-HDI countries.

When considering specific types of internet use, striking patterns emerged. Using the internet for entertainment was more strongly tied to both depression (see figure 3) and anxiety (see figure 7) in high-HDI countries. For sharing news and information, remarkably the direction of association reversed. In high-HDI countries it correlated with higher depression (see figure 4), but in low-HDI countries it was linked with lower depression. Anxiety (see figure 8) told a similar but weaker story, yielding a positive association in high-HDI contexts, though non-significant at the low-HDI level.

Social use of the internet also diverged across settings. Connecting socially online was associated with higher depression (see figure 5) in high-HDI countries, whereas in low-HDI countries the relationship leaned in the opposite direction, though this was only marginally non-significant. However, the interaction with anxiety, did not reach significance. Likewise, frequency of communicating with family and friends online showed no significant interaction either.

Finally, there were no significant interactions of HDI in the relationships between the predictors, entertainment, sharing information, connecting socially, or communicating with family and friends, and life satisfaction. These results emphasize that the strongest contrasts across HDI settings lie in the associations with depression and anxiety, rather than in overall life satisfaction.

Explanation of findings

To the researcher's knowledge HDI has not been explored as a moderator for the relationship between internet use and subjective wellbeing. Through statistical analysis the present research showed that more time online was related to lower life satisfaction in high-HDI countries, but not in low-HDI countries. The negative relationship observed in high-HDI contexts aligns with recent research from a study of 21 predominantly high-rated-HDI European countries which found that spending 5 hours or more online was also associated with lower life satisfaction scores (Álvarez and Vicente, 2024). On the other hand, it was intriguing to find that no significant relationship was observed for the time online-life satisfaction relationship in low-HDI contexts. Though research is limited in low-HDI regions, research in China by Nie et al. (2016) also investigated hourly time-use and found a non-significant result between hours per day and life satisfaction in a sample of Chinese adults ($b = -.005$).

More time online was also associated with higher depression and anxiety symptoms in high-HDI countries compared with low-HDI contexts. Broadly speaking, the present results align with the exposure-response hypothesis which posits that as internet use moves from light to heavy use, wellbeing becomes progressively worse (Twenge et al., 2018; Twenge & Campbell, 2019). By using a general population sample, the present research builds on these prior studies that were conducted primarily with adolescents and young adults. Furthermore, the present study extends current knowledge to include underrepresented samples from low-HDI contexts. Moreover, results align with a Chinese study that also found a positive relationship between hours online and depression (Nie et al. 2016).

Multiple experimental research studies from high-HDI countries highlight a pattern of improved subjective wellbeing, life satisfaction and less depression symptoms in abstaining from social media use (Allcott et al., 2020; Brailovskaia et al., 2023; Mosquera et al., 2020;

Tromholt, 2016). The present research is consistent with the reverse of these studies. Suggesting that people who regularly use the internet for long-periods of time also experience lower life satisfaction and higher depression symptoms in high-HDI contexts.

When it comes to using the internet for entertainment, associations with depression and anxiety were also returned stronger in high-HDI regions. Though research of entertainment and life satisfaction has returned non-significant findings when investigating entertainment and life satisfaction and quality of life (Erickson & Johnson, 2011; Mohan & Lyons, 2024), the present research differs from both of these studies which are focused primarily on older adults which may explain the different outcomes. However, Nie et al., (2016) previously found a small and significant negative relationship between entertainment and life satisfaction ($r = -.035^{*}$). Even though research suggests, internet-related entertainment can be a positive distraction from life's pressures, this is not consistent with the results of the present study. Furthermore, as the present research measured time-spent using the internet for entertainment, it is plausible that more time spent using entertainment was beyond controlled use. That the relationships were stronger in high-HDI contexts might suggest that people in high-HDI countries are more prone to use entertainment online to avoid responsibilities more than people in low-HDI countries (Beutel et al., 2011).

Alternatively, it may have something to do with the social environment. In further explaining the observed results with both time online and entertainment, it is plausible that in low-HDI countries internet use may offset disadvantages of the political, social, or economic life by filling gaps in quality of life. Conversely, as basic needs are already met in high-HDI countries, time spent online may more easily displace other activities that support wellbeing (Dienlin et al., 2017). As previous researched linked internet use to stronger positive outcomes in poorer nations, this suggests that populations in low-HDI settings may have more to gain from internet access (Graham & Nikolova, 2013; Kushlev, 2018).

Comparable patterns have been found in other domains of research. Bagdadli et al., (2021) showed that HDI moderated the relationship between career development and perceived financial success across 28 countries. Although individuals in low-HDI countries received smaller pay increases, they reported greater perceived financial success compared to those in high-HDI countries. The authors suggest that even modest improvements hold greater meaning in contexts where resources are limited. By analogy, internet use may similarly provide disproportionate benefits in lower-HDI environments.

A contrasting example by Ribeiro et al. (2025) found that HDI moderated the effects of frailty on health-related quality of life in older adults across 24 European countries. In this case, Ribeiro et al. (2025) argue that being in a high-HDI country likely buffered against the negative effects of frailty due to better healthcare and social support systems available in high HDI contexts. Unlike internet use (which has the potential to positive or negative associations), frailty is universally harmful, but its impact is softened by socioeconomic conditions.

Taken together, these findings suggest that the overall quality of life afforded in HDI contexts may change how the internet is experienced. In low-HDI countries, internet access may substitute for missing resources which may attenuate some of the negative association with depression and anxiety symptoms. In high-HDI countries, where wellbeing is already supported by broader socioeconomic systems, internet use may displace beneficial offline activities and thus carry more risks. Therefore, it may be that HDI provides the contextual template within which the consequences of internet use are played out.

Alternatively, the difference in life satisfaction may also be explained by other means, as poorer nations tend to value financial satisfaction it is possible that status drawn from having access to the internet contributes to a sense of wellbeing for people in poorer countries (Bartikowski et al., 2018; Oishi et al., 1999). For instance, mobile internet access is linked to status in that citizens feel good about being in a position to own a mobile and be connected to the internet (Bartikowski et al., 2018).

Finally, it is important to note the possibility that poorer mental health may shape internet behaviours, especially in high-HDI countries. As correlation does not mean causation, the relationship could be in the opposite direction. Such that lower depression might be influencing how people connect and interact online. For instance, in a longitudinal, Heffer et al., (2019) did not find a significant relationship between more social media use and depressive symptoms in adolescents or young adults. However, greater depressive symptoms were found to predict greater use in females. Future research could investigate the reverse or reciprocal relationship that may also exist.

Other internet use

The positive news-depression relationship observed in high-HDI contexts is more consistent with prior research from high-HDI contexts which has linked online news consumption with more depression symptoms and other adverse emotional experiences (Andersen et al., 2024; Mousoulidou et al., 2024). Though HDI was found to moderate the news and information-anxiety relationship, the conditional coefficient was only statistically significant in high-HDI contexts. So, an associated relationship with anxiety was only observed in high-HDI contexts. This follows the general discourse of news related literature outlining a negativity bias and linking news consumption to stress and anxiety (Mousoulidou et al., 2024; Van Bavel et al., 2021). On the other hand, the negative sharing news-depression relationship in low-HDI contexts means that users who more frequently engage with sharing news and information are more likely to have lower depression symptoms in low-HDI contexts which is in contrast to at the high HDI-level.

So, sharing news and information is related to lower depression is not related to lower anxiety in low-HDI countries. These contrasting patterns might suggest that the social meaning and emotional consequences of sharing news may be shaped by broader socio-economic context, with the same behaviour potentially fostering connection and agency in low-HDI settings (Kümpel et al., 2015).

The contrast between high and low-HDI countries for the relationship between connecting socially and depression symptoms further highlights the pattern of stronger associations in high-HDI countries. The positive association with depression symptoms that was observed in high-HDI contexts aligns with meta-analytic research investigating social networking which show a general trend of a small increase in depressive symptoms Cunningham et al. (2021) or negative associations with combined constructs of subjective wellbeing (Huang, 2017). These meta-analyses contain predominantly western and affluent countries. However, in contrast to the present research, these meta-analyses focused on social media. Moreover, while social networking and connecting socially are different constructs, the present research extends knowledge by providing richer qualitative detail about specific online behaviours beyond that of Facebook or other social media.

One plausible reason for the contrasting relationship is that there may be less digital saturation in low-HDI contexts. In 2019 with the data was collected for the present research, lower-income countries had much less percentage of connectivity (34%) compared to high income countries at 88% (International Telecommunication Union, 2024). Less digital saturation would mean that internet use is not so ingrained in society such that being connected all the time is a burden on one's perception of their life. So, there is less obligation to be online and more choice to be online. Furthermore, less time online may translate to more face-to-face interactions with other people (Dienlin et al., 2017).

Alternatively, other research in this area suggests that the quality and type of social interactions online mark what is important for wellbeing. For example, Burke & Kraut (2016) found that engaging with strong ties (e.g., close friends and family) on Facebook was linked to improved wellbeing in a large cross-national sample including 93 studies. Similarly, Escobar-Viera et al. (2018) reported that actively engaging with others through using online social features such as “likes” and “comments” was associated with decreased depressive symptoms, a finding consistent with other evidence linking active online social engagement to lower depression (e.g., Verduyn et al., 2015). Being active and engaged online is thought to positively build social capital and fosters social connectedness (Verduyn et al., 2017). Despite these findings, the present research found the opposite result of connecting socially online in high-HDI countries.

Although the intermediary mechanisms mentioned such as the quality of social interactions, communicating with strong-ties and actively engaging with social features were not used in the present research, the present findings suggest it is possible that social internet users in high-HDI countries are engaging in more passive online behaviours these experiencing less supportive or meaningful interactions online. Though what may undermine the plausibility of this premise, are the present correlational results for communicating with family and friends. The correlational data (see table A.6 in Appendix F) shows that many high-HDI countries yield a positive relationship with life satisfaction and no relationship with depression symptoms. This implies that people in high-HDI contexts who spent time communicating with strong ties (family and friends) also experience higher life satisfaction. Which raises the question, what are social users in high-HDI contexts doing online that they consider to be social? This discussion really highlights the importance of measurement and strongly emphasizes more standardized measures of internet use that can capture more granular information about people’s online practices.

The present research fills a knowledge gap as it provides a more balanced perspective of internet use and subjective wellbeing and is more inclusive of underrepresented populations. However, future research might build on this by examining a clearer definition of connecting socially across broader socioeconomic environments to gain further understanding of social interactions online.

Limitations:

First and foremost, this is a cross-sectional study which describes internet use and subjective wellbeing at a point in social, economic and political history when the data was collected (between December 6, 2018, to Jan 24, 2019). Though potential causal mechanisms have been discussed to suggest underlying explanations of the relationships, causal inferences cannot be made based on the results of this study. Future preregistered research could be carried out to carry out more rigorous tests of HDI and the relationships between specific internet uses.

Secondly, there are important considerations regarding the collection of internet use data and the coding of the time online variable which likely impact the validity of inferences of present research. Firstly, this research relied on self-report of internet use data. Data collection of internet use is a known challenge in this area of research as there is a general tendency to over-estimate time spent using the internet (Araujo et al., 2017; Scharkow, 2016). Therefore, it is plausible that this impacted all of the measures of internet use as they were all time-based. However, most affected was likely the time online variable as this contained a free-text option, whereas the specific types of internet use were frequency-based Likert questions. Though the use of anchoring and open-ended questions may have served to reduce some over-estimation (Araujo et al., 2017), no additional analysis took place to measure the extent of the potential over-estimation.

Furthermore, there is potential ambiguity as to what the time online question means and therefore what it is measuring. Even though it specified "waking hours," there were responses over 15 hours, and up to 24 hours. Firstly, people need to sleep so it is not clear whether these participants were not sleeping, or if they considered themselves to be connected while sleeping. In addition, streamers and gamers do spend a lot of time online. In addition, smartphones, smart watches also mean that people may consider themselves to be connected but may not always be actively using the internet. What could improve this question is to include a qualitative response as to what connected all the time means. This may have introduced further measurement error which potentially introduces more bias regarding the results of this study as the correlation and multi-level regression analyses could be under or over estimated. This is of particular importance given some of the small effect sizes observed in the present research (Williams et al., 2013).

Lastly, a more specific issue of time measurement is dealing with the concept that people are connected all the time. An option was included in the preset study "Almost all the time." These responses were coded to match the highest daily time estimations (see appendix G). As approximately 50% of the sample selected "almost all the time," this process essentially may have introduced a ceiling effect to the data, consequently reducing variance of the time online item. This also meant that the assumption of normal distribution was likely not met.

Ceiling effects may weaken the generalizability of the results as variation at the top end of internet use may not reflect variation in the true population (Jennings & Cribbie, 2021; Uttl, 2005). As such, the internet use time-data may not be a true or accurate reflection of internet use, especially at the higher amounts of internet use (Jennings & Cribbie, 2021; Uttl, 2005). This potentially introduces further biased towards the inferences of the present research as it this increased the possibility of underestimating the true relationship between more time online and subjective wellbeing (Jennings & Cribbie, 2021; Uttl, 2005).

So, the measure of time spent online, may not accurately reflect actual internet use. This impacts the validity of conclusions concerning time spent online. This limits generalizability because the value of time online may not reflect that of the true population. Risk of overinterpreting small effect sizes. This is relevant for the present research as it is dealing with small effect sizes in some cases (Jennings & Cribbie, 2021). Nevertheless, for future research, where objective measurement is not feasible, future research should endeavour to develop and incorporate the use of standardized and validated measures of internet use to minimise potential issues of bias.

There were two areas of the present research process that warrant attention. First, though quantitative research is generally positioned as objective, not all quantitative research is entirely objective (Pilcher & Cortazzi, 2024). This is especially pertinent in finding and interpreting patterns from large sets of correlational data as occurred (Drapeau, 2015; Pilcher & Cortazzi, 2024). In identifying patterns of variation in the large set of correlational data from the present research, there is potential for over-analysing or over-extending interpretations of these patterns based on researcher expectations. Second, the data-driven and exploratory nature of the present research may introduce bias from post-hoc theory explanation (Hollenbeck & Wright, 2017). This should be taken into consideration when in assessing conclusions and inferences of the present data, especially those relating to the moderation of HDI. However, through transparency in disclosing the research process this emphasises the strength of the current research in generating hypotheses for future research in this topic area (Hollenbeck & Wright, 2017). Future preregistered research that is theory driven could test HDI as a moderator where theory and literature are reviewed and hypotheses are generated explicitly before data analysis. This could fill the gap in the present literature to provide more precise statements regarding HDI as a moderator of internet use and subjective wellbeing.

Measuring culture, we looked at our data through an HDI lens, therefore have not considered other sociocultural factors that may be different between the studied regions. Cultural backgrounds and values are implicit within the HDI lens however these were not specifically included in the model. Comparing internet use and subjective wellbeing through explicit measurement of cultural values may provide more specific information into the mechanisms of variation across cultural contexts.

Lastly, a team of translators in each country translated the survey questions. Some questions or wording may not have translated with exact meaning essentially increasing error or including a confounding variable. This is particularly relevant given the contrasting results of low and high-HDI countries where there were more non-significant results in

The gender item in the survey only specified male or female under gender responses. This is potentially exclusive of non-binary or other minority genders that do not identify with male or female. Consequently, there is the potential for non-participation if the correct gender cannot be chosen. As such this potentially limits generalisability to gender diverse populations. Future research should consider more culturally diverse and inclusive survey questions to reduce sample bias.

Lastly, there was no screening for problematic internet use. This study was not focused on problematic internet use however, high amounts of use may be problematic, so it is possible that people engaging in problematic use were included in this study. As such, this may conflate the validity of findings and limit generalisability. Future research should take provisions to account for problematic internet use.

Conclusion

In conclusion, the present research set out to explore the relationship between internet use and subjective wellbeing across 42 countries and investigate whether a countries level of human development moderated this relationship. Using a cross-sectional design, correlational evidence observed global perspectives and regional variation for internet use and subjective wellbeing. Moreover, multilevel analyses, while controlling for age and gender, found evidence for HDI as a moderator of the relationship between internet use and subjective wellbeing. In exploring both positive and negative outcomes of subjective wellbeing, the present research highlighted that the most remarkable contrasts across low and high-HDI contexts sit within the associations of depression and anxiety, rather than in overall life satisfaction. An implication of this research is the relationship between internet use and wellbeing may partly depend on the type of activity online as well as the country environment. However, that targeted use may be the key to understanding how to fully harness the potential benefits that live within this great tool of society. This research makes several contributions to further the knowledge of a growing literature by uniquely applying a cross-cultural approach and paving the way for more future global research.

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Appendices

Appendix A

Table A.1
Individual-Level Descriptive Demographic Statistics (N = 24,009)

Region	Country	N	Age (Mean)	Age (SD)	Male	Female
Scandinavia	Sweden	496	41.6	13	238	258
	Finland	459	40.1	13	211	248
Anglo	Australia	486	43.3	14	211	275
	UK	507	41.4	13	222	285
	New Zealand	479	40.7	13	215	262
	Canada	463	43.0	13	209	254
	United States	458	41.5	13	196	260
Western Europe	Germany	468	43.4	13	229	238
	Netherlands	863	44.9	14	410	453
	Spain	497	39.9	12	235	262
	Italy	847	41.0	12	381	466
	Greece	500	39.1	12	240	260
	Portugal	525	37.7	12	240	285
Confucian Asia	Hong Kong	498	36.3	11	236	263
	South Korea	446	41.2	11	190	256
	Taiwan	482	36.5	11	222	259
	Japan	510	47.8	12	250	260
	China	571	30.9	9	271	300
Eastern Europe	Poland	977	38.9	13	475	502
	Hungary	463	39.9	13	211	251
	Russia	427	39.2	11	211	216
	Turkey	583	33.5	10	319	261
	Serbia	463	38.1	12	213	249
South-East Asia	Singapore	536	38.8	12	273	262
	Malaysia	569	33.6	10	300	269
	Indonesia	590	33.3	10	328	259
	Philippines	499	33.9	11	228	271
Latin America	Argentina	462	34.2	11	244	218
	Panama	489	30.7	10	240	249
	Mexico	534	33.2	11	249	285
	Peru	529	33.5	10	246	283
	Colombia	514	33.6	11	259	252
	Brazil	1126	34.2	11	470	655
	Bolivia	466	29.8	9	253	213
	Venezuela	515	35.1	12	269	243
South Asia	India	462	32.4	11	742	563
	Pakistan	926	28.1	8	711	213
Northern Africa	Egypt	562	29.4	9	313	249
	Morocco	495	31.2	10	267	226
Sub-Saharan Africa	South Africa	476	34.2	11	244	232
	Kenya	470	30.1	9	242	228
	Nigeria	466	30.6	9	267	199

Appendix B

Table A.2

Country-level correlations for time online(TO) and measures of subjective wellbeing.

Region	Country	N	TO (M)	Life Satisfaction	Depression	Anxiety
Scandinavia	Sweden	495	15.5	-.07	.21**	.19**
	Finland	455	14.2	-.10*	.28**	.28**
Anglo	Australia	486	13.0	-.11*	.26**	.26**
	United States	458	15.8	-.05	.25**	.23**
	Canada	463	14.0	-.07	.24**	.21**
	United Kingdom	507	13.8	-.08	.20**	.18**
	New Zealand	479	13.1	-.13**	.21**	.23**
Western Europe	Germany	468	14.9	-.08	.12*	.18**
	Netherlands	863	12.0	-.14**	.24**	.25**
	Spain	497	13.7	-.10*	.21**	.17**
	Italy	847	14.1	.03	.17**	.11**
	Greece	500	13.1	-.16**	.19**	.17**
	Portugal	525	15.7	-.07	.05	.04
Confucian Asia	Hong Kong	498	17.2	-.08	.13**	.07
	Japan	510	12.6	-.15**	.15**	.14**
	South Korea	446	16.9	-.07	.18**	.13**
	Taiwan	482	15.5	-.03	.10*	.08
	China	571	19.0	.04	.10*	.11*
Eastern Europe	Poland	973	13.1	-.01	.16**	.15**
	Hungry	462	15.2	-.09	.15**	.16**
	Turkey	577	17.5	-.03	.10*	.12**
	Russia	427	14.2	.01	.13**	.14**
	Serbia	462	8.6	-.14**	.24**	.21**
South-East Asia	Singapore	533	15.8	-.05	.16**	.19**
	Malaysia	569	17.5	-.04	.17**	.11**
	Indonesia	578	18.6	-.01	.12**	.15**
	Philippines	497	15.7	-.04	.10*	.09
Latin America	Argentina	462	17.3	.08	.13**	.11*
	Panama	489	16.0	-.01	.19**	.14**
	Mexico	534	16.2	.01	.16**	.14**
	Venezuela	515	16.4	.03	.13**	.05
	Brazil	1126	19.9	.10**	.12**	.08**
	Peru	529	15.2	-.06	.09*	.09*
	Colombia	514	15.3	.02	.07	.07
	Bolivia	466	16.2	-.01	.11*	.08
North Africa	Egypt	559	15.6	-.11**	.17**	.18**
	Morocco	490	15.0	-.03	.16**	.19**
Sub-Saharan Africa	South Africa	472	15.1	.05	.03	.03
	Kenya	469	14.7	-.05	.03	.06
	Nigeria	465	17.1	.05	.04	.03
South Asia	India	1300	15.1	.02	.08**	.08**
	Pakistan	910	16.7	-.05	.13**	.16**

Note. Regions and countries are in descending order of Human Development Index. * = *p < 0.05*, ** = *p < 0.01*

Appendix C

Table A.3

Country-level correlations for entertainment(E) and measures of subjective wellbeing.

Region	Country	N	E (M)	Life Satisfaction	Depression	Anxiety
Scandinavia	Sweden	495	4.45	-.05	$.21^{**}$	$.20^{**}$
	Finland	455	4.36	.01	$.22^{**}$	$.26^{**}$
Anglo	Australia	486	4.14	.02	$.20^{**}$	$.19^{**}$
	United States	458	4.69	$.13^{**}$	$.10^{*}$	$.10^{*}$
	Canada	463	4.33	.02	$.09^{*}$	$.10^{*}$
	United Kingdom	507	4.05	.05	.07	$.09^{*}$
	New Zealand	479	4.36	-.04	$.15^{**}$	$.20^{**}$
Western Europe	Germany	468	4.21	.01	$.14^{**}$	$.16^{**}$
	Netherlands	863	3.85	-.05	$.25^{**}$	$.26^{**}$
	Spain	497	4.49	.04	$.15^{**}$	$.10^{*}$
	Italy	847	4.24	$.07^{*}$	.05	.05
	Greece	500	4.45	.05	$.12^{**}$	$.15^{**}$
	Portugal	525	4.43	.00	$.09^{*}$	$.11^{*}$
Confucian Asia	Hong Kong	498	4.8	-.01	.04	$.11^{*}$
	Japan	510	3.33	-.03	$.10^{*}$	$.12^{**}$
	South Korea	446	4.49	-.02	$.14^{**}$	$.10^{*}$
	Taiwan	482	4.64	.05	.08	.07
	China	571	4.86	$.17^{**}$	.02	.05
Eastern Europe	Poland	973	4.88	$.09^{**}$	.05	.04
	Hungry	462	4	-.01	$.15^{**}$	$.15^{**}$
	Turkey	577	4.97	.07	.06	.02
	Russia	427	4.55	.07	$.11^{*}$	$.11^{*}$
	Serbia	462	5.17	-.06	$.15^{**}$	$.12^{**}$
South-East Asia	Singapore	533	4.47	.01	$.16^{**}$	$.16^{**}$
	Malaysia	569	4.98	.07	$.17^{**}$	$.17^{**}$
	Indonesia	578	5.1	$.14^{**}$	.05	.08
	Philippines	497	5.29	.06	.07	$.12^{**}$
Latin America	Argentina	462	4.84	.02	$.12^{**}$	.09
	Panama	489	5.27	.05	.06	.05
	Mexico	534	4.93	.08	$.12^{**}$	$.11^{*}$
	Venezuela	515	5.32	.06	$.10^{*}$	.07
	Brazil	1126	5.13	$.13^{**}$	.05	$.06^{*}$
	Peru	529	4.73	.03	.04	-.02
	Colombia	514	4.79	.04	.06	.07
	Bolivia	466	4.76	$-.12^{*}$	.09	$.12^{**}$
North Africa	Egypt	559	4.85	.06	.06	.08
	Morocco	490	4.53	.02	.08	.07
Sub-Saharan Africa	South Africa	472	4.72	$.10^{*}$	$.10^{*}$	$.12^{*}$
	Kenya	469	5.26	.03	.03	.05
	Nigeria	465	4.9	.06	.01	.04
South Asia	India	1300	5.11	$.10^{**}$	$.13^{**}$	$.13^{**}$
	Pakistan	910	4.42	.05	.03	.05

Note. Regions and countries are in descending order of Human Development Index. $^{*} = p < 0.05$, $^{**} = p < 0.01$

Appendix D

Table A.4

Country level correlations for sharing news and information(SN) and measures of subjective wellbeing

Region	Country	N	SN (M)	Life Satisfaction	Depression	Anxiety
Scandinavia	Sweden	495	3.49	-.01	.18**	.19**
	Finland	455	3.74	.05	.09*	.17**
Anglosphere	Australia	486	3.53	.10*	.10*	.09*
	United States	458	3.99	.18**	.09	.12*
	Canada	463	3.67	.11*	.14**	.17**
	United Kingdom	507	3.76	.10*	.06	.10*
	New Zealand	479	3.95	.03	.03	.08
Western Europe	Germany	468	3.77	.09	.04	.11*
	Netherlands	863	3.57	.05	.13**	.16**
	Spain	497	4.00	.11*	.09*	.12**
	Italy	847	4.17	.13**	.01	-.02
	Greece	500	4.53	.10*	.06	.07
	Portugal	525	4.21	.04	-.04	.03
Confucian Asia	Hong Kong	498	4.1	.04	.12**	.13**
	Japan	510	3.46	.16**	-.06	-.05
	South Korea	446	3.86	.16**	-.03	.04
	Taiwan	482	4.21	.13**	.03	.09
	China	571	4.59	.27**	-.06	-.03
Eastern Europe	Poland	973	4.85	.09**	.06	.10**
	Hungary	462	3.49	-.03	.07	.17**
	Turkey	577	4.94	.12**	.01	.01
	Russia	427	4.29	.10*	.07	.15**
	Serbia	462	4.26	.01	-.01	.03
South-East Asia	Singapore	533	4	.16**	.13**	.17**
	Malaysia	569	4.49	.18**	.01	.06
	Indonesia	578	5.05	.25**	-.12**	-.04
	Philippines	497	4.75	.15**	-.04	-.01
Latin America	Argentina	462	4.37	.14**	-.06	.04
	Panama	489	4.77	.09	.03	.04
	Mexico	534	4.37	.18**	-.02	-.02
	Venezuela	515	5.12	.15**	-.09*	-.05
	Brazil	1126	4.91	.15**	-.05	.02
	Peru	529	4.7	.17**	-.15**	-.05
	Colombia	514	4.63	.24**	-.13**	-.05
	Bolivia	466	4.43	.09*	-.03	.08
North Africa	Egypt	559	4.57	.11*	.03	.06
	Morocco	490	4.59	.08	.01	.04
Sub-Saharan Africa	South Africa	472	4.58	.07	.08	.13**
	Kenya	469	5.14	.16**	-.17**	-.10*
	Nigeria	465	5.24	.03	-.03	.05
South Asia	India	1300	4.83	.20**	.06*	.05
	Pakistan	910	4.51	.18**	-.07*	-.01

Note. Regions and countries are in descending order of Human Development Index. * = $p < 0.05$, ** = $p < 0.01$

Appendix E

Table A.5

Country level correlations for connecting socially (CS) and measures of subjective wellbeing.

Region	Country	N	CS (M)	Life Satisfaction	Depression	Anxiety
Scandinavia	Sweden	495	4.59	.05	.10*	.10*
	Finland	455	4.9	.12*	.11*	.14**
Anglo	Australia	486	4.26	.18**	.06	.09
	United States	458	4.65	.15**	.12**	.13**
	Canada	463	4.41	.08	.13**	.19**
	United Kingdom	507	4.47	.03	.12**	.13**
	New Zealand	479	4.73	.01	.07	.11*
Western Europe	Germany	468	3.98	.09*	.02	.02
	Netherlands	863	4.2	.02	.14**	.14**
	Spain	497	4.68	.08	.11*	.14**
	Italy	847	4.82	.10**	-.01	.01
	Greece	500	4.69	.16**	.02	.04
	Portugal	525	4.25	.01	.02	.06
Confucian Asia	Hong Kong	498	4.88	.10*	.01	.04
	Japan	510	3.9	.09*	-.01	-.01
	South Korea	446	4.38	.11*	.04	.04
	Taiwan	482	4.6	.08	.04	.08
	China	571	5.33	.21**	-.12**	-.11**
Eastern Europe	Poland	973	4.1	.10**	.08*	.10**
	Hungry	462	4.62	-.03	.12*	.17**
	Turkey	577	4.81	.07	.07	.09*
	Russia	427	4.96	.12*	.09	.17**
	Serbia	462	4.88	.03	.09	.09
South-East Asia	Singapore	533	4.75	.16**	.07	.06
	Malaysia	569	5.25	.14**	.01	.03
	Indonesia	578	5.44	.24**	-.07	-.01
	Philippines	497	5.55	.23**	-.01	.03
Latin America	Argentina	462	5.28	.10*	-.07	.03
	Panama	489	5.36	.12*	.07	.04
	Mexico	534	5.22	.12**	.03	.01
	Venezuela	515	5.72	.08	-.03	-.03
	Brazil	1126	5.55	.15**	-.03	.01
	Peru	529	5.31	.07	-.04	-.02
	Colombia	514	5.28	.17**	-.09	-.01
	Bolivia	466	5.19	.01	.04	.07
North Africa	Egypt	559	5.26	.09*	.01	.05
	Morocco	490	4.97	.16**	.01	-.01
Sub-Saharan Africa	South Africa	472	5.33	.08	.11*	.13**
	Kenya	469	5.67	.05	-.04	.04
	Nigeria	465	5.78	0	-.12*	-.01
South Asia	India	1300	5.29	.23**	.03	.03
	Pakistan	910	5.06	.20**	-.08*	.01

Note. Regions and countries are in descending order of Human Development Index. * = *p < 0.05*, ** = *p < 0.01*

Appendix F

Table A.6

Country-level correlations for communication(C) and measures of subjective wellbeing.

Region	Country	N	C (M)	Life Satisfaction	Depression	Anxiety
Scandinavia	Sweden	495	4.31	.08	.08	.09
	Finland	455	4.32	.14**	.09	.10*
Anglo	Australia	486	4.21	.12**	.02	.04
	United States	458	4.77	.20**	.05	.07
	Canada	463	4.4	.12*	.14**	.17**
	United Kingdom	507	4.35	.08	.06	.11*
	New Zealand	479	4.46	.06	.07	.07
Western Europe	Germany	468	4.06	.13**	.02	.06
	Netherlands	863	4.34	.07	.07*	.10**
	Spain	497	4.7	.13**	.06	.10*
	Italy	847	4.85	.10**	-.01	.03
	Greece	500	4.87	.12**	.03	.07
	Portugal	525	4.95	.14**	-.05	-.01
Confucian Asia	Hong Kong	498	4.7	.13**	-.02	.03
	Japan	510	3.52	.24**	-.07	-.02
	South Korea	446	4.19	.22**	-.02	-.05
	Taiwan	482	4.4	.17**	.05	.04
	China	571	4.53	.30**	-.10*	-.07
Eastern Europe	Poland	973	5.29	.24**	-0.0	.01
	Hungry	462	4.88	.05	.02	.11*
	Turkey	577	4.65	.19**	-.05	.01
	Russia	427	4.68	.14**	.09	.14**
	Serbia	462	5.44	.05	.01	-.03
South-East Asia	Singapore	533	4.59	.14**	.10*	.14**
	Malaysia	569	4.96	.15**	.11**	.09*
	Indonesia	578	3.38	.24**	.03	.09*
	Philippines	497	5.49	.23**	-.03	-.01
Latin America	Argentina	462	5.07	.20**	-.05	-.01
	Panama	489	5.32	.22**	-.15**	-.09
	Mexico	534	5.02	.21**	-.04	-.01
	Venezuela	515	5.66	.11*	-.18**	-.12**
	Brazil	1126	5.23	.22**	-.07*	-.02
	Peru	529	5.09	.13**	-.08	-.07
	Colombia	514	5.15	.19**	-.03	.01
	Bolivia	466	5.15	.08	-.02	.03
North Africa	Egypt	559	4.63	.12**	-.04	.06
	Morocco	490	4.79	.13**	.01	.10*
Sub-Saharan Africa	South Africa	472	5.22	.10*	.02	.06
	Kenya	469	5.26	.09*	-.06	.02
	Nigeria	465	5.4	0	-.05	.03
South Asia	India	1300	5.2	.17**	.04	.07**
	Pakistan	910	4.75	.20**	-.08*	.01

Note. Regions and countries are in descending order of Human Development Index. * = *p < 0.05*, ** = *p < 0.01*

Appendix G

This appendix includes a description of data driven decisions that were made throughout the process of exploring this topic and available data to align the research topic with the literature. This is important to report because there are implications to the validity and credibility of the findings of this research. As selecting HDI as a moderator was partly data driven, no a priori hypothesis was made regarding the potential moderation of HDI on the relationship between internet use and subjective wellbeing. Therefore, this analysis was not a true test of scientific hypotheses. However, the data can be used to generate hypotheses for future pre-registered to test more appropriately.

Data Driven Decisions

1. The use of regions in research question 2: We initially ran correlations by country and viewed the data in this way (see Appendix B through F). However, given the number of correlations it was difficult to identify meaningful patterns in the data. Therefore, the region-level analysis was used to summarise the data succinctly which became part of the main analysis.
2. The decision to investigate HDI: In identifying patterns we were aware that regions outside of WEIRD psychology may differ in some way, simply because historical literature has not studied these areas and they are culturally and socioeconomically different from WEIRD countries. So, the decision was made to investigate country-level differences that divides the countries and regions within this study. Previous literature had described some evidence for differences in outcomes of internet use with wellbeing between rich and poor countries. Therefore, the decision was made to investigate and explore Human Development Index as this takes into account the broader socioeconomic environment of a country. Comparing countries outside of the WERID paradigm was considered. However, this would have meant unfairly

grouping all countries who were not WEIRD into a single sample, whereas the ethos of this research is that these cultural contexts may have their own relationships with internet use and subjective wellbeing.

3. Other moderators: Other country-level moderators were considered such as HFI, cultural distance index and Individualism/Collectivism. Initial multilevel models were run which returned some significant findings (see table H.12 and H.13 in Index H). These were run after the analysis with HDI to check for suitability.

Appendix H

This appendix contains the multilevel models with Cultural Fixation Index and Individualism/Collectivism were used as potential moderators. These were secondary options that were considered after running the analysis with HDI as the country-level moderator. While CFST provides a more comprehensive index of cultural and geographical distance between countries this ultimately is a tool more appropriate for comparing two cultures as the measure of distance is relative. The country-level values used in this analysis were cultural distance indexes in relation to the US; essentially providing a value showing the difference between all countries and the US. This resulted in countries such as Sweden and Kenya as having a similar CFST index; however, these countries are culturally and socioeconomically different from each other, though according to CFST are at a similar cultural distance from the United States.

Moreover individualism/collectivism was considered as it is a popular index describing the differences between global cultures however, this is a value-based index which ignores the socioeconomic element defined in the literature.

Table H.12

Multilevel Models of the Association Between Internet Use and Subjective Wellbeing Indicators, and Their Interactions With Cultural Fixation Index (CFI).

	Life Satisfaction	Depression	Anxiety
Predictors	*Estimates*	*Estimates*	*Estimates*
(Intercept)	4.43 (p <.001)	16.86 (p <.001)	14.88 (p <.001)
	[4.20 – 4.65]	[16.16 – 17.56]	[14.19 – 15.56]
TO	-0.07 (p =.002)	0.74 (p <.001)	0.56 (p <.001)
	[-0.12 – -0.03]	[0.56 – 0.92]	[0.40 – 0.73]
E	-0.01 (p =.64)	0.38 (p <.001)	0.29 (p =.001)
	[-0.06 – 0.04]	[0.19 – 0.57]	[0.12 – 0.47]
SN	0.06 * (p =.031)	0.16 (p =.134)	0.35 (p <.001)
	[0.01 – 0.12]	[-0.05 – 0.38]	[0.16 – 0.55]
CS	0.03 (p =.209)	0.15 (p =.166)	0.12 (p =.222)
	[-0.02 – 0.09]	[-0.06 – 0.36]	[-0.07 – 0.32]
C	0.17 (p <.001)	-0.37 (p <.001)	-0.30 (p =.001)
	[0.12 – 0.22]	[-0.57 – -0.17]	[-0.48 – -0.12]
CFST	-0.21 (p =.832)	-2.79 (p =.345)	-3.41 (p =.25)
	[-2.17 – 1.74]	[-8.59 – 3.01]	[-9.21 – 2.40]
age	0.01 (p <.001)	-0.07 (p <.001)	-0.06 (p <.001)
	[0.01 – 0.01]	[-0.08 – -0.07]	[-0.07 – -0.06]
Gender	-0.09 (p <.001)	0.79 (p <.001)	1.03 (p <.001)
	[-0.12 – -0.05]	[0.65 – 0.93]	[0.90 – 1.16]
TO:CFST	-0.22 (p =.339)	-1 (p =.275)	-0.48 (p =.57)
	[-0.69 – 0.24]	[-2.80 – 0.80]	[-2.12 – 1.17]
E:CFST	0.07 (p =.777)	-0.16 (p =.863)	-0.11 (p =.901)
	[-0.40 – 0.53]	[-1.99 – 1.66]	[-1.77 – 1.56]
SN:CFST	0.34 (p =.213)	-2.06 (p =.054)	-2.14 * (p =.028)
	[-0.20 – 0.88]	[-4.15 – 0.04]	[-4.05 – -0.23]
CS:CFST	0.47 (p =.089)	-2.03 (p =.059)	-1.35 (p =.169)
	[-0.07 – 1.01]	[-4.14 – 0.08]	[-3.27 – 0.57]
C:CFST	0.21 (p =.386)	0.78 (p =.415)	2.02 * (p =.021)
	[-0.27 – 0.70]	[-1.10 – 2.66]	[0.31 – 3.74]
Random Effects			
σ^2	1.92	29.36	24.39
τ_{00}	0.07 Country	0.61 Country	0.62 Country
ICC	0.04	0.02	0.02
N	42 Country	42 Country	42 Country
Observations	23112	23108	23111
Marginal R^2 / Conditional R^2	0.039 / 0.074	0.060 / 0.079	0.061 / 0.084

Table H.13

Multilevel Models of the Association Between Internet Use and Subjective Wellbeing Indicators, and Their Interactions With Individualism/Collectivism

	Life Satisfaction	Depression	Anxiety
Predictors	*Estimates*	*Estimates*	*Estimates*
(Intercept)	4.41 (p <.001)	16.61 (p <.001)	14.52 (p <.001)
	[4.29 – 4.53]	[16.21 – 17.00]	[14.14 – 14.91]
TO	-0.09 (p <.001)	0.64 (p <.001)	0.51 (p <.001)
	[-0.11 – -0.07]	[0.56 – 0.71]	[0.44 – 0.58]
E	0 (p =.637)	0.37 (p <.001)	0.28 (p <.001)
	[-0.03 – 0.02]	[0.29 – 0.45]	[0.21 – 0.36]
SN	0.09 (p <.001)	-0.03 (p =.489)	0.15 (p <.001)
	[0.07 – 0.12]	[-0.12 – 0.06]	[0.07 – 0.23]
CS	0.08 (p <.001)	-0.04 (p =.313)	-0.01 (p =.791)
	[0.06 – 0.10]	[-0.13 – 0.04]	[-0.09 – 0.07]
C	0.19 (p <.001)	-0.29 (p <.001)	-0.11 (p =.005)
	[0.17 – 0.21]	[-0.38 – -0.21]	[-0.18 – -0.03]
Collectivism	0.02 (p =.595)	0.32 (p =.004)	0.2 (p =.106)
	[-0.06 – 0.10]	[0.10 – 0.55]	[-0.04 – 0.43]
age	0.01 (p <.001)	-0.07 (p <.001)	-0.06 (p <.001)
	[0.00 – 0.01]	[-0.08 – -0.07]	[-0.07 – -0.05]
Gender	-0.09 (p <.001)	0.79 (p <.001)	1.03 (p <.001)
	[-0.12 – -0.05]	[0.65 – 0.93]	[0.90 – 1.16]
TO:Collectivism	-0.01 (p =.127)	0.11 (p =.004)	0.12 (p <.001)
	[-0.03 – 0.00]	[0.03 – 0.18]	[0.05 – 0.19]
E:Collectivism	0.01 (p =.268)	0 (p =.903)	0.01 (p =.685)
	[-0.01 – 0.03]	[-0.08 – 0.07]	[-0.06 – 0.09]
SN:Collectivism	-0.04 (p =.001)	0.16 (p <.001)	0.10 (p =.015)
	[-0.06 – -0.01]	[0.07 – 0.24]	[0.02 – 0.18]
CS:Collectivism	-0.01 (p =.001)	0.06 (p =.21)	0.03 (p =.426)
	[-0.03 – 0.01]	[-0.03 – 0.14]	[-0.05 – 0.11]
C:Collectivism	-0.02 (p =.151)	-0.02 (p =.712)	-0.02 (p =.657)
	[-0.04 – 0.01]	[-0.10 – 0.07]	[-0.09 – 0.06]
Random Effects			
σ^2	1.92	29.33	24.37
τ_{00}	0.07 $_{Country}$	0.51 $_{Country}$	0.59 $_{Country}$
ICC	0.03	0.02	0.02
N	42 $_{Country}$	42 $_{Country}$	42 $_{Country}$
Observations	23112	23108	23111
Marginal R^2 / Conditional R^2	0.040 / 0.073	0.060 / 0.076	0.060 / 0.082

Appendix I

This index provides a set of rules and parameters that were coded in R to clean the hours per day survey field. This was a free text field where participants recorded the amount of time they spent online per day. A majority of the responses were whole numbers only. However, in a number of cases there were; symbols; ($, #, $, -), time ranges (i.e. 3-6) or words hours, hrs, horas, oras and other non-English characters. Therefore, the following rules were coded to remove additional characters, ranges, symbols, words and punctuation.

1. When a participant provided a range (i.e. 4-8) to their time online, the median value of the range was used
2. When a participant provided a time multiplier (i.e. Lakh, crore, mil, jut), it was converted to the respective numerical value
3. When a participant provided a time symbol the value was recoded as the numerical value the participant provided at the time of data collection
4. When a participant provided an ambiguous time symbol this was removed
5. When a participant provided written word for the amount of time online, it was converted to its respective numerical value (When in English)
6. When a participant provided written word in a language other than English, it was translated using multiple translation software (for reliability) and then recoded to its numerical value
7. When a participant provided + or - at the end of their time online, the value was recoded as the numerical value the participant provided at the time of data collection

8. When a participant described their time online as approximate / about, the value was recoded as the numerical value the participant provided at the time of data collection
9. When a participant reported their time online as unsure / not sure, that was recoded as NA
10. When a participant reported that they spent no time online (English), that was recoded as 0
11. When a participant reported in a foreign language they spent no time online, that was translated using multiple foreign language translation programs for reliability then recoded as 0
12. When a participant used a written word with a numerical value, the written word was stripped from the participants response
13. When a participant reported their income using h to describe hours (i.e 10h), it was recoded as 10
14. When a participant used symbols that had no numerical information (i.e # or ~) in conjunction with their time online, that symbol was stripped from the response
15. Both . and , were stripped from to ensure only numerical values were used
16. When a participant left spaces in their time online, those spaces were stripped (i.e 12 000 = 12000)
17. When a participant provided exact minute to their time online, their value was rounded up or down to the nearest hour (i.e. 2.15 = 2)

Appendix J

This index is provided to clearly articulate a data problem with generating the time online variable from the survey data. In addition, it outlines the rationale supporting the resolution.

Problem: The survey item relating to time spent online offered the option of free typing a number to indicate the average amount of time spent online. The alternative option was to tick a box that indicated "almost all the time." This resulted in approximately 50% of participants that defined the number of hours they spent online using the free text option, and 50% checked the tick box (N = 11776). Both time survey items were essential for the present research to ensure the maximum number of participants possible.

Solution: Therefore, excluding participants who ticked almost all the time from the time spent analysis would have meant losing almost 50% of the sample size. The solution was to combine these items and recode the checkbox item to 24.

Rationale: Firstly, free typed responses ranged from 1 to 24 hours. 500 participants stated that they use the internet for more than 16 hours per day implying that they either sleep less that 6-8 hours per night or consider themselves to be connected while sleeping. 11776 participants selected 'almost all the time' which is a substantial number of participants. The subjectivity and ambiguity of the question means it could be unclear what it means to be connected "almost all the time." In establishing a workaround, it was deemed that if converting 'almost all the time' this could not be lower than the highest response provided by participants who explicitly stated the amount of time they spent online. By coding almost all the time to 24 hours this preserved those participants who stated their time online and also matched the highest response selected by other participants. Limitations of this decision are discussed in the discussion.