Investigating the associations between well-being and digital technology use in a UK university student population

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The candidate confirms that the work submitted is her own and that appropriate credit has been given where reference has been made to the work of others.

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Abstract

Introduction: Understanding and protecting the well-being of university students is of increasing importance to universities and support services. Problematic digital technology use has been associated with poorer student well-being internationally, but little is known about this relationship in the UK university student population. The current research investigated whether digital technology use and wellbeing are associated in the UK student population, which factors of well-being are important to this relationship and how they are associated with digital technology use.

Method: Students from the University of Leeds (n = 544) completed an online survey composed of standardised measures of factors relating to psychological well-being, mental health, physical health and problematic digital technology use. Nine models were analysed using structural equation modelling. Theoretical relationships between well-being and digital technology use and moderating effects of basic psychological need satisfaction, social support and mental health were assessed, as well as the goodness of fit for each model.

Results: The superior model, 5.0, hypothesised that greater problematic digital technology use would be associated with lower well-being. Mental health and basic psychological need satisfaction were hypothesised to moderate this relationship. In model 5.0, digital technology use was significantly negatively associated with well-being ($\beta = -0.16$, $p < .01$). Basic psychological need satisfaction did not moderate the relationship. Mental health moderated the relationship and was significantly negatively associated with well-being ($\beta = -0.90$, $p < .001$) and significantly positively associated with digital technology use ($\beta = 0.26$, $p < .001$).

Discussion: Digital technology use is related to well-being in the UK university student population. Students with mental health difficulties are more likely to have a problematic relationship with digital technology and for their use of digital technology to negatively impact on their well-being. It is recommended that universities work to increase awareness of the impact of problematic technology use on well-being and its relationship with mental health difficulties.

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List of abbreviations

AUDIT-C - Alcohol Use Disorders Identification Test-Concise

BAME - Black, Asian and minority ethnic

BPNSF - Basic Psychological Need Satisfaction and Frustration

BRS - Brief Resilience Scale

CORE-10 - Clinical Outcomes in Routine Evaluation - 10 (referred to as 'psych need.' in figures of structural equation models)

DUDIT-C - Drug Use Disorders Identification Test-Concise

EQ-5D-5L - EuroQol **-** 5 Dimension **-** 5 Level measure

GAS - Gaming Addiction Scale

IAT - Internet Addiction Test

IMD - Index of Multiple Deprivation

MAAS - Mindful Attention Awareness Scale

MH - Mental health (used in figures of structural equation models)

MSPSS - Multidimensional Scale of Perceived Social Support

POLAR 4 - UK Participation of Local Areas 4 (indicating rates of participation in higher education)

PSQI - Pittsburgh Sleep Quality Index

PSS - Perceived Stress Scale

PWB - Psychological well-being (used in figures of structural equation models)

SAS - Smartphone Addiction Scale

SEM - Structural Equation Modelling

Introduction

This research seeks to increase understanding of how well-being and the use of digital technology are associated in UK university students. As such, the broad research question is ‘is digital technology use associated with well-being in UK university students?’. More specifically, this research aims to investigate the relationships between constructs within well-being (psychological and physical) and digital use in this population. Therefore, a second research question of ‘what are the relationships between digital technology use and the factors of well-being in UK university students?’ is asked.

It is hypothesised that greater levels of problematic digital technology use will be associated with poorer well-being and that the strength of these relationships will, in part, be dependent on how people use digital technology. This research will provide information that universities, students and support services can use to better understand and support well-being in this digital age.

In this chapter, the ways in which well-being, psychological well-being and mental health are defined in the current research will be outlined. Definitions, prevalence rates and the impact of problematic digital technology use will also be outlined. The importance of university student well-being and its relationship with digital technology use will be discussed broadly and in relation to the specific factors of well-being that have been identified as important to this relationship. Finally, a summary of the research identified in a systematic search of the literature around the relationship between psychological well-being and digital technology use in university students will be presented.

Defining well-being, psychological well-being and mental health

The concepts of well-being, psychological well-being and mental health are complex, interlinked and often discussed as an amalgamation of concepts rather than having clear definitions. So much so that finding a unified definition of well-being has been identified as a problem within psychological research literature (Dodge, Daly, Huyton, & Sanders, 2012). As such, the definitions for well-being, psychological well-being and mental health for use in the current research will now be outlined.

Defining well-being

Well-being can be defined as the set point between the challenges an individual faces and the resources they have to manage these challenges. In that, positive well-being is experienced when an individual has the resources they need to meet the challenges they face (Dodge et al., 2012). It is often measured in terms of quality of life, which combines subjective well-being and social indicators, e.g. poverty, academic attainment (Rees, Goswami, & Bradshaw, 2010). Generalisations can be made about a person's well-being based on these social and demographic indicators, alongside their subjective measures of well-being. This definition takes a holistic view of psychological, physical and social factors which contribute to well-being and this is how well-being has been conceptualised in the current research.

Defining psychological well-being and mental health – the dual continuum model

Psychological well-being is one component of well-being and often refers to a person's emotional and cognitive experiences. Psychological well-being can be defined as the absence of negative symptoms or conditions and the presence of life satisfaction, positive self attributes and a social support network (Noble et al., 2008). However, such definitions are problematic due to their reliance on positive feelings and functioning and assumption that a person with good psychological well-being should not experience negative emotions or reduced functioning (Galderisi, Heinz, Kastrup, Beezhold, & Sartorius, 2015).

Definitions of mental health are often similar to those of psychological well-being. The World Health Organisation defines good mental health as "a state of well-being in which the individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community" (World Health Organisation, 2005). As such, psychological well-being and mental health are often used interchangeably in research.

The current research is particularly interested in well-being and views psychological well-being as a distinct construct to mental health. The dual continuum model of mental health (Tudor, 2013) posits that psychological well-being and mental health operate on a dual continuum (see Figure 1). This model suggests that it is possible for a person to experience positive psychological well-being whilst also having a diagnosed mental health condition (which would be deemed poor mental health). This model allows psychological well-being and mental health to influence each other but be considered independent concepts. The dual continuum model informs the current research and outlines the way in which psychological well-being and mental health are conceptualised throughout the current research.

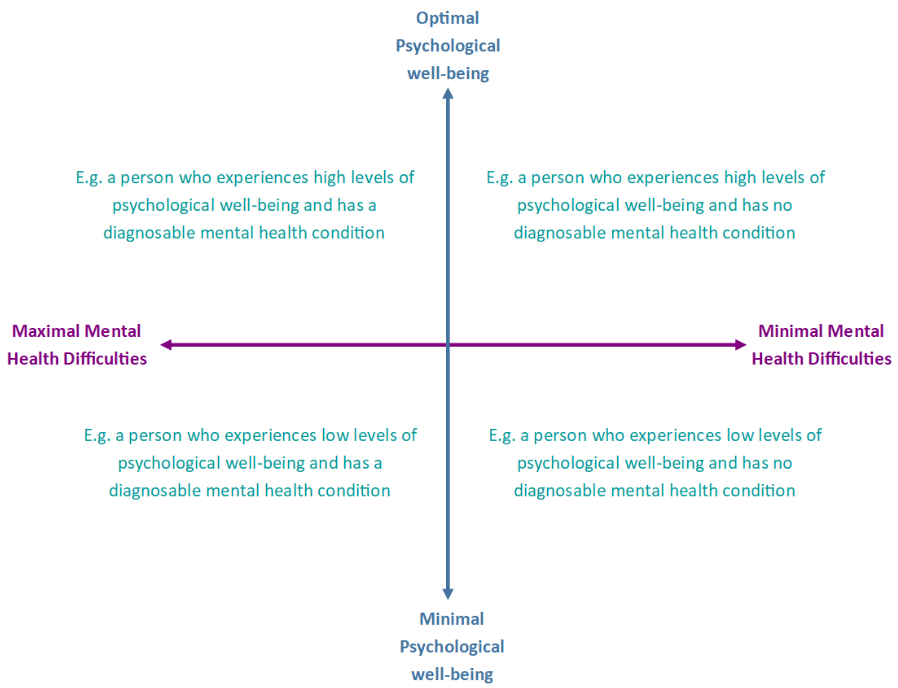

Figure 1 - *The Dual Continuum Model of Metal Health (Adapted from Tudor, 1996)*

Why is the well-being of university students important?

The psychological health and well-being of young people is of increasing interest to the general public, government and support service commissioners. A significant proportion of the young people in the population enter higher education. Fifty percent of young people (18-30 year olds) in England entered higher education in the 2017/18 academic year (Department for Education, 2019) and 34.1% of 18-year olds in England entered higher education in 2019 (UCAS, 2019).

The transition to and experiences whilst at university can be difficult for some students and university has been found to be a time of heightened stress and anxiety (Bewick, Gill, Mulhern, Barkham, & Hill, 2008; Stallman & Hurst, 2016). Starting university requires students to navigate several challenges, including new social groups, novel academic pressures and independent living, alongside the transition into adulthood. As such, university students have been identified as being at risk of poorer well-being than their non-student peers (Cvetkovski, Reavley, & Jorm, 2012; Stallman, 2010; Stewart-Brown et al., 2000).

There has been an increase in demand for university support services over time. Between 2006 and 2016, 94% of UK Universities included in the Not By Degrees project (Thorley, 2017) reported an increase in demand for counselling services and 86% reported an increase in demand for disability services, which support students with a range of disabilities, including those related to mental health and psychological well-being. With regards to mental health specifically, the number of university students disclosing a mental health condition increased by around 390% between 2006/7 and 2015/16. Mental health conditions now make up 17% of disabilities disclosed by first year students, compared to 5% in 2006/7 (Thorley, 2017).

There may have been an actual increase in the number of students with poor psychological well-being and mental health difficulties as the data would suggest. However, other factors may also have contributed to the reported worsening in university student psychological health. It is possible that reduced stigma and a change in culture around mental health have impacted on the increase in students disclosing mental health difficulties. The Higher Education Funding Council for England

(HEFCE) concluded that an increase in demand for student psychological well-being and mental health support is due to a more open culture around mental health, detection of difficulties at a younger age, institutions promoting a culture of support and increased financial and academic pressures (Williams et al., 2015). Increasing student numbers, student mental health difficulty disclosures and demand on support services have meant that universities are now more aware of the well-being of their students. As such, they are becoming more actively involved in understanding, promoting and supporting student psychological well-being and mental health. In practice this includes investing in mental health advisor teams and holding an annual university mental health day (Universities UK, 2015).

How does university student psychological well-being and mental health change over time?

Psychological well-being and mental health are not static constructs, both will ebb and flow within an individual across time. For university students this is likely to be related to the changes in personal and environmental circumstances across the time spent completing university education and to developmental changes as students move through early adulthood.

Research in UK universities has demonstrated how student psychological well-being and mental health changes over time. Psychological well-being tends to be at its highest pre-registration to university and to reduce in the first year of university (Bewick et al., 2010; Cooke et al., 2006). Whilst well-being does rise and fall throughout the year it does not reach pre-registration levels (Cooke et al., 2006).

Bewick et al. (2010) tracked psychological well-being in university students from pre-registration to degree completion and found that, overall, well-being worsened over time. Levels of psychological distress were at their lowest pre-registration and peaked in semester one of first year. In line with Cooke et al. (2006), psychological distress reduced in semester two but did not reach pre-registration levels. Additionally, levels of anxiety where highest in semester one of second and third year and levels of depression where highest in semester two of third year. These results suggest that university has a negative impact on student mental health and well-being over time. The research cited here used the GP-CORE (Evans et al., 2005) as a measure of psychological well-being. Under the dual continuum model of mental health the GP-CORE may be better conceptualised as a measure of mental health, although it is not a clinical measure. Although the researchers intended the GP-CORE to measure psychological well-being, and have reported the results as such, the findings should be interpreted with caution as they may reflect changes in student mental health rather than psychological well-being.

With regards to mental health specifically, levels of depression and anxiety have been found to be significantly higher in second year than first and third year (Macaskill, 2013). As such, second year appears to be a particularly anxiety-provoking time for university students. Further research into the student experience of the second year of university has highlighted the impact of first year concerns, changes in course structure (e.g. marks counting to final degree classification, reduction in academic support, gaps in knowledge from first year), living more independently and concern about future employment and debt as having a negative impact on psychological well-being in second year students (Macaskill, 2018).

These findings illustrate that psychological well-being and mental health change over time for university students and that these fluctuations are related to the university experience and year of study, with levels of psychological distress increasing over time at university. These findings give additional context which should be considered when interpreting the psychological well-being and mental health of students, particularly when measured at one time point.

Identifying terms for the degree of digital technology use and defining problematic use

Most of the research into the impact of digital technology use on well-being is focused on what can be termed ‘pathological use’ ‘problematic use’ or ‘addictive’ levels of use. Often, these terms are used in reference to the standardised measures used. For example, the Internet Addiction Test (Young, 1996) responses can be put into four categories ranging from ‘normal’ levels of internet use to a ‘severe dependence’ on the internet. Those in the severe dependence category, and other such categories on other measures, are often referred to as ‘addicted’, ‘problematic’ or ‘pathological’ users in the literature. As such, the phrases ‘addiction’, ‘pathological’ and ‘problematic’ will be used throughout the current research to reflect the terminology that the research article being referenced used.

The term ‘problematic digital technology use’ will most commonly be used in relation to the results from the current research. This term is used to describe those who have a problematic relationship with digital technology. In the current research, problematic digital technology use is defined as difficulties regulating the use of digital technology and experiencing negative consequences in daily lives due to this relationship with digital technology (van Velthoven, Powell, & Powell, 2018).

Digital technology addiction is not currently a diagnosable condition in UK, nor does it have a unified definition. It is difficult to reach a unified definition of these terms as such a definition would need to encompass time spent on/ frequency and purpose of this digital technology use, habituation of these behaviours and the emotional impact of use of or being unable to use digital technology (Christakis, 2019).

There have been some attempts to define addictive or problematic use of specific types of digital technology use. Gaming disorder has been added to the latest version of the International Statistical Classification of Diseases, Eleventh Edition (ICD-11) but this disorder refers only to digital or video gaming and no other forms of digital technology use (World Health Organisation, 2018). However, the most recent edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) stated that internet gaming disorder needed further study and is not currently included a diagnosable condition (American Psychiatric Association, 2013). Some suggest that internet overuse can constitute an addictive behaviour as it can be aligned with the diagnostic criteria for gambling addiction (Spada, 2014). High levels of smartphone use have also been termed problematic when behaviours associated with smartphone use become habitual and repetitive (Oulasvirta, Rattenbury, Ma, & Raita, 2012). Due to the lack of clarity around a definition of addictive or problematic digital technology use, the current research is interested in use of digital technology across the spectrum of severity but it is acknowledged that the majority of research presented refers to addictive, pathological or problematic levels of digital technology use.

Risk factors for problematic digital use

Risk factors for problematic digital use in young people and adults include depression, low self-esteem and negative family functioning, social interaction, anxiety and external locus of control (Fumero et al., 2018; Lee, Chang, Lin, & Cheng, 2014). Protective factors include higher levels of self-esteem, social skills and positive family functioning (Fumero et al., 2018).

Demographics such as socio-economic background have also have also been associated with problematic digital use (Lee & McKenzie, 2015). Kayri & Günüç (2016) found that young people from high socio-economic backgrounds were more likely to display internet addictive behaviours than those from low socio-economic backgrounds (26.7% and 9.1% respectively). Gender may also be a risk factor for problematic digital use. Some have suggested that pathological internet users are more likely to be males, particularly related to the use of online games (Aljomaa, Al.Qudah, Albursan, Bakhiet, & Abduljabbar, 2016; Morahan-Martin & Schumacher, 2000) whereas others have found that women are more likely to be addicted to smartphone use (Billieux, Van der Linden, & Rochat, 2008). In addition, the type of programme students study at university may also predict problematic use of digital technology, with full-time students being more likely to exhibit internet addiction (Chak & Leung, 2004). However, due to the problems with defining and measuring digital addiction in a UK population, it is likely that this is not an exhaustive list.

Understanding why people become addicted to digital technology: theories of digital technology use

Whilst the prevalence of digital addiction in the UK student population is unclear, it is helpful to understand how and why people might become addicted to technology from a psychological perspective. As such, relevant psychological theories will now be outlined.

The Uses and Gratifications Theory is most commonly used to explain peoples' media use choices (Rubin, 2009). It proposes that motivations to use digital technology are determined by the purpose of using the internet (use) and the things people get from using it (gratifications). The uses and gratifications are often satisfying needs (social, psychological cognitive) and usage is seen as a goal driven behaviour.

Some researchers have used the uses and gratifications theory to explain why people may use and become addicted to digital technology. A number of factors have been identified as gratifications of using digital technology, such as escapism, socialisation, entertainment, communication and peer identity (Charney & Greenberg, 2001; Korgaonkar & Wolin, 1999; Larose, Mastro, & Eastin, 2001; Papacharissi & Rubin, Alan, 2000; Stafford, Stafford, & Schkade, 2004). However, these proposed gratifications have not been shown to strongly predict digital technology use and therefore cannot be considered a robust explanation of digital addiction. This theory has some relevance as a broad framework for understanding problematic digital use. However, it does not provide a full explanation for a more complex relationship with the digital world, such as internet addiction.

Digital technology may also be used as a way of managing negative emotions and distress (Caplan, 2002). We can make sense of this research through the Compensatory Internet Use Theory, which proposes that the internet is used to alleviate negative feelings and may, in some cases, be used as a form of coping (Kardefelt-Winther, 2014). This theory suggests that internet use is determined by motivations for use (gratifications), usual online behaviours (habits), psychosocial vulnerabilities (such as mental health difficulties) and problematic outcomes of internet use (such as increased social isolation). For example, an online gamer who is socially anxious but wants to interact with other players may be more likely to neglect real life socialisation and other responsibilities in favour of gaming. This theory and the research around digital technology use and coping has some relevance to the current research and clearly shows that digital technology use is linked to managing psychological states. It may help us to understand the motivations for using digital technology when experiencing lowered psychological well-being and higher levels of stress.

The social-cognitive theory of internet use (Larose et al., 2001) goes some way to explaining why people become addicted to digital technology. This theory incorporates enactive learning (Bandura, 1986) into the uses and gratifications theory. The theory posits that interaction with digital technology creates rules and expectations about the impact of using it in the future. The rules and expectations that we build from enactive learning then become the gratifications which incentivise us to use digital technology again. For example, a person may engage with social media for the purpose of downward social comparisons with peers, which in turn allows them to feel more positive about their own life.

Whilst this theory does explain how people come to build habits and expectations about technology use it does not help us understand why people continue to use digital technology for social comparison when it negatively impacts on their well-being and there are no gratifications. It is possible that the behaviour has become habitual at this point and that the presence of a gratification is not needed to incentivise technology use, but this does not capture the complexities of digital technology addiction.

Self-determination theory (Ryan & Deci, 2000) provides some explanation as to why people continue to use the digital technology, even when it is problematic. This theory assumes that we all have the basic needs for autonomy, competency and relatedness and satisfying these needs motivates our behaviour. Autonomy refers to the need to have control over our lives and belief that our actions will effect change. Competency refers to the need for mastery and the development of skills that will help us achieve our goals. Relatedness refers to the need to experience a sense of belonging and connection to others (Deci & Ryan, 2008). Satisfaction of these needs is related to better well-being in adolescents and university students (Chen et al., 2015; Cordeiro, Paixão, Lens, Lacante, & Luyckx, 2016; Sheldon & Bettencourt, 2002).

In relation to digital technology use, we may be motivated to use digital technology as a way of satisfying our unmet needs. For example, using social media to satisfy the need for relatedness to others when our real-life social interactions do not meet these needs. Digital technology use has been shown to be related to the three basic psychological needs in young people and university students. Specifically: belonging, connectedness and competence (Hsu, Wen, & Wu, 2009; Sheldon, Abad, & Hinsch, 2011; Yee, 2006).

Psychological distress mediates the relationship between need satisfaction and problematic internet use (Wong, Yuen, & Li, 2014). Therefore, it is possible that psychological distress leads to higher unmet needs and that the use of digital technology increases to satisfy these needs, despite the possibility of it being counterproductive. As such, people can become trapped in a cycle of using digital technology to satisfy their unmet needs but then neglecting other areas of their lives which could help to meet these needs. Therefore, finding that their basic psychological need satisfaction does not improve and so they are more compelled to use digital technology to satisfy them.

The basic psychological need satisfaction theory fits well with the current research and allows for greater complexity in the relationship between well-being and the use of digital technology. As such, self-determination theory and basic psychological need satisfaction is considered as an important theory for understanding the relationship between well-being and the use of digital technology.

What do we know about when digital use becomes 'problematic' in the UK university student population?

As there is no definition of ‘problematic’, ‘pathological’ or ‘addictive’ levels of digital technology use in the UK it is difficult to ascertain reliable figures for problematic digital use or addiction in UK university students. Most of the research investigating the personal and social factors involved in technology addiction has been conducted in Asian counties such as Taiwan, China and Korea (Fumero et al., 2018). Morahan-Martin and Schumacher (2000) investigated the prevalence of pathological internet use in 277 American undergraduate university students. They found that most American undergraduate university students, 64.7%, reported one to three symptoms of pathological internet use, 27.2% reported no symptoms and 8.1% met criteria for pathological internet use. The researchers defined pathological internet use as the presence of evidence that the internet was used to regulate moods and that internet use was causing distress, academic difficulties and social difficulties. It is likely that the culture around digital technology use is similar in both American and the UK. However, this research may not be fully generalisable to the UK university student population.

Research into prevalence rates of problematic digital use in a UK student population is scarce and has yielded varying results. Kuss, Griffiths, & Binder (2013) reported that only 3.2% of their sample met criteria for internet addiction. They defined internet addiction by overall amount of internet use and number of problems experienced related to internet use. However, Niemz, Griffiths, & Banyard (2005) reported that 51% of their sample reported one to three symptoms of pathological internet use and 18% were defined as pathological internet users (as defined by the criteria in Morahan-Martin and Schumacher, 2000). Discrepancies in prevalence rates may, in part, be due to differing definitions of problematic digital use and the tools used for measurement.

What do we currently know about the relationship between digital use, well-being and mental health in general?

Digital technology is an integral part of modern life and it has been found to have a detrimental impact on well-being (Huang, 2010). It is estimated that 87% of people in the UK use the internet (Poushter, 2016) and 97% of 25-34 year olds in Great Britain use smartphones to access the internet ‘on the go’ (Office for National Statistics, 2018). Use of the digital world is particularly important for young people, who have grown up using digital technology for learning, socialising and communication at a much younger age than older generations have previously (Fumero, Marrero, Voltes, & Peñate, 2018). Digital technology is frequently used to access social networking sites, such as Facebook and Instagram, with 96% of 16-24-year olds using social media in 2017 (The Office for National Statistics, 2017). Internationally there have been studies which have helped our understanding of university students' relationship with digital technology and there is evidence to suggest that the use of digital technology is associated with student well-being.

What factors are associated with well-being in university students and how are they associated with digital technology use?

The concept of well-being can be broken down into multiple components. A systematic review of research into student well-being by Noble et al. (2008) identified the key components in definitions of student well-being. These were emotional (positive affect), coping (resilience), cognitive (satisfaction with one's life and relationships) and performance (effective functioning) components.

Research into university student well-being tends to focus on measures of psychological well-being (Bewick, Koutsopoulou, Miles, Slaa, & Barkham, 2010; Cooke, Bewick, Barkham, Bradley, & Audin, 2006), stress and coping (Denovan & Macaskill, 2017; Stallman, Ohan, & Chiera, 2018), physical health (Penedo & Dahn, 2005; Scully, Kremer, Meade, Graham, & Dudgeon, 1998), academic attainment (Babenko & Mosewich, 2017; Işik, Ulubey, & Kozan, 2018) and emotional components such as positive and negative affect, distress and symptoms of mental health conditions (Gunnell, Mosewich, McEwen, Eklund, & Crocker, 2017; Macaskill, 2018).

The factors associated with university student well-being and mental health will now be outlined. Their relationship with digital technology use will also be considered. Broadly, these factors are:

1. Mental health and risk factors for mental health difficulties
2. Psychological well-being (stress, coping and resilience, social support and mindfulness)
3. Physical health and sleep

4. Academic success (sometimes conceptualised as academic performance or attainment)

In line with the dual continuum model of mental health, many of these relationships are complex and interrelated. It is difficult to fully illustrate the complexities of these relationships here but this strengthens the rationale for using complex modelling to analyse and clarify the ways in which all the factors interact.

How does Mental Health impact on university student well-being?

In line with the dual continuum model of mental health (Tudor, 2013) it is important to consider common mental health difficulties, such as anxiety and depression, when measuring psychological well-being and mental health as the two concepts interact. Some estimates suggest that mental health conditions, such as anxiety and depression, are more common in university students than the general population with university students experiencing significantly higher levels of high psychological distress than that of the general population, 19% and 3% respectively (Stallman, 2010).

Risk factors for mental health difficulties in university students

Age has been highlighted as a risk factor for university students experiencing mental health difficulties. Early adulthood is an important time for the emergence of mental health difficulties, with three quarters of mental health difficulties being diagnosed by 24 years of age (Kessler et al., 2005). As 69% of HE students are 24 years of age or under (Higher Education Statistics Agency, 2019) it is important that we understand the psychological health and well-being of university students and ensure they are well supported through their time at university.

Women are often cited as being more likely to suffer from common mental health problems in the general population, with women who are aged 16 to 24 years of age being almost three times more likely to experience a common mental health difficulty than men, 28% and 10% respectively (Thorley, 2017). This holds for university students. Sixty-seven percent of university students who report a mental health problem which requires professional support and 70% of those who have a formal mental health diagnosis are female (Pereira et al., 2019).

The type of programme a student is enrolled in has been related to prevalence of mental health difficulties. A report by Thorley (2017) found that undergraduate students (particularly first degree undergraduates) are more likely than postgraduate students to disclose a mental health difficultly (2.2% and 1.4% respectively). Additionally, full-time first year students are more likely to disclose a mental health difficulty than their part-time counterparts (2.3% and 1.4% respectively). It is important to consider that the research outlined relies on cross-sectional data. The relationship between an individual characteristic, such as studying part-time, and mental health difficulties is likely to be dependent on several other factors and unlikely to be a simple causal relationship. The use of cross-sectional data does not allow for these relationships to be explored therefore inferences about causation cannot be made.

Social and economic components also contribute to university student mental health. Financial difficulties (Andrews & Wilding, 2004) and financial concern (Cooke, Barkham, Audin, Bradley, & Davy, 2004; Jessop, Herberts, & Solomon, 2005) have been associated with poorer mental health in UK students. Tuition and accommodation fees, alongside the implications of greater financial freedom that students often experience mean that university may be a time of increased financial concern. This is evidenced by The Sodexo University Lifestyle Survey (2016) which found that 48% of UK university students report being worried about their day-to-day finances.

Research also suggests that there is a relationship between poorer mental health, financial difficulties and drug and/or alcohol use. In a longitudinal study of British undergraduate students Richardson, Elliott, Roberts, & Jansen (2016) found a bi-directional relationship between these variables whereby poorer mental health and alcohol dependence predicted a worsening financial situation. Drug and alcohol use have also been associated with increased psychological distress, mental health difficulties, loneliness and lower satisfaction with life in university students (Sæther, Knapstad, Askeland, & Skogen, 2019; Tembo, Burns, & Kalembo, 2017).

Identifying as Lesbian, Gay or Bisexual, Transgender or Queer (LGBT+Q) is associated with poorer mental health outcomes when compared to the heterosexual population. An extensive review of inequality among LGBT+Q groups in the UK concluded that poorer mental health in these groups is due to the impact of experiencing higher levels of discrimination and stigma in society and services, with mental health services most often perceived as discriminatory by those from LGBT+Q groups (Hudson-Sharp & Metcalf, 2016). This increased prevalence in mental health difficulties is also seen in the student population, with LGBT+Q students experiencing twice the mental health difficulties as their heterosexual peers (YouGov, 2016). A Stonewall report into the experiences of LGBT students identified that people from these groups experienced discrimination, bullying and abuse from peers and university staff (Bachmann & Gooch, 2018), suggesting that these experiences may contribute to the increased prevalence of mental health difficulties in students who identify as LGBT+Q.

Ethnicity also impacts on mental health prevalence rates in the general population, with those from Black, Asian and minority ethnic (BAME) backgrounds being more likely to be diagnosed with a mental health condition and to be admitted to mental health hospitals (Bhui & McKenzie, 2008; McManus, Bebbington, Jenkins & Brugha, 2016). The intersectionality between mental health difficulties and being from a BAME background, particularly Black ethnic backgrounds, has negative implications for university students. Only 77.1% of Black university students who report a mental health condition continue into their second year of university, which is 8 percentage points lower than students with mental health conditions of any other ethnicity. Furthermore, only 53% of Black university students who report a mental health condition are awarded a 1st or 2:1 in their degree, which is 14 percentage points lower than students with mental health conditions of any other ethnicity (Office for Students, 2019).

Several mechanisms that facilitate this relationship and that are relevant for the student population have been identified. Broadly, evidence suggests that living in an area of high own-group ethnic density, particularly for those from BAME communities, can be a protective factor for mental health difficulties (Das-Munshi, Becares, Dewey, Stansfeld, & Prince, 2010). With 76% of UK higher education students in 2017/18 being from a white ethnic background (Higher Education Statistics Agency, 2018), it is possible that the low own-group ethnic density environment at university for students from BAME backgrounds adds to the risk of developing mental health difficulties. The impact of race related discrimination and lack of culturally sensitive mental health services also facilitate the relationship between students from a BAME background experiencing greater mental health difficulties (Arday, 2018).

In summary, there are several factors which impact on the mental health of university students. There is no clear evidence that factors such as sexuality and ethnicity have a greater impact on the mental health of students than that of the general population, but these factors do contribute to the mental health of students and their outcomes at university. Some of the factors outlined such as age and gender may not have a greater impact on student mental health than that of the general population, but the student population is more likely to be made up of those from the risk categories e.g. being in the 16-24 age bracket and being female. Factors related to the university experience (transition, programme of study, novel financial difficulties and increased drug/ alcohol use) specifically impact on university student mental health, rather than that of the general population.

How are mental health and digital technology use associated?

In the general population greater smartphone use in young adults is associated with symptoms of depression, even after excluding those with diagnosed mental health difficulties (Thomée & Härenstam, 2011). Using the internet for an average of 2 ½ hours per week increases loneliness and depression (Kraut et al., 1998) and frequency of social media use (Instagram) is positively associated with depressive symptoms, a relationship that is mediated by social comparison (Lup, Trub, & Rosenthal, 2015).

The relationship between mental health and digital technology use is also evidenced in university students. Digital technology use has been shown to be positively related to anxiety and depression in university students (Bahrainian, Haji Alizadeh, Raeisoon, Hashemi Gorji, & Khazaee, 2014; Demirci, Akgönül, & Akpinar, 2015; Orsal & Sinan, 2013; Younes et al., 2016). The use of Facebook has been linked to lowered self-esteem (Kalpidou, Costin, & Morris, 2010), lowered mood, increased feelings of engaging in meaningless activity (Sagioglou & Greitemeyer, 2014) and decreased life satisfaction (Kross et al., 2013) in university students, all of which are symptoms of mental health difficulties such as depression. In addition, internet and smartphone use have been positively related to psychological distress in university students specifically (Al-Gamal, Alzayyat, & Ahmad, 2016; Anand et al., 2018b, 2018a; Beranuy, Oberst, Carbonell, & Chamarro, 2009). This research suggests that problematic use of digital technology is associated with mental health difficulties in university student populations.

How does psychological well-being impact on university student well-being and mental health?

The relationship between stress, resilience and university student psychological well-being and mental health.

Stress is an inevitable part of everyday life and it is often cited as being part of the overall picture of well-being in university students and the general population. University has been found to be a time of increased stress (Bewick, Gill, Mulhern, Barkham, & Hill, 2008; Stallman & Hurst, 2016). The types of stressors that have been cited as relevant for university students include funding and finances (Andrews & Wilding, 2004; Jessop et al., 2005), transition to university, change in routine, need to develop new social links (Dyson & Renk, 2006; Fisher & Hood, 1987), academic pressure, deadlines and assessment (Abouserie, 1994; Robotham & Julian, 2006).

The Transactional Model proposes that stress is experienced when a person perceives that their internal or environmental demands outweigh their coping resources (Lazarus & Folkman, 1984). An example of this within UK university student population comes from Denovan & Macaskill (2013), who found that an increasing range of stressors on UK undergraduate students had a cumulative negative effect on coping.

University students have been found to use adaptive and non-adaptive coping strategies to manage these increasing stressors. Stallman, Ohan, and Chiera (2018) found that the coping strategies of self-kindness, social support and being present were all negatively related psychological distress and stress. Positive attitude, ability to reframe and problem solving have been positively correlated with well-being in a university student sample. Conversely, helplessness and lack of social support (alienation) were negatively correlated with university student well-being (Sagone & De Caroli, 2014).

A key part of increasing coping is building resilience. Resilience can broadly defined as "a set of attitudes and behaviours which are associated with an individual's ability to bounce back and to adapt in the face of risk and stress" (Holdsworth, Turner, & Scott-Young, 2018, p. 1837). Resilience is considered a key component of psychological well-being (Ryff & Singer, 2003) and is related to increased retention rates and life satisfaction in university students (Neale, Piggott, Hansom, & Fagence, 2016).

Resilience requires both internal and external characteristics. Internal characteristics include self-efficacy, optimism, and psychological well-being (Johnson, 2008). External characteristics include positive and caring relationships, support structures and others who nurture learning (Constantine, Benard, & Diaz, 1999). More specifically for university students, developing support networks, keeping healthy and maintaining perspective have been identified as key aspects of resilience (Holdsworth et al., 2018). As such, resilience is considered an important skill for university students to build (Dickinson & Dickinson, 2015; Walker, Gleaves, & Grey, 2006) as it can help them to cope with the pressures of university and adult life after university (Caruana, Clegg, Ploner, Stevenson, & Wood, 2011).

Whilst resilience has been found to be an important part of psychological well-being there is not an exclusively positive relationship between them. The majority of people in the UK (65.6%) report that they experience a positive relationship between well-being and resilience, whereby higher levels of well-being are experienced with higher levels of resilience (Mguni, Bacon, & Brown, 2012). However, some people do not experience an exclusively positive relationship between well-being and resilience with 17.8% of people reporting low levels of well-being but high levels of resilience and 16.6% of people reporting high levels of well-being but low levels of resilience (Mguni et al., 2012). This paradox mirrors the dual continuum model of mental health (Tudor, 2013) with resilience and psychological well-being being two distinct but related concepts.

How are stress, resilience and digital technology use associated?

Smartphone addiction has been shown to be positively related to perceived stress (Samaha & Hawi, 2016) and the use of Facebook has been related to increased stress and social overload in university students (Maier, Laumer, Eckhardt, & Weitzel, 2012).

Stress may also be related to the motivations for university students to use digital technology. A study of American university students found that motivations for using the internet were associated with stress (Deatherage, Servaty-Seib, & Aksoz, 2014). Their results show that using the internet to cope and having an avoidant-emotional coping style were positively related to stress, whereas using it to enhance emotions was negatively related to stress. Stress has also been found to moderate motivations to use smartphones and problematic smartphone use (Wang, Wang, Gaskin, & Wang, 2015). These findings indicate that digital technology use may be considered a coping strategy for stress, as psychologial theories suggest, and that the purpose of using technology may influence how digital technology use impacts on stress.

Levels of resilience also have an impact on digital technology use in university students. For example, French university students in the ‘risk group’ for smartphone addiction were found to have significantly lower resilience (Kim et al., 2014) and level of smartphone addiction was negatively correlated with resilience in South Korean students (Kim & Sim, 2018).

There is evidence that resilience impacts on the relationship between digital technology use and well-being in young people; specifically that it moderates the relationship between depression and internet addiction in female high school students (Choi, Shin, Bae, & Kim, 2014) and partially mediates the relationship between depression and smartphone addiction in middle school students. This research suggests that increased stress and lower levels of resilience are associated with higher levels of problematic digital technology use.

The relationship between social support and university student psychological well-being and mental health.

Good social support is often cited as an indicator of good psychological well-being (Noble et al., 2008) and has been shown to explain 43% of variance in subjective well-being (Gülaçt, 2010). Research also suggests that social support is positively associated with psychological well-being in the university student population (Reifman & Dunkel-Schetter, 1990; Stallman et al., 2018).

Resilience and coping are closely linked to social support (Stallman et al., 2018) and these factors all contribute to the wider picture of psychological well-being in university students. Starting university can bring additional social challenges, with changes to existing social support networks and the need to create new sources of social support. The relationship between psychological well-being and social support appears to be particularly important when starting university. The success of adjustment to university has been shown to be related to social support from friends and family (Demaray, Malecki, Davidson, Hodgson, & Rebus, 2005; Awang, Kutty, & Ahmad, 2014). Social support is also impacted by personal characteristics, such a socio-economic background. Significantly higher numbers of university students from professional backgrounds report that their social support meets their needs than peers from lower socio-economic backgrounds (Cooke, Barkham, & Bradley, 2004). As such, social support is considered an important factor that is related to well-being in university students.

How are social support and digital technology use associated?

Digital technology is often used for social communication and the literature suggests that there is a link between social support and digital technology use. Internet use has been associated with social difficulties, increased isolation and hostility in adolescents (Fumero et al., 2018) and to be negatively correlated with social support in university students (Özcan & Buzlu, 2007). Conversely, the use of Facebook has been associated with reduced loneliness (Burke, Marlow, & Lento, 2010). Smartphone use has also been positively related to relationships with parents and friends in student populations and increased social capital in the adult general population (Chen & Lever, 2005; Ellison, Steinfield, & Lampe, 2007).

Digital technology use appears to have both a positive and negative relationship with social support in the general and student populations. The relationship between digital technology use, social support and well-being also appears to be bi-directional with social support being influenced by both well-being and digital technology use. Whilst this relationship remains unclear, the research suggests that social support is associated with digital technology use in university students.

The relationship between mindfulness and university student psychological well-being and mental health.

In recent years, mindfulness practice has become a part of everyday stress relief strategies and ‘third wave’ approaches within psychotherapy (Hofmann & Asmundson, 2008). Several meta-analyses have reviewed the impact of mindfulness practice and mindfulness-based interventions. In such meta-analyses, mindfulness has been linked to improved psychological and physical well-being in both clinical and non-clinical populations (Chiesa & Serretti, 2009; Eberth & Sedlmeier, 2012; Grossman, Niemann, Schmidt, & Walach, 2004). It has also been shown to have a significant positive effect on mental health and stress (Spijkerman, Pots, & Bohlmeijer, 2016).

Mindfulness has been shown to be beneficial for the university student population. Benefits include increased psychological well-being (Hassed, De Lisle, Sullivan, & Pier, 2009), stress reduction (Gallego, Aguilar-Parra, Cangas, Langer, & Mañas, 2014; Messer, Horan, Turner, & Weber, 2016) and supporting transition to university through increased life satisfaction and decreased depression, anxiety, sleep issues and alcohol use in first year students (Dvořáková et al., 2017).

Mindfulness is also related to some of the factors already identified as influencing psychological well-being. Resilience has been closely linked to mindfulness in university students (Pidgeon & Keye, 2014) and the mechanisms of mindfulness have been identified as relating to emotion regulation and coping (Coffey, Hartman, & Fredrickson, 2010). These findings suggest that mindfulness may act as a way of coping or remaining resilient for university students, thus impacting on their psychological well-being.

How are mindfulness and digital technology use associated?

Mindfulness has been shown to negatively predict internet addiction in university students (İskender & Akin, 2011). There is some evidence from an adolescent population to suggest which specific components of problematic/ addictive internet use are associated with mindfulness. Higher levels of mindful awareness have been shown to significantly reduce the negative outcomes of problematic internet use, the preference for online interactions and the use of the internet for emotion regulation (Gámez-Guadix & Calvete, 2016). Specifically, higher levels of the ‘non-judging’ dimension of mindfulness have been shown to predict a reduction in preference for online interactions (Calvete, Gámez-Guadix, & Cortazar, 2017).

Greater smartphone use has also been shown to be significantly associated with lower trait mindfulness in university students (Woodlief, 2017). Mindfulness has also been shown to mediate the relationship between depression, anxiety and problematic smartphone use in university students (Elhai, Levine, O'Brien, & Armour, 2018). Mindfulness based interventions have also been utilised as treatments for internet gaming disorder and shown to have a positive effect by reducing the amount of behaviours and cognitions related to gaming addiction (Li et al., 2017). This research suggests that higher levels of mindfulness may serve as a predictor of lower levels of problematic digital technology use and as a protective factor in the development of problematic digital technology use.

How does physical health impact on university student psychological well-being and mental health?

The relationship between physical health and university student psychological well-being and mental health.

In the general population, good physical health and physical activity are associated with positive psychological well-being (Penedo & Dahn, 2005), specifically self-efficacy, self-esteem, cognitive functioning, anxiety and depression (Scully et al., 1998). Aerobic exercise in particular has been shown to be positively associated with mood, psychological well-being and life satisfaction (Haworth & Lewis, 2005; Reed & Buck, 2009).

It follows that those in the general population who experience long term health conditions are more likely to experience poor psychological well-being and mental health. Evidence suggests that around 30% of people with a long-term health condition also have a mental health difficulty (Cimpean & Drake, 2011) and that they are 2 to 3 times more likely to experience mental health difficulties than the general population (Naylor et al., 2012). The well-being of people with long-term health conditions also impacts support services, with 12-18% of the NHS expenditure on long-term health conditions being related to poor mental health (Naylor et al., 2012).

Due to their age, university students tend to be in low risk groups for physical health problems (Hussain, Guppy, Robertson, & Temple, 2013). However, physically unwell students often face additional complexities when accessing physical health services due to the transient nature of their location and the complexities of navigating services independently in a new locations. However, there is also some evidence that students may experience poorer physical health than their non-student peers (Stewart-Brown et al., 2000) and that the university environment increases the likelihood of experiencing symptoms of physical ill-health (Kasparek, Corwin, Valois, Sargent, & Morris, 2008; Moos & Van Dort, 1979).

There appears to be little research into the association between physical health, psychological well-being and mental health in university students. Perhaps because university students are perceived as being a privileged and physically well group within the general population (Hussain et al., 2013). However, physical exercise has been shown to reduce stress-reactivity in university students during an academic exam (von Haaren, Haertel, Stumpp, Hey, & Ebner-Priemer, 2015) and to be positively related to academic attainment (El Ansari & Stock, 2010; Shephard, 1996). Therefore, physical health is considered a factor of university student well-being. This also fits with the holistic definition of well-being, outlined earlier, which is used in the current research.

The relationship between sleep and university student psychological well-being and mental health.

Physical health, psychological well-being, mental health and sleep are closely linked in the general population. Insufficient sleep is linked to increased risk of developing physical health problems, such as cardiovascular disease, a lowered immune system and stroke. Furthermore, sleep disturbance is seen in all major psychiatric conditions and is linked to increased emotional irrationality and lowered mood (Walker, 2018, pp. 146–152).

Estimates of sleep disturbance prevalence rates in university students have ranged from 18.4% to 45.0% (El Ansari et al., 2011; Steptoe et al., 1997; Webb, Ashton, Kelly, & Kamali, 1996), with female students reporting higher rates of sleep disturbance (Buboltz, Brown, & Soper, 2001; Lindberg et al., 1997). University students may experience disturbed sleep due to inconsistent routines, living in shared accommodation, increased stress and increased drug and alcohol use (Buboltz et al., 2001).

As with the general population, sleep disturbance in university students has been correlated with increased mental health difficulties, such as anxiety and depression (Taylor et al., 2011), lowered quality of life and fatigue (Taylor, Bramoweth, Grieser, Tatum, & Roane, 2013), higher levels of stress and lower levels of optimism (Sing & Wong, 2010).

Sleep disturbance has also been linked to impaired cognitive performance in general and university student populations (Pilcher & Huffcutt, 1996; Pilcher & Walters, 1997). As such, there is some evidence to suggest that sleep quality, length and onset is related to learning capacity and academic performance in university students (Curcio, Ferrara, & De Gennaro, 2006; Gaultney, 2010; Önder, Beşoluk, İskender, Masal, & Demirhan, 2014; Trockel, Barnes, & Egget, 2000). However, others have not found a significant relationship between sleep and academic performance (Patrick et al., 2017). The majority of studies which investigate the impact of sleep on academic performance use correlational data. Therefore, the lack of clarity in results may suggest that other mechanisms are influencing the relationship between sleep and academic performance. For example, personality traits, such as perfectionism (Ellis & Fox, 2004) or thinking styles, such as catastrophising (Gray & Watson, 2002). The specific link between academic success and well-being will be outlined in detail in the following section.

In summary, greater physical health problems and sleep distance being associated with poorer well-being and mental health. Therefore, physical health and sleep are important factors associated with university student well-being and mental health.

How are physical health, sleep and digital technology use associated?

There appears to be little research around the relationship between the use of digital technology and physical ill-health in the university student population specifically. However, the use of digital technology is generally a sedentary behaviour, the likes of which are often associated with physical health problems (Williams, Raynor, & Ciccolo, 2008). Internet use has been associated with poorer physical health (Kelley & Gruber, 2013) and greater use of digital technology has been associated with higher levels of physical health symptoms (Zheng et al., 2016), poorer physical fitness and poorer cardiorespiratory fitness (Lepp, Barkley, Sanders, Rebold, & Gates, 2013). There is also some evidence to suggest that having a physical disability increases the likelihood of using digital technology excessively. The presence of a physical disability has been positively correlated with internet addiction in high school students (Pallanti, Bernardi, & Quercioli, 2006) and associated with excessive computer use in young people (Griffiths, 2000). The scarcity of this research highlights the need for further investigation into the relationship between physical ill-health or physical disabilities and digital technology use.

Digital technology use has been associated with sleep difficulties in university students. Students who report problematic levels of internet use are more likely to report that their online activity negatively impacts their sleep pattern (Anderson, 2010). Using digital technology after sleep onset (answering text messages) also predicts poorer sleep quality in university students. In addition, sleep quality was found to mediate the positive relationship between using digital technology after sleep onset and depression/ anxiety (Adams & Kisler, 2013). Smartphone use has also been associated with decreased sleep quality in university students (Matar Boumosleh & Jaalouk, 2017). This research suggests that problematic digital technology use is associated with greater sleep disturbance and physical health problems in university students.

What is the relationship between academic success and university student well-being and mental health?

There are many personal and social benefits of university but the main purpose of attending university is to obtain an academic qualification. Academic success, attainment and retention, have been linked to physical health and well-being in university students (Chow, 2010; Dubuc, Aubertin-Leheudre, & Karelis, 2017; El Ansari & Stock, 2010). Importantly, level of academic attainment is a lifelong predictor of health and well-being (Schoenbaum & Waidmann, 1997) suggesting that the relationship between academic attainment and well-being persists across time.

Student factors have been shown to explain up to 95% of variance in academic success and retention in university students (Van Den Berg & Hofman, 2005). Several variables have been linked to academic success in university students. These include demographics such as age, with younger students performing better (Murtaugh, Burns, & Schuster, 1999; Van Den Berg & Hofman, 2005), gender, with females generally performing better than males (Paura & Arhipova, 2014; Smith & Naylor, 2001) and ethnicity, with White students performing better academically and having higher retention rates than students from other ethnicities (Office for Students, 2019). Socio-economic background has also been linked to academic attainment and retention, particularly with regard to state versus public schooling (Smith & Naylor, 2001, 2005). However, the impact of socio-economic background on academic attainment is not clear, with some finding no significant effects (Van Den Berg & Hofman, 2005).

Academic success is also related to psychological wellbeing and mental health. Coping (DeBerard, Spielmans, & Julka, 2004), self-efficacy (Robbins et al., 2004), social support (Cutrona, Cole, Colangelo, Assouline, & Russell, 1994; Robbins et al., 2004) and mental health difficulties (Andrews & Wilding, 2004) have all been shown to be associated to academic success in university students.

It is unclear in the research which direction the relationship between well-being and academic attainment works but likely that they influence each other in a circular way. For example, greater academic success leads to increased well-being, which increases motivation to study and results in further academic success. This research suggests that it is important to consider academic success when building an overall picture of well-being in university students.

How are academic success and digital technology use associated?

The use of digital technology has been associated with academic success and studying in university students. Mobile phone use is negatively associated with academic attainment (Lepp, Barkley, & Karpinski, 2014), as is the use of social networking sites (Karpinski, Kirschner, Ozer, Mellott, & Ochwo, 2013) and online games (Lau, 2017). It has been suggested that the negative relationship between use of social networking sites and academic attainment may be partly due to ineffective multitasking (Kirschner & Karpinski, 2010) and reduced productivity (Dukea & Montag, 2017). In addition, academic stress has been shown to be associated with smartphone addiction (Chiu, 2014). Digital technology use may also have a positive impact on academic study with students citing ‘help with studying’ as one of the advantages of internet use (Rayan et al., 2017). With digital technology being such an integral part of university student life, it is unsurprising that it impacts on academic studying and success and therefore well-being.

Summary of the literature outlined

The literature outlined evidences the relationship between digital technology use and factors that are relevant to well-being in the university student population. Much of this research uses a quantitative approach and relies on validated measures of digital technology use and the factors of well-being. These measures are often created with clinical populations in mind and therefore the research may be more attuned to finding relationships between those with clinical levels of difficulties, such as mental health difficulties, and problematic digital technology use. In addition, quantitative approaches are unlikely to capture the nuances of the relationship between digital technology use and well-being. Qualitative approaches may provide more in-depth, experiential data on the relationship between digital technology use and well-being.

As the majority of the research outlined focuses on clinical populations, namely those with mental health difficulties, a more specific search of the literature around the relationship between psychological well-being and digital technology use was conducted. The systematic search of this literature will now be outlined.

Systematic review

The bulk of the research outlined thus far is focused on the relationship between mental health difficulties and digital technology use. The importance of university student well-being, as well as mental health, has been highlighted and therefore we need to know more about the impact of digital technology use on psychological well-being in the university student population. To address this, a systematic search of the literature in this area was completed. The aim of this systematic review was to shift the focus in the research literature from digital technology use and mental health to digital technology use and psychological well-being.

Introducing the systematic search

The research area of psychological well-being and digital technology use is vast with varying definitions of psychological well-being and constructs considered relevant to psychological well-being. A systematic search of the literature was completed to identify the articles most relevant to the current research. The question for this search was 'what are the associations between digital technology use and university student psychological well-being?'.

The search was run on the Ovid MEDLINE and PsycINFO databases in September 2019. Search terms related to different types of digital technology, e.g. social media, smartphone and internet, and descriptions of psychological well-being, e.g. psychological health, mental well-being. See Appendix A for full search terms.

The search yielded 887 results. These abstracts were screened and coded based on the following criteria:

- Population – University students, young people or other.
- Type of well-being investigated – Psychological well-being, physical well-being, holistic well-being or mental health/ other.
- Type of technology use investigated - Internet, smartphone, gaming, social media, multiple or other.

Articles which used a university student population, investigated psychological well-being and measured any type of technology use were included (*n* = 62) and 825 articles were excluded at this point. The current research applies the dual continuum model of mental health and therefore, at this stage in the selection process, it was important to distinguish between literature which used measures of the clinical indicators of mental health difficulties, for example anxiety, depression or psychological distress, to make inferences about psychological well-being and that which used a measure psychological well-being specifically that was independent of mental health.

The current search sought to identify evidence of the association between digital use and student well-being. Therefore, the remaining articles were further filtered to only include articles which used a specific measure of psychological well-being (*n* = 9). A specific measure of psychological well-being was defined as a measure which was designed to measure the construct of psychological well-being, such as the WEMWBS or Ryff Scales of Psychological Well-being. To be eligible for inclusion measures could not include measures of constructs which are closely related to but separate from psychological well-being, such as self-esteem or anxiety. See Figure 2 for PRISMA diagram of results.

Included research was conducted in China, Germany, Israel, Palestine, Turkey and USA with 3,200 university student participants in total. See Appendix B for further information on the articles. The final nine articles were read in full and their findings will now be summarised in relation to the systematic search question.

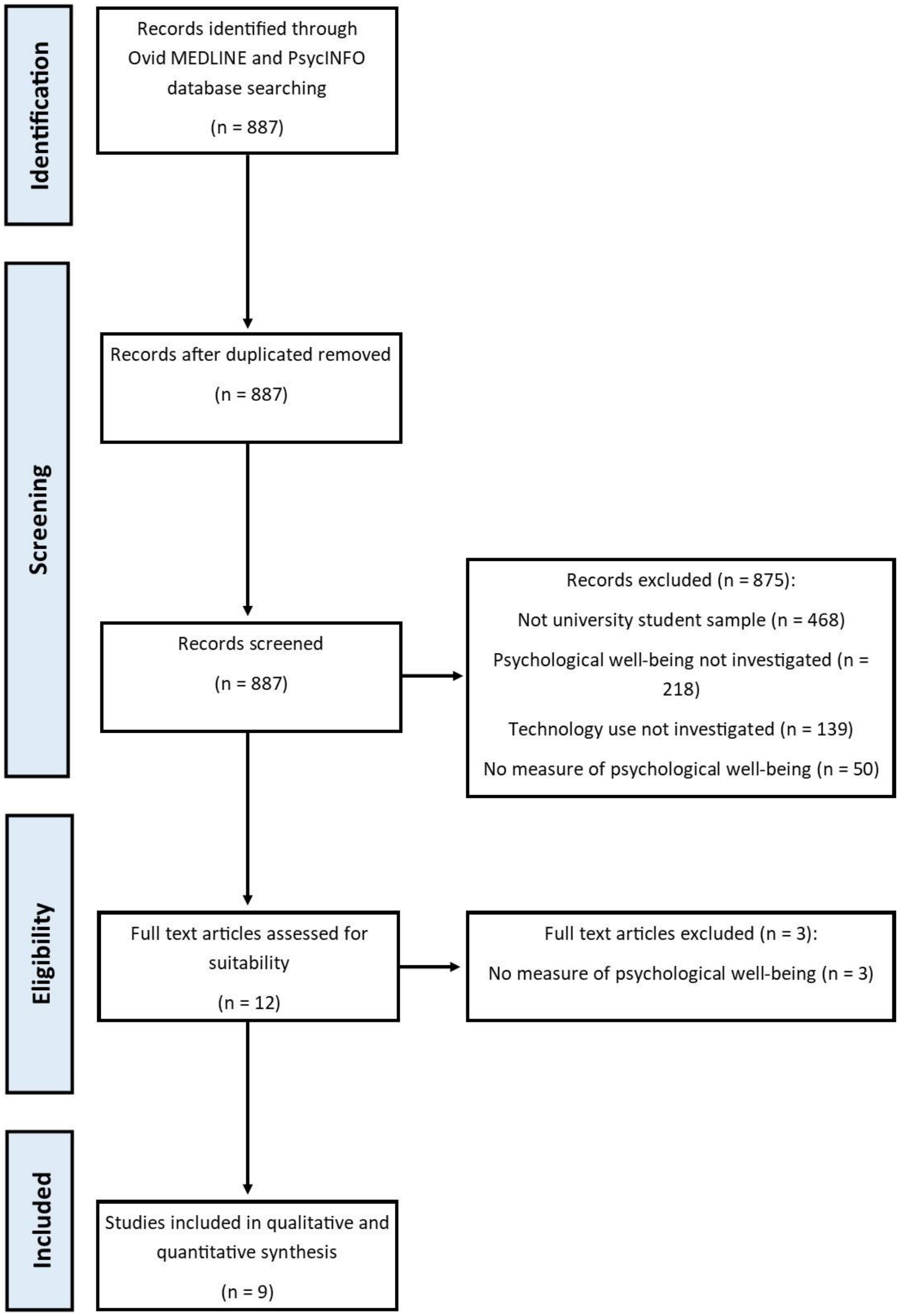

Figure 2 - *PRISMA diagram of systematic search strategy*

How is psychological well-being specifically associated with digital technology use in university students?

In the articles reviewed, psychological well-being was negatively associated with internet addiction (Çardak, 2013; Ouyang, Wang, & Yu, 2017), problematic internet use (Odaci & Çikrikçi, 2014), social media use and amount of digital communication (Sacco, 2018), Facebook use (Sultan, 2019; Turel, Poppa, & Gil-Or, 2018) and preference for online social interaction (Ye & Lin, 2015). The results from these studies suggest that the more problematic, intense and frequent university students' use of digital technology is the greater the negative impact on psychological well-being will be. This fits with the narrative already outlined in the research into the negative association between mental health and problematic digital use.

Internet use was also found to have a negative impact on social, educational and psychological aspects of students' lives. A strong correlation was found between students holding opinions about the negative impact of internet use and having lower psychological well-being (Rayan et al., 2017). Consistent with much of the research in this area, the research identified here tends to focus on and measure problematic or addictive levels of technology use. This focus on problematic use may have made it more likely that research identified negative relationships between digital technology use and psychological well-being as problematic use is, in part, measured by the presence of negative psychological experiences.

Positive associations between digital technology use and psychological well-being were also found. Rayan et al., (2017) found that university students identified educational and social benefits from internet use. Mean scores for the advantages of internet use were higher than that of the disadvantages; suggesting that this sample of university students thought that the advantages of internet use outweigh the disadvantages. This would make sense when considering why people continue to use digital technology, despite it having negative effects on their well-being.

What factors influence the relationship between university student psychological well-being and digital technology use?

The research reviewed suggests that there is a relationship between digital technology use and psychological well-being in students. The specific factors of well-being which were identified as being important to this relationship will now be discussed.

Which factors related to well-being influence the relationship between psychological well-being and digital technology use in university students?

Social support appears to be one of the most important factors of well-being that is associated with digital technology use. Intense users of the internet have been shown to report higher levels of online support. Although they also reported lower levels of peer and family support in real life (Ouyang et al., 2017). Self-esteem has also been shown to mediate the relationship between psychological well-being and digital technology use. Ouyang et al. (2017) found that more intense internet users reported lower levels of perceived social support and psychological well-being in a sample of male undergraduates in China. Self-esteem was found to be a partial mediator between online or perceived (real-life) social support, whereby higher levels of social support contributed to higher levels of self-esteem and therefore increased psychological well-being. This relationship was true for both online and real-life social support, highlighting the potentially positive impact of online social support for self-esteem and psychological well-being.

The quality of social interactions may also impact on digital technology use and psychological well-being. Sacco (2018) found that increased psychological well-being on one day predicted higher quality social interactions the next day in American university students. Rumination moderated the relationship between quality of social interaction and depressive cognitions. This suggests that perceptions of online social interactions and rumination influence the relationship between digital technology use and psychological well-being in university students.

Loneliness and locus of control also play a role in the way digital technology use and psychological well-being are associated. Ye & Lin, (2015) found that Chinese undergraduate students with an external locus of control were more likely to prefer online interactions and have higher levels of loneliness. Psychological well-being and loneliness had a mediating effect on the relationship between locus of control and preference for online interaction in this research. These results suggest that locus of control and loneliness influence the relationship between digital technology use and psychological well-being.

It is unclear whether those who have less social support in real life use the internet more for social support or whether higher use of the internet for social support has a negative impact on this support in real life. The use of social media for social grooming, whereby interactions serve as signals to strengthen social relationships, has also been shown to significantly increase the positive emotional outcomes of social media use (Suphan & Mierzejewska, 2016). This research suggests that digital technology use and social support are intrinsically linked for university students and that this relationship also impacts on their psychological well-being

What other factors influence the relationship between psychological well-being and digital technology use in university students?

Several factors which would not be considered a part of psychological well-being were also identified as being relevant to the relationship between psychological well-being and digital technology use. Çardak (2013) found that diminished impulse control, social comfort and distraction accounted for 47% of the variance in the psychological well-being of a Turkish undergraduate student population. This research suggests that there may be specific behaviours or psychological states which influence the relationship between digital technology use and psychological well-being in university students.

Attachment style has been shown to influence the relationship between digital technology use and psychological well-being. Problematic internet use was significantly negatively correlated with dismissing and preoccupied attachment styles in a sample of Turkish university students (Odaci & Çikrikçi, 2014). In addition, those with a secure attachment style were shown to have lower levels of problematic internet use. These findings suggest that the ways in which we relate to others and conceptualise relationships impacts on the relationship between digital technology use and psychological well-being.

Turel et al., (2018) found that neuroticism was associated with a stronger negative relationship between social networking site addiction symptoms and psychological well-being in female Israeli university students. This relationship was not present for men. These results suggest that personality traits interact with gender to influence the relationship between digital technology use and psychological well-being.

Many of the factors identified as influencing the relationship between psychological well-being and digital technology use overlap with those outlined in earlier research set out in this introduction. Other factors, such as neuroticism and attachment style, had not previously been outlined as they are not specifically factors of well-being. This highlights the range of the factors which may influence and the complexities of the relationship between psychological well-being and digital technology use in students.

It is important to note that self-report measures of technology use and psychological well-being were used in most of the research identified. The use of digital technology is an integral part of university student life and it is unlikely that self-report measures can capture the full extent to which they are used. Similarly, self-report measures of psychological well-being are limited in their ability to capture the complexities of and fluctuations in a person's psychological well-being. Whilst subjective measurement tools have limitations, it is acknowledged that they are the most practical tools to collect large sets of data.

Summary of systematic search

In summary, the literature identified in the systematic search found that digital technology use and psychological well-being are associated in university students. See Table 1 for a summary of the relationship between digital technology use and psychological well-being in each article.

Table 1 - Summary of the findings of literature reviewed in systematic search

Article	*Relationship between digital technology use and psychological well-being*
(Çardak, 2013)	Significant negative correlation between internet addiction and psychological well-being.
Odaci (2014)	Significant negative correlation between pathological internet use and psychological well-being. Psychological well-being found to be a significant negative predictor of pathological internet use.
Ouyang et al. (2017)	Significantly lower well-being in those with intense internet use. Self-esteem found to partially mediate the relationship between support and psychological well-being.
Rayan et al. (2017)	Internet use has a positive and negative impact on educational, social and psychological aspects of students. Advantages include updating themselves, help with studying, problem solving. Disadvantages include negative impact on academic work and family relationships
Sacco (2018)	Moderate to strong positive correlation between perceived quality of online social interactions and well-being. Lower well-being on one day predicted less enjoyment of social media use on the next day.
Sultan (2019)	Significant negative correlation between overuse of social media and psychological well-being.
Suphan et al. (2016)	Using social media for social grooming significantly increases the positive emotional outcomes of social media use and well-being.
Turel et al. (2018)	High levels of social media addiction related to lower levels of psychological well-being. Higher levels of neuroticism associated with a stronger negative relationship between social media addiction and psychological well-being.
Ye & Lin (2015)	Negative relationship between preference for online interaction and psychological well-being.

The relationship between digital technology use and well-being was most commonly a negative, whereby higher levels of problematic digital technology use were associated with poorer psychological well-being. Therefore, it is hypothesised that there will be a negative relationship between digital technology use and well-being in the current research.

Most of the research has focused on a small number of variables which moderate or mediate the relationship between psychological well-being and digital technology use and all were conducted with non-UK university samples. As such, the overall picture of how the complexities of these relationships work in the UK student population is unclear. This research aims to provide further insight into the factors which influence and how they influence the relationship between digital technology use and psychological well-being in university students.

Summary of the current research

The importance of university student well-being and the link between well-being, mental health and the use of digital technology in this population have been discussed. The evidence reviewed outlines the common factors which are associated with well-being and digital use in university students. There is currently little evidence of the ways in which each of these factors interact and are associated with digital technology use in the UK student population and which does not focus on mental health over well-being. Therefore, the current research seeks to better understand the relationship between digital use and the factors highlighted as being associated with well-being in a UK university student population.

Method

Methodology

Research Philosophy

The current research is conducted from a realist ontological stance which assumes the existence of an external, stable reality independent of subjective opinion (Audi, 2011). A positivist epistemological position was adopted, which holds that knowledge is an observable phenomenon that can be tested via empirical research methods (Crotty, 1998). As such, the current research assumes that the concepts being investigated, such as resilience and psychological distress, are a part of a shared reality and can be measured objectively, regardless of subjective experience. In line with this, a quantitative design was employed and data was gathered via the use of validated tools and measures of well-being and digital technology use.

Research design

A cross-sectional survey design was employed. Participants were asked to complete an online survey, which was estimated to take 25-30 minutes to complete. The survey was created using OnlineSurvey (formally Bristol Online Survey). This method of data collection was chosen because online data collection and cross-sectional designs lend themselves to the collection of information on range of factors for a large number of participants. This design is also in line with the research philosophy as it assumes that the variables of interest are objectively measurable via validated tools.

It is acknowledged that the main limitation of the cross-sectional design is that it only provides data for one time point. Thus, making it is impossible to identify causal relationships or changes across time (Rothman, 2008). A longitudinal design would overcome these difficulties. However, this design was not chosen due to potential difficulties with participant retention and collection of follow-up data while retaining anonymity. In addition, due to resource and time constraints a longitudinal design was not feasible for the current research.

A further limitation is that self-report measures, particularly for variables such as sleep or drug and alcohol use, are likely to be less reliable and valid due to a lack of objectivity. Standardised scales with good psychometric properties were used throughout to ensure that data collected was as reliable and valid as can reasonably be expected.

Population and Sample

Opportunistic sampling, whereby the sample is obtained by asking those from the target population to participate, was used to recruit university students from across the University of Leeds. Opportunistic sampling may introduce self-selection bias and reduce how representative the participants are of the population (Bethlehem, 2010). While random sampling would be a more robust method of selection, it was not possible to randomly select students to participate due to data protection legislation. The University of Leeds does not have permission from its students to use their data to contact them directly for research purposes. However, the recruitment strategy ensured that the online survey was advertised across the University of Leeds campus and range of faculties. The demographics of the sample and general student population were compared to assess how representative the current sample is.

Inclusion / exclusion criteria

Inclusion and exclusion criteria were used to ensure that data was only collected from the target population.

Inclusion:

Those eligible to participate were students registered on an undergraduate or postgraduate programme at the University of Leeds. Both taught and research students were eligible. To ensure that recruitment was open to the majority of University of Leeds students, this also included those who were between programmes of study, e.g. summer months between completing a BSc and beginning an MSc, and those completing a short period of study at the University of Leeds, e.g. ERASMUS (European Community Action Scheme for the Mobility of University Students) programme students.

Exclusion:

Those who were not currently enrolled on an undergraduate or postgraduate programme at the University of Leeds were excluded. In addition, those who were completing study programmes other than undergraduate and postgraduate programmes at the University of Leeds were excluded as such programmes tend to draw from different populations than that of the undergraduate and postgraduate programmes (e.g. foundation degrees or higher education summer school programmes). Students who were studying undergraduate or postgraduate programmes at universities other than the University of Leeds were also excluded.

Measures

The measures used in the online survey and rationale for using each measure will now be outlined. The selection of these measures was informed by the literature around digital technology use and university student well-being and mental health outlined in the introduction of this document and a review of the psychometric properties of available scales. As a guiding principle, shorter scales were used where possible with the aim of making the length of the OnlineSurvey more acceptable to participants. See Table 2 for an overview of the measures selected.

Selecting measures of well-being

Psychological well-being

The construct of psychological well-being is defined in the current research as being distinct from other related constructs, such as mental health or physical health, as posited by the dual continuum model of mental health (Tudor, 2013). Therefore, it was necessary to measure psychological well-being as a variable in its own right.

The Warwick-Edinburgh Mental Wellbeing Scale, WEMWBS (Warwick, 2006), was developed by a panel of experts following a review of existing mental well-being measures. The WEMWBS is widely used in research and is validated for use with people from different cultural backgrounds, geographical locations and settings (Stewart-Brown et al., 2011). It has been shown to have good internal consistency (Cronbach's alpha = .98 in a student sample), good content validity and high test-retest reliability (Tennant et al., 2007). In addition, results have been shown to be normally distributed in the general population and therefore the WEMWBS is appropriate for measuring psychological well-being in population samples.

The development and validation of the UK WEMWBS was conducted with a student and representative population sample (Tennant et al., 2007). The sample was similar to that used in the current research, undergraduate and postgraduate students of two large British universities (Warwick and Edinburgh), providing further evidence that the WEMWEBS was appropriate for use in the current research.

In summary, the WEMWBS was chosen as the measure of psychological well-being for this research due to its good psychometric properties, wide use in research and validation for use with a student sample. The full 14-item scale was chosen over the 7-item scale as it provides a fuller picture of mental well-being and because the majority of research around psychometric properties refers to the 14-item scale.

Mental health and psychological distress

In line with the dual continuum model mental health was measured separately from psychological well-being. As the research aim was to investigate the relationship between well-being and digital technology use a broad measure of mental health was required.

The Clinical Outcomes in Routine Evaluation 10, CORE-10 (Barkham et al., 2012), is a screening tool for psychological distress. The items cover depression, anxiety, trauma, functioning and physical problems. It is used widely in both research and practice. It has been shown to have good internal reliability (Cronbach's alpha = .90) and is both feasible and acceptable to its users (Barkham et al., 2013).

Longer versions of the CORE measures, such as the CORE-OM (Evans et al., 2000), were not selected as some of the constructs measured overlap with those of the WEMWBS e.g. generic mental well-being. The CORE-10 was selected over measures of specific mental health conditions, such as the PHQ-9 (Kroenke, Spitzer, & Williams, 2001) or GAD-7 (Spitzer, Kroenke, Williams, & Löwe, 2006), as it provides a broader picture of psychological distress and mental health. In addition, the CORE-10 allows for an appropriate level of measurement of psychological distress with fewer items than if separate measures for each mental health condition were used. Due to its brevity the CORE-10 does not provide an in-depth assessment of risk, nor does it provide a measure of historical mental health difficulties or trauma. However, this level of detail was not deemed necessary for the current research, therefore the CORE-10 was selected.

Stress

University students are known to experience stress in response to academic pressure (Abouserie, 1994), finances (Andrews & Wilding, 2004) and transition to university (Dyson & Renk, 2006). As increased stress has also been linked to problematic digital technology use (Maier, Laumer, Eckhardt, & Weitzel, 2012; Samaha & Hawi, 2016; Wang et al., 2015) a measure of stress was included.

The Perceived Stress Scale (Cohen, Kamarck, & Mermelstein, 1983) was the only widely used measure of perceived stress identified in the literature. It has been shown to have good reliability (Cronbach's alpha = .89) and validity for use with university student populations (Roberti, Harrington, & Storch, 2006). The 10-item version was chosen over the 14-item version as it has been found to have superior psychometric properties, with good internal consistency (Lee, 2012) and this is in line with efforts to be conservative with the number of items on the online survey.

Resilience

Resilience is considered a key skill for university students to develop (Dickinson & Dickinson, 2015; Walker et al., 2006) and is associated with better well-being (Ryff & Singer, 2003). Resilience has been associated with psychological well-being and digital technology use, although the relationship between resilience is unclear (Mguni et al., 2012). As such, a measure of resilience was included.

In a methodological review of the quality and psychometric properties of nineteen resilience scales by Windle, Bennett, & Noyes, (2011) the Brief Resilience Scale (Smith et al., 2008) was rated as being high quality and one of the top three scales based on psychometric properties and has been shown to have good internal consistency, with Cronbach's alpha ranging from .80 to .91 (Smith et al., 2008). The scale is comprised of 6-items, allowing for valid and reliable measure of resilience with a small number of items. Therefore, the Brief Resilience Scale was selected.

Social Support

Social support has been shown to be associated with better well-being and successful transition to university (Demaray et al., 2005; Mahzan Awang et al., 2014; Reifman & Dunkel-Schetter, 1990; Stallman et al., 2018). Digital technology use has also been shown to have both positive and negative effects on social support (Burke, Marlow, & Lento, 2010; Y. Chen & Lever, 2005). As such a measure of social support was included.

The Multidimensional Scale of Perceived Social Support, MSPSS (Canty-Mitchell & Zimet, 2000), is widely used in research. It has been shown to have strong factorial validity and good internal validity across populations (Zimet, Powell, Farley, Werkman, & Berkoff, 1990). The MSPSS has also been shown to be reliable (Cronbach's alpha = .91) for use with a university student population (Dahlem, Zimet, & Walker, 1991). In addition, the MSPSS yeilds 3 subscales, family, friend and significant other support allowing for more specific analysis of the impact of perceived social support, which is appropriate for this research due to the complex relationship between social support, well-being and digital technology use. Therefore, the MSPSS was selected.

Mindfulness

Mindfulness has been shown to increase psychological well-being in university students (Hassed et al., 2009) and has also been associated with less problematic digital technology use in university students (İskender & Akin, 2011; Woodlief, 2017). Therefore, a measure of mindfulness was included.

Due to the large opportunistic sample, it was necessary to use a measure of mindfulness which focused on mindful attention and which did not require/ assume prior experience of practicing mindfulness. In an assessment of mindfulness self-report measures Bergomi, Tschacher, & Kupper, (2013) concluded that the Mindfulness Attention Awareness Scale (Brown & Ryan, 2003) was an appropriate measure of attention and acceptance of mindfulness in people who may not have previous experience of meditation. It has been shown to have good reliability (Cronbach's alpha = .80) and validity for use with normative and clinical populations (Brown & Ryan, 2003; Brown, West, Loverich, & Biegel, 2011) and to be a valid measure of the construct of mindfulness in university student populations (Mackillop & Anderson, 2007; Ruiz, Suárez-Falcón, & Riaño-Hernández, 2016).

Other measures of mindfulness reviewed by Bergomi et al. (2013) were not suitable for the current research. The Freiburg Mindfulness Inventory (Buchheld, Grossman, & Walach, 2001) and Toronto Mindfulness Scale (Lau et al., 2006) were not suitable as they assume previous experience of meditation. The Philadelphia Mindfulness Scale (Cardaciotto, Herbert, Forman, Moitra, & Farrow, 2008) was not recommended for use due its narrow scope. The Cognitive and Affective Mindfulness Scale-Revised (Feldman, Hayes, Kumar, Greeson, & Laurenceau, 2007) and Southampton Mindfulness Questionnaire (Chadwick et al., 2008) are more suitable for use with clinical populations. Finally, the

Kentucky Inventory of Mindfulness Scale (Baer, Smith, & Allen, 2004) and Five Facet Mindfulness Questionnaire (Baer, Smith, Hopkins, Krietemeyer, & Toney, 2006) were not suitable due to the high number of items. Therefore, the Mindfulness Attention Awareness Scale was selected.

Basic Psychological Need Satisfaction

Self-Determination Theory (Deci & Ryan, 2000) suggests that our behaviour is motivated by satisfying our basic needs for autonomy, competency and relatedness (Johnston & Finney, 2010). Satisfaction of basic psychological needs is associated with higher well-being and digital technology use in university students (Cordeiro et al., 2016; Hsu et al., 2009; Sheldon & Bettencourt, 2002). Therefore, it was necessary to measure basic psychological need satisfaction.

The Basic Psychological Need Satisfaction and Frustration in General Scale (Chen et al., 2015) was developed to measure satisfaction and frustration with the three basic psychological needs associated with self-determination. The scale has been shown to have high reliability (Cronbach’s alphas range from .81 to .86) and validity in a university student population (Li et al., 2019; Liga et al., 2020; Nishimura & Suzuki, 2016). No other measures of basic need satisfaction and frustration were available therefore the Basic Psychological Need Satisfaction and Frustration in General Scale was selected.

The Basic Psychological Need Satisfaction and Frustration in General Scale yields two subscales, the satisfaction sub-scale and the frustration subscale. Only the items which make up the satisfaction sub-scale were used in analysis. The satisfaction and frustration sub-scales have been shown to be significantly negatively correlated with each other (Chen, Vansteenkiste, Beyers, Liesbet Boone, et al., 2015; Del Valle, Matos, Díaz, Victoria Pérez, & Vergara, 2018) so it was deemed unnecessary to use both sub-scales in analysis. In addition, basic psychological need satisfaction has been found to predict well-being and basic psychological need frustration has been found to predict ill-being (Chen, Vansteenkiste, Beyers, Liesbet Boone, et al., 2015). Therefore, the use of the satisfaction sub-scale was deemed most appropriate for the current research's aim to focus on well-being over clinical or problem populations.

Physical Health

Physical health is an integral part of the overall picture of a person's well-being (Penedo & Dahn, 2005; Scully et al., 1998) and digital technology use is associated with poorer physical health (Kelley & Gruber, 2013; Zheng et al., 2016). As such, a specific physical health measure was required to build a full picture of well-being.

A review of 99 self-report well-being measures (Linton, Dieppe, & Medina-Lara, 2016) was used to identify potential measures of physical health. The majority of measures that included a physical health dimension were mainly focused on global mental and social well-being. Such measures were discounted due to the overlap with psychological well-being and mental health measures that had already been selected.

The EuroQol – 5 Dimension – 5 Level (EQ-5D-5L), (The EuroQol Group, 1990) and the Short Form Health Survey (SF-12), (Ware, Kosinski, & Keller, 1996) were identified as being appropriate for use. Both provide scales for physical health, mental health and overall health. The EQ-5D-5L was selected over the SF-12 as it is free to use in research.

Limitations of the EQ-5D-5L are acknowledged. The majority of research into the psychometric properties of the EQ-5D-5L have used participants with chronic health conditions, such as people who have suffered a stroke (Chen et al., 2016; Golicki et al., 2015), or have HIV/AIDS (Tran, Ohinmaa, & Nguyen, 2012). However, it has been shown to have good validity, responsiveness and clinical relevance (Macran, Weatherly, & Kind, 2003).

The EQ-5D-5L was developed from the EQ-5D due to issues with ceiling effects in the in the EQ-5D. Janssen et al., (2013) concluded that the EQ-5D-5L has reduced ceiling effects and improved discriminatry power. The EQ-5D-5L has also been shown to have superior inter~~b~~observer reliability (ICC = .57) and test-retest relability (ICC = .69) than than EQ-5D, with ICCs of .49 and .52 respectively (M. Janssen, Birnie, Haagsma, & Bonsel, 2008). However, it is likely that ceiling effects may impact on results of the current resaerch due to the sample being predominantly young and largely free of chronic illnesses. Despite these limitations it was the only appropriate scale identified that did not overlap significantly with other measures and that was free to use in research. Therefore, the EQ-5D-5L was selected for use.

Sleep Quality

Good sleep quality is associated with better psychological well-being, mental health and physical health (Taylor et al., 2011, 2013) and less problematic digital technology use (Kim, Kim, Park, Kim, & Choi, 2018; Thomée & Härenstam, 2011). Therefore, sleep quality was measured in the current research. It is accepted that subjective measures of sleep are much less valid than objective measures. However, due to the scope of the current research validated self-report measures were the only feasible method of measuring sleep.

The Pittsburgh Sleep Quality Index, PSQI (Buysse, Reynolds, Monk, Berman, & Kupfer, 1989), is widely used in research. It has been shown to have high sensitivity and specificity and acceptable levels of reliability (Cronbach’s alpha = .83) when used with non-clinical populations (Buysse et al., 1989). Other measures, such as the Leeds Sleep Evaluation Questionnaire (Zisapel & Nir, 2003) and the Medical-Outcomes Sleep Scale (Stewart & Ware, 1992) were considered but were less comprehensive than the PSQI. As sleep is a key construct related to physical health, psychological well-being and digital technology use it was appropriate to use a more comprehensive measure of sleep, thus the PSQI was selected.

Alcohol and Drug Use

Poor psychological well-being and physical health and increased mental health difficulties are associated with increased drug and alcohol use (Richardson, Elliot, & Roberts, 2013). Drug and alcohol use has also been associated with more problematic use of digital technology (Frangos, Frangos, & Sotiropoulos, 2012; Yen, Ko, Yen, Chen, & Chen, 2009) Therefore, drug and alcohol use were measured.

The Alcohol Use Disorders Identification Test Concise, AUDIT-C (Saunders, Aasland, Babor, de la Fuente, & Grant, 1993) and Drug Use Disorders Identification Test Concise, DUDIT-C (Berman, Bergman, Palmstierna, & Schlyter, 2005) are widely used as screening tools for alcohol and drug use. The AUDIT-C has been shown to have good test-retest reliability (ICC = .91) and acceptable levels of validity and the DUDIT-C has been shown to have good reliability (Cronbach's alpha = .80) and acceptable levels of validity (Berman et al., 2005; Jeong et al., 2017).

More comprehensive versions of each measure are available but due to the depth of information needed for the current research and the effort to keep the number of response items to a minimum, the shorter versions were selected.

Other measures identified were not appropriate as they were developed for use with clinical populations and therefore asked questions which implied that a substance dependency was present. For example, the Severity of Alcohol Dependence Scale (Stockwell, Murphy, & Hodgson, 2010) and the Leeds Dependence Questionnaire (Raistrick et al., 1994). The Drug Abuse Screening Test (Skinner, 1982) was considered. It has been shown to have moderate to high levels of validity and reliability and to be appropriate for use in research (Yudko, Lozhkina, & Fouts, 2007). However, the measure comprises of

10 items, which only measure drug use. Therefore, the AUDIT-C and DUDIT-C were selected as they provide an appropriate depth of measurement with relatively few items.

Academic Success

Academic success is a key part of attending university and has been shown to be associated with good well-being (Chow, 2010; Dubuc et al., 2017; El Ansari & Stock, 2010). Digital technology use has also been shown to have both a postiive and negative relationship with academic success (Kirschner & Karpinski, 2010; Lau, 2017; Lepp et al., 2014; Rayan et al., 2017).

It was not possible to measure actual academic attainment via university records due to participant anonymity. As no other standardised measures of academic attainment were available, questions from research by El Ansari & Stock (2010) into the associations between health and well-being in university students and academic performance were adapted for the online survey.

El Ansari & Stock, (2010) asked “How important is it for you to have good grades at university?” and “How do you rate your performance in comparison with your fellow students?”. These were adapted for use in the current research to be “How important is academic success to you?”, in line with more common British phrasing, and “How satisfied are you with your current academic performance?” to reflect the timeframe used in the majority of the other measures in the online survey and to emphasise the satisfaction with performance rather than performance in comparison with peers.

Selecting Measures of digital technology use

There are relatively few validated self-report measures of digital technology use. The measures available are often separated into different types of technology use (e.g. internet use or smartphone use). This type of measurement may be less relevant to young people, who integrate technology and internet use into their everyday lives across a number of platforms. The measures available also tend to focus on the pathological use of digital technology, which indicates an 'addiction'. Whilst the current research is assessing the impact of digital technology use across the spectrum of use it was not within the scope of this research to use objective measures of digital technology use. Therefore, despite their limitations, validated measures were selected.

Internet, gaming, and smartphone use were selected as the three areas to measure as they are widely cited in the literature around digital technology use and well-being. In addition, internet and smartphone use are the most common ways in which we interact with digital technology and pathological gaming disorder is the only type of digital addiction that is currently diagnosable. It is acknowledged that there will be overlap between the measures and that this is not an exhaustive list of ways in which university students use digital technology. However, it was hoped that measuring these three mediums of use would capture the most common uses of digital technology.

Internet Addiction

The Internet Addiction Test, IAT (Young, 1996) is widely used across the world as a measure of internet addiction and was one of the first measures developed to assess internet addiction. It has been shown to have high face validity, good concurrent validity between factors and moderate to good levels of internal consistency, with Cronbach's alphas ranging from .54 to .82 (Widyanto, Griffiths, & Brunsden, 2010; Widyanto & McMurran, 2004), particularly with university students (Frangos et al., 2012). Therefore, it was selected for use.

The wording in the Internet Addiction Test has recently been amended by Turner, Bewick, Bryant, & Summers (2019) to be more representative of current internet use. For example, item 7 in the original IAT asked 'How often do you check your email before something else that you need to do?'. This has been modified to ask 'How often do you check social media (e.g. Facebook, Messenger, WhatsApp, Snapchat, Viber), email online and/ or on your phone before something else you that you need to do?'. The amended version was used in the current research.

Smartphone Addiction

Two measures of smartphone use were identified in the literature, the Smartphone Addiction Scale (Kwon et al., 2013) and the Smartphone Addiction Inventory (Lin et al., 2014). The Smartphone Addiction Scale was developed from the Internet Addiction Scale and has been shown to have good reliability (Cronbach's alpha = .97) and validity in a student sample (Demirci, Orhan, Demirdas, Akpinar, & Sert, 2016). The Smartphone Addiction Inventory has also been shown to have good reliability and validity (Lin et al., 2014) and convergent validity with the Internet Addiction Test (Pavia, Cavani, Di Blasi, & Giordano, 2016).

The Smartphone Addiction Scale yields 6 factors (daily-life disturbance, withdrawal, cyberspace-oriented relationship, tolerance, positive anticipation, and overuse), whereas the Smartphone Addiction Inventory yields 4 factors (functional impairment, withdrawal, compulsive behaviour, and tolerance). As the Smartphone Addiction Scale allows for more specific analysis, across 6 factors, it was selected for use.

Gaming Addiction

The Game Addiction Scale (Lemmens, Valkenburg, & Peter, 2009) was the only validated scale of gaming use identified in the research literature. It has been shown to have good psychometric properties, with high reliability (Cronbach's alpha ranging from .88 to .90) and good validity (Lemmens et al., 2009). The 7-item version was selected use in because it reduces the number of response items whilst maintaining good psychometric properties (Lemmens et al., 2009).

Table 2 - ***Summary of measures used in online survey***

Construct	*Measure*	*Summary of measure*
Psychological well-being	Warwick-Edinburgh Mental Wellbeing Scales (Tennant et al., 2007)	14-item scale measuring general aspects of well-being and psychological functioning in clinical and non-clinical populations
Stress	Perceived Stress Scale (Cohen et al., 1983)	10-item scale measuring perceived stress over the past month
Resilience	Brief Resilience Scale (Smith et al., 2008)	6-item scale measuring resilience
Social support	Multidimensional Scale of Perceived Social Support (Canty-Mitchell & Zimet, 2000)	12-item scale measuring social support across family, friends and significant other domains
Mindfulness	Mindfulness Attention Awareness Scale (Brown & Ryan, 2003)	15-item scale measuring mindfulness awareness
Basic psychological need satisfaction and frustration	Basic Psychological Need Satisfaction and Frustration Scales (B. Chen, Vansteenkiste, Beyers, Boone, et al., 2015)	24-item scale measuring autonomy, competence, and relatedness need satisfaction and frustration
Psychological distress	Clinical Outcomes in Routine Evaluation-10 (Barkham et al., 2012),	10-item scale measuring anxiety, depression, trauma, physical problems and functioning
Physical health	EuroQol – 5 Dimension – 5 Level measure (The EuroQol Group, 1990)	6-item scale measuring physical health across 6 scales; mobility, self-care, usual activities, pain/discomfort, anxiety/depression and overall health
Sleep quality	Pittsburgh Sleep Quality Index (Buysse et al., 1989)	10-item scale measuring sleep quality and disturbances over the past month
Drug use	DUDIT-C (Berman et al., 2005)	4 item scale measuring drug use and problem behaviours
Alcohol use	AUDIT-C (Saunders et al., 1993)	3-item scale measuring alcohol consumption and problem behaviours

Construct	Measure	Summary of measure
Adademic success	Questions adapted from El Ansari & Stock, (2010)	Two questions measuring the importance of and satisfaction with academic success
Internet use	Internet Addiction Test (Young, 1996),	20-item scale measuring the incidence and level of internet and technology dependency
Smartphone use	Smartphone Addiction Scale (Kwon et al., 2013)	33-item scale measuring maladaptive behaviours related to smartphone use
Gaming use	7-item Gaming Addiction Scale (Lemmens et al., 2009)	7-item scale measuring problematic online gaming behaviours

Procedure

Ethical Considerations

Ethical approval was granted by the University of Leeds School of Medicine Research Ethics Committee on 16th May 2019 (see Appendix C for letter of ethical approval).

The main ethical considerations when conducting this research were participants giving informed consent to their data being collected and used for research purposes, participants understanding their right to withdraw from the research and the implications this would have for the data that was already submitted, attending to the well-being of participants in the context of the online survey asking detailed questions about their mental health, well-being, and functioning and ensuring that all data was stored securely

Consent

Informed consent was obtained online prior to completion of the survey. After reading the participant information sheet participants were asked to give informed consent. Participants were asked to consent to taking part in the survey, for anonymised data to be stored, for their data to be used in the current research and use for it to be used in future research. See Appendix D for participant information sheet.

Withdrawal from the study and withdrawal of data

Participants were informed that they could choose to exit the study at any time by closing their browser but that any data already submitted (from previous pages) would be captured by OnlineSurvey. Participants were also made aware that once their data had been submitted, they would be unable to withdraw it from the study as survey responses were downloaded and stored separately from any identifiable information. None of the participants contacted the researcher to withdraw their data.

Well-being of participants

As the online survey asked detailed questions about participants' physical and psychological well-being, it was possible for participants to disclose high levels of distress, poor well-being, and/ or difficulties with physical or mental health. To address this, the webpage at the beginning of and after completing the survey detailed local and national services that offer support for students' mental health and well-being. For example, University of Leeds support services (Counselling service, Mental Health Team), Nightline and Samaritans. See Appendix D for exact survey wording.

Data storage and security

OnlineSurvey was chosen because it can be accessed free of charge via the University of Leeds account and it is a secure service with the necessary encryption and data protection in place. The data collected was held on OnlineSurvey until analysis. The OnlineSurvey survey and data could only be accessed by logging in to a password protected account and access was only granted to the lead researcher (Azaria Khyabani) and the Lead Supervisor (Dr Bridgette Bewick).

Once recruitment was complete, survey responses were downloaded and stored separately from email addresses. Survey data was given a unique identifier, but email addresses were not. This identifier enabled data checks to be made against the original data download should subsequent files be corrupted. Once downloaded, the data was deleted from OnlineSurvey and was stored on the researcher's personal University of Leeds drive (M: Drive). This drive has a high level of encryption, is password protected and only available to the lead researcher (Azaria Khyabani).

Once analysis began, a copy of the data was kept on the University of Leeds N: Drive in a folder which could only be accessed by the lead researcher (Azaria Khyabani) and supervisors (Dr Bridgette Bewick and Dr Tracey Farragher). Email addresses were stored separately from the survey data and the data used for analysis contained no identifiable information (i.e. email addresses could not be subsequently linked back to individual survey responses). Email addresses provided solely for the purposes of receiving the incentives were deleted once participants had been contacted. On completion of this research the anonymised data will be deleted from the lead researcher's M: Drive but will remain on the N:Drive (or equivalent) of the lead supervisor and, where consent was given, will be stored for at least three years after publication for potential use in future related research.

Recruitment

Recruitment advertisements were distributed from June to November 2019. Participants were recruited through several channels. These were:

- Posters and flyers displayed in university of Leeds buildings (Appendix E). The posters gave a brief overview of the research and had both a QR code and tear off URL links to access the participant information sheet, consent form and online survey.

- Emails sent directly to university email addresses of students who had participated in previous research with Dr Bridgette Bewick and consented to being contacted for future research (Appendix F). The email contained a brief overview of the research and a link to the online participant information sheet, consent form, and survey.

- Emails sent out by the University of Leeds Mental Health Team Manager to 175 staff across the University were disseminated to students (Appendix G). These were; Student Support Officers for all university faculties, the Student Counselling and Wellbeing Service staff, Disability Services staff, Chaplaincy staff, Leeds University Union staff, University Accommodation Services staff, International Students Office staff, The Edge (University of Leeds gym) staff, and Leeds Student Medical Practice staff. The email contained a brief overview of the research and a link to the online participant information sheet, consent form, and survey

Incentives

Recruitment was incentivised using a mixture of approaches. The first 100 participants who gave their email address received £5 cash. In addition, all participants who gave their email address were entered into a prize draw to win £20 (3 prizes) or £5 (45 prizes). The incentives totalled £740.

The first 100 participants who provided a contact email address (n=96) were emailed to notify them that they were eligible to receive £5 cash (see Appendix H for chain of emails send to prize winners). Of these, seven of the emails were undeliverable due to the email address provided no longer being active. Participants were offered five dates to collect their £5 cash. A further session was added due to the low rates of collection.

Once the survey was closed three participants were selected at random to win the £20 cash prizes. A further forty-five were selected at random to win the £5 prizes. Due to the COVID-19 pandemic it was not possible to give participants their prize in cash, as stated in the recruitment advertisements. Therefore, they were emailed and offered bank transfers (see Appendix H).

Data Collection

The URL links given to potential participants gave access to the participant information sheet, consent form, and online survey (see Appendix D). If participants clicked "next" from the title page they were taken to the informed consent page. If participants consented to participating, they clicked "next" to begin the survey.

Once participants had completed the survey, they were asked to submit their responses. Participants were thanked for their time and asked to close the webpage to end the survey. The survey was closed on 16th March 2020 as participant numbers were over the minimum requirement of 500 and it was necessary to begin data analysis.

Measures

The rationale for the use of each measure has been outlined above. A brief summary of the standardised measures is provided in Table 1.

Personal characteristics

Personal characteristics of participants were collected as they have been cited in the literature as being related to well-being and/ or use of digital technology in university students. These included demographic variables such as, age, gender and sexuality, information related to socio-economic background such as, deprivation level and highest education level of either parent, and information about academic context, such as school, year of study and programme level (see Appendix I).

Sample Size

Sample size considerations are still a matter of debate and research when using Structural Equation modelling (SEM) approaches. A typical sample size in research where SEM approaches are used is around 200 cases, although this may not be enough data when analysing a more complex model (Kline, 2011). However, others have found sample sizes analysed by SEM ranging from 30 to 450

(Wolf, Harrington, Clark, & Miller, 2013). Due to the complexity of the SEM model the target sample size for this research was set as 500. In 2019-2020 academic year 37,739 students were registered at the University of Leeds (University of Leeds Equality Policy Unit, 2020), and were therefore eligible to participate in the current research. A sample of 500 would represent 1.3% of the target population.

Statistical Analysis

Responses were downloaded from the OnlineSurvey platform into IBM SPSS 26. Data for standardised measures was reformatted to match the original measure for use in analysis e.g. correct scoring, adding cut offs, and calculating total scores. Demographic data was reformatted for use in analysis (e.g. collapsing categories). Postcode at 16 was run through the UK Participation of Local Areas database, POLAR4 (Office for students, 2020), and English, Northern Irish, Scottish and Welsh Index of Multiple Deprivation databases, IMD (Ministry of Housing, 2019; Northern Ireland Statistics and Research Agency, 2017; Scottish Government, 2020; Statistics and Research Wales, 2019), to produce quintiles for both the POLAR4 and IMD. See Appendix I for further information on each variable and how it was used in analysis. Appropriate descriptive statistics were run in IBM SPSS 26, namely number and proportions for categorical variables. Continuous variables were assessed for normality using histograms.

Following appropriate summary analysis of the participants' responses, structural equation modelling was used to investigate the associations between well-being, and digital technology use (Kline, 2015). Structural equation modelling was chosen because it allows theoretical relationships between variables, which are informed by previous literature, to be tested. The multivariate analysis allows for measurement of the relationships between measured variables and latent constructs, which are unobserved variables measured by a number of observed variables. Latent variables were created based on hypothetical assumptions, informed by previous literature, about how the factors being measures were related to each other. Some latent variables remained stable throughout all models. For example, the 'digital use' latent variable was consistently constructed of the measures of internet, smartphone and gaming use. Other latent variables were adjusted to test different hypotheses about which factors most appropriately contributed to each construct. For example, the measures which contributed to the 'mental health' and 'well-being' latent variables changed throughout models to test whether constructs such as resilience or social support were more appropriately conceptualised as being part of a person's mental health or psychological well-being.

In addition, structural equation modelling produces significance estimates for each model, which allow for the assessment of the fit of the model for the data ($p<0.05$ was deemed as statistically significant) and comparisons of fit between models. The nature of these associations was informed by the research literature, with each model testing different assumptions about the relationships between well-being and digital technology use. Structural equation modelling was run in IBM AMOS 26 (Byrne, 2010).

Proposed models

Model 1.0 – Basic psychological need satisfaction as moderator

Self-determination theory informs the current research, as such model 1.0 hypothesised that basic psychological need satisfaction moderates the relationship between the mental health and well-being latent variable and the digital technology use variable. Whereby, mental health and well-being impact on a person's basic psychological need satisfaction and this in turn, impacts on their use of digital technology. See Figure 3 for picture of model 1.0.

In model 1.0 mental health and well-being is a latent variable which is composed of psychological well-being, physical health, mental health, and academic success. Psychological well-being is a latent variable composed of psychological well-being, stress, resilience, mindfulness and social support. Physical health is a latent variable composed of subjective health, sleep quality, drug use and alcohol use. Mental health is measured by psychological distress. Academic success is a latent variable composed of importance of and satisfaction with academic success. Digital technology use is a latent variable composed of measures of problematic internet, smartphone, and gaming use. Digital technology use is hypothesised to have a relationship with mental health and psychological well-being.

Personal characteristic variables are also hypothesised to be associated with the mental health and well-being variable and the digital technology use variable. Personal characteristics were age, gender, ethnicity, domicile, sexuality, disability, and a socio-economic status latent variable comprised of highest level of parent education, POLAR4 and IMD quintile data.

Error terms were required on each of the observed and latent variables as it is assumed that they do not completely capture all that a variable is trying to measure. Therefore, there will be an element of error in the completeness of the measure. The error terms were applied to all models and are depicted as ovals in figures of the models.

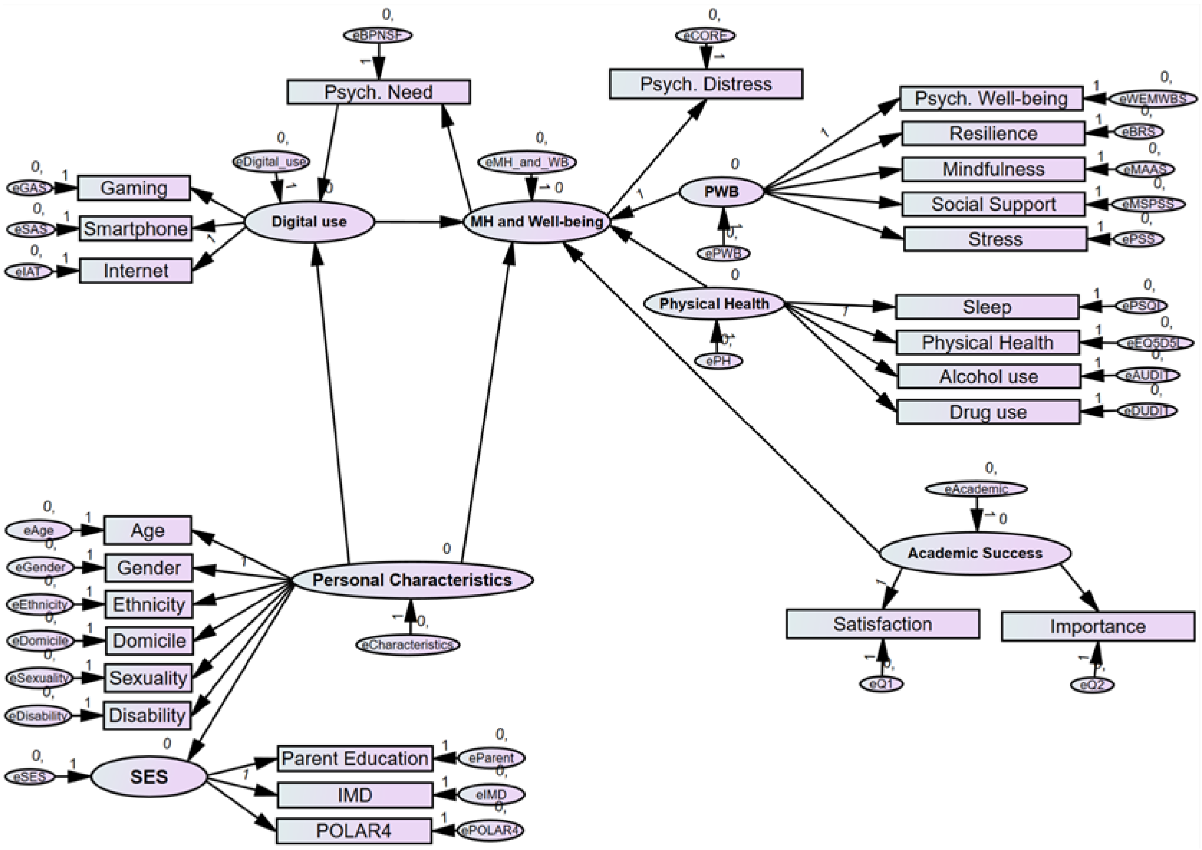

Figure 3 – *Overview of model 1.0*

Model 1.1 – Basic psychological need satisfaction as moderator

Model 1.1 held the same structure as 1.0, with the addition of an academic context latent variable which feeds into the personal characteristics variable. See Figure 4 for picture of model 1.1.

Academic context is composed of school, programme level, year, and type (full or part time) of study. This variable was not added initially as it was hypothesised that it may be adding too many contextual variables. All further models were adjusted to include/ exclude the academic context variable dependent on whether model 1.0 or 1.1 was a better fit for the data. Given the number of variables, Model 1.0 was created as the basic model and was tested for goodness of fit and stability of results in comparison to model 1.1.

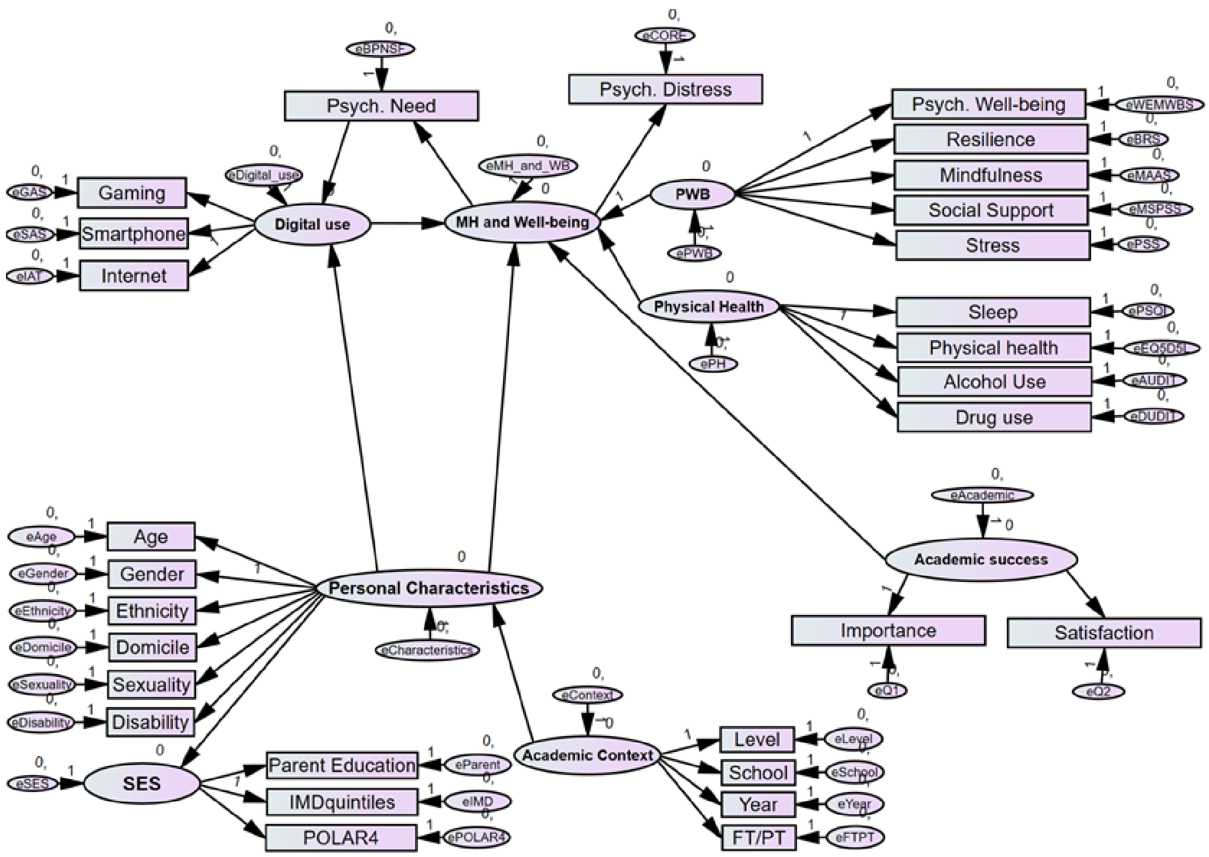

Figure 4 - *Overview of model 1.1*

Model 2.0 – Basic psychological need satisfaction and social support as moderators

Model 2.0 hypothesised that basic psychological need satisfaction and social support moderate the relationship between mental health and well-being and digital technology use (see Figure 5 for picture of model 2.0). Social support is often cited as an important factor in the relationship between well-being and digital technology use (Burke et al., 2010; Chen & Lever, 2005; Lup et al., 2015; Ouyang et al., 2017; Suphan & Mierzejewska, 2016). As such, social support is hypothesised to moderate this relationship whereby, mental health and well-being impacts on a person's social support which in turn impacts on their use of digital technology. Basic psychological need satisfaction remained as a moderator in this model.

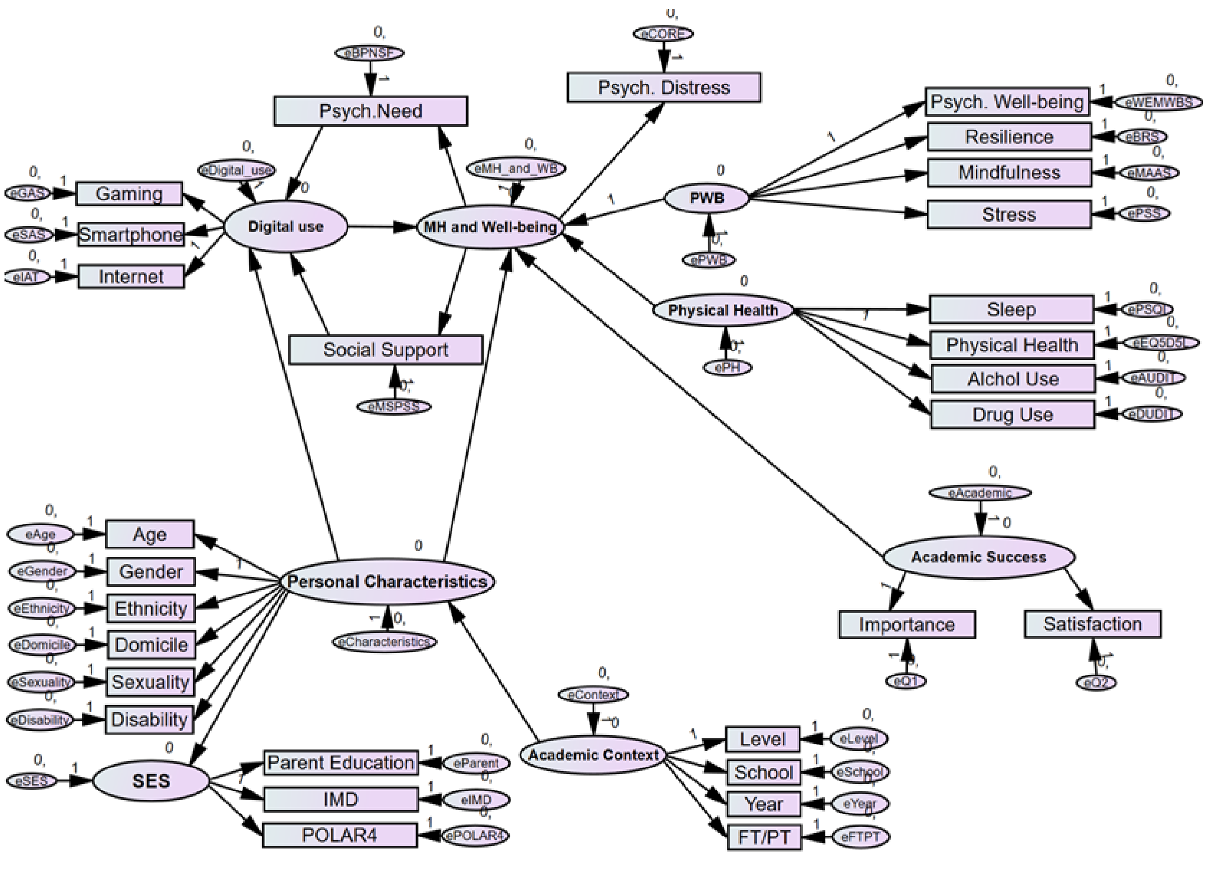

Figure 5 - *Overview of model 2.0*

Model 2.1 – Basic psychological need satisfaction and social support as moderators

Model 2.1 was developed because, as previously outlined, the direction in which the relationship between social support, well-being and digital technology use works is unclear. This model broadly held the same structure as 2.0, basic psychological need satisfaction remained as a moderator (see Figure 6 for picture of model 2.1). However, the direction of the relationship between mental health and well-being, social support and digital technology use was reversed. Whereby digital technology use impacts on a person's social support, which in turn has an impact on their mental health and well-being.

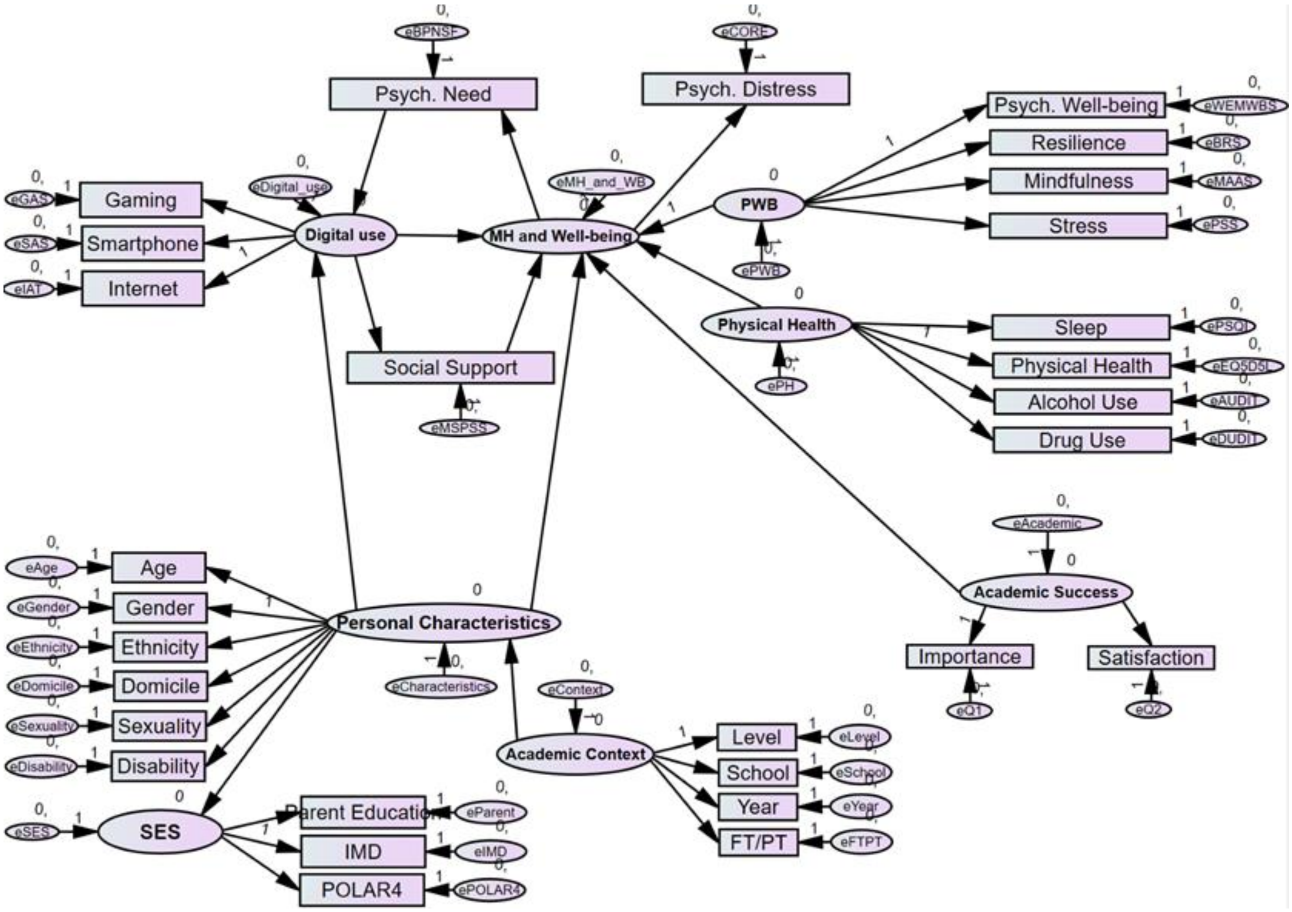

Figure 6 - *Overview of model 2.1*

Model 3.0 – Basic psychological need satisfaction and psychological distress as moderators

Model 3.0 hypothesised that basic psychological need satisfaction and mental health moderate the relationship between well-being and digital technology use. See Figure 7 for picture of model 3.0.

This model was developed because the bulk of the research into the relationship between digital technology use and well-being has focused on mental health and clinical populations. As such, this model hypothesised that a person's well-being impacts on their mental health, which in turn impacts on their digital technology use. This hypothesis sits within the dual continuum model of mental health. The direction of the relationship was determined by which of models 2.0 and 2.1 fit the data best.

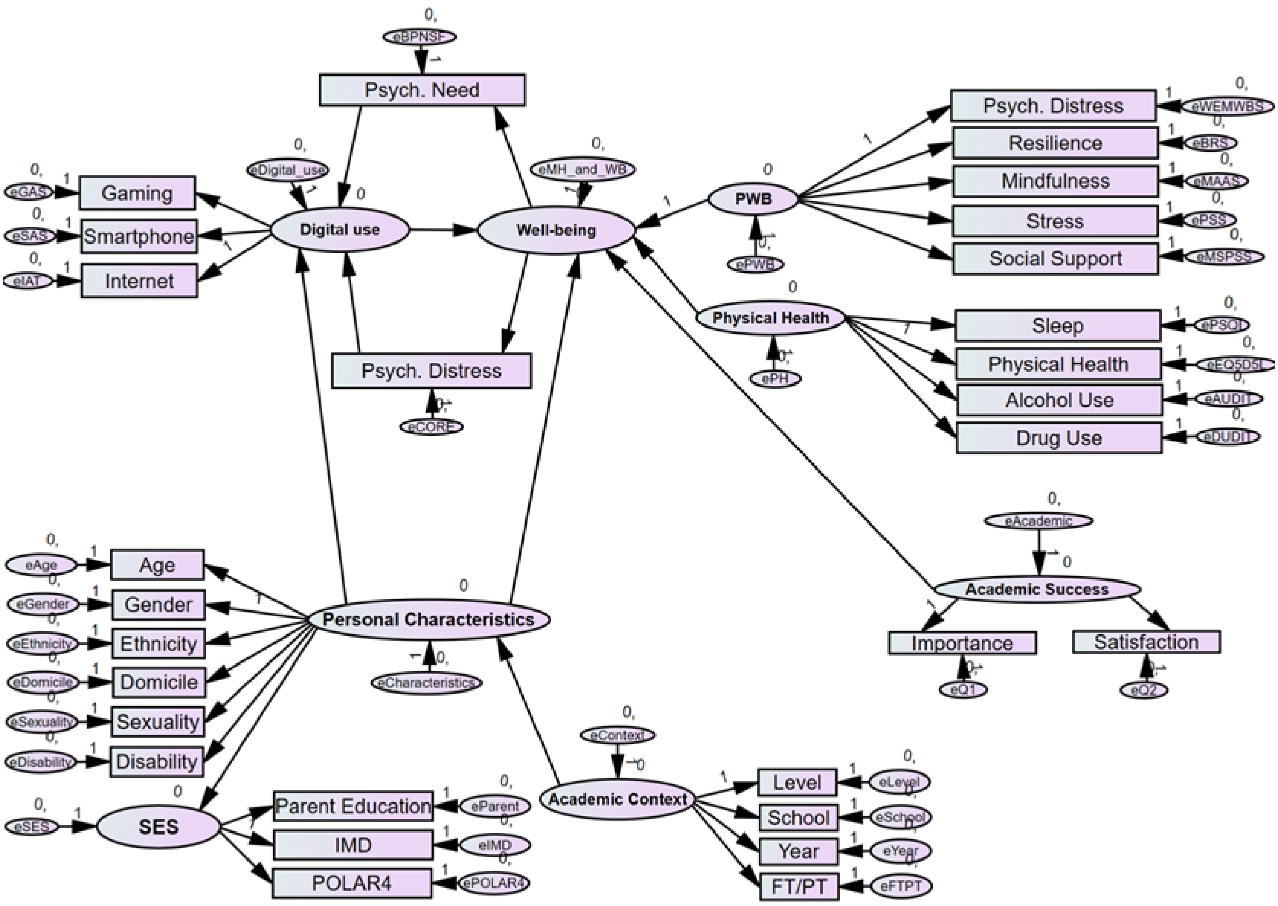

Figure 7 - *Overview of model 3.0*

Model 4.0 – Basic psychological need satisfaction, psychological distress, and social support as moderators

Model 4.0 was a combination of models 2.0 and 3.0. See Figure 8 for picture of model 4.0. It hypothesised that basic psychological need satisfaction, social support and mental health moderate the relationship between well-being and digital technology use. Both social support and mental health (measured by psychological distress) are commonly identified in the literature as being associated with well-being and digital technology use. Therefore, this model hypothesised that social support and mental health are the key factors in the relationship between well-being and digital technology use. The direction of the relationship was determined by which of models 2.0 and 2.1 fit best.

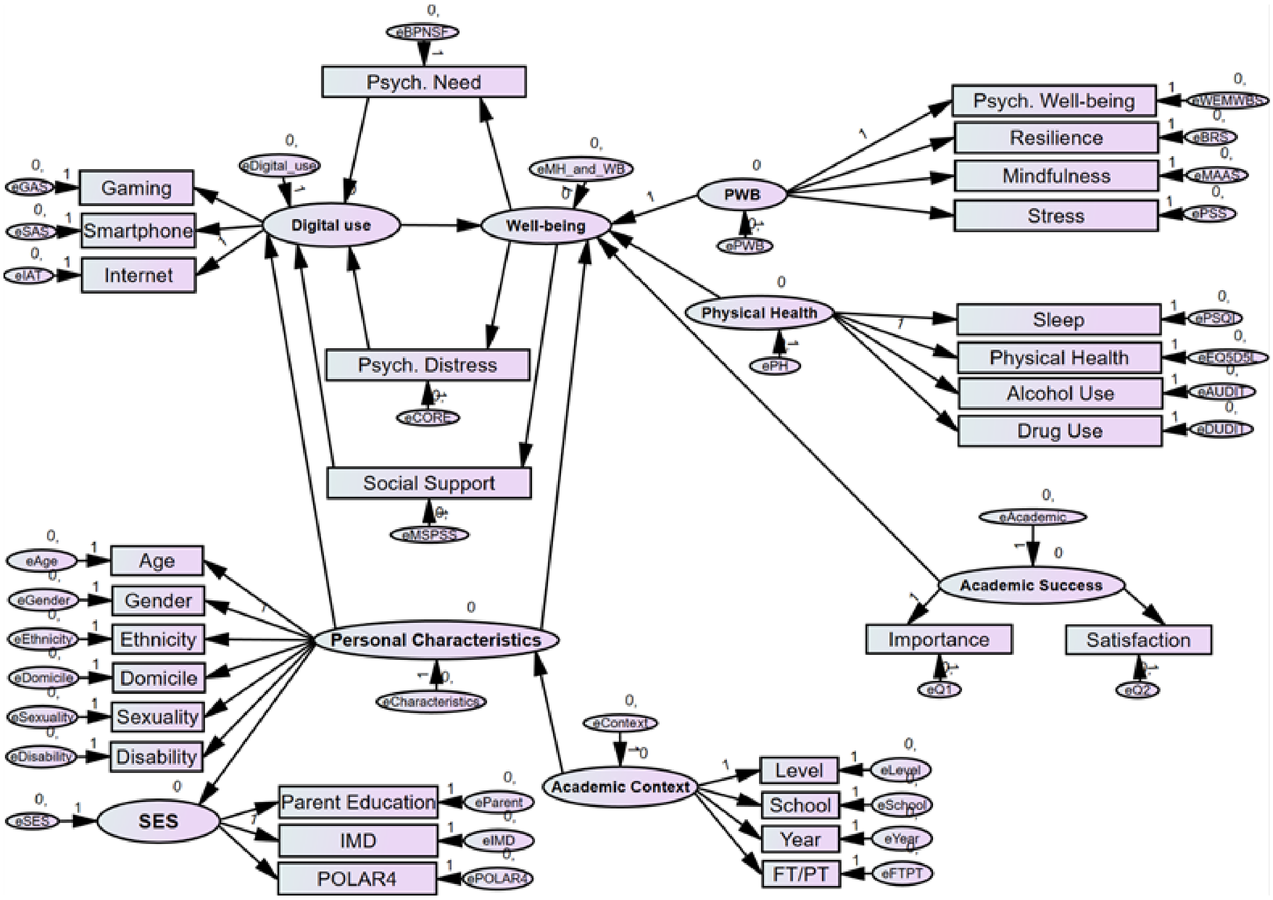

Figure 8 - *Overview of model 4.0*

Model 5.0 – Basic psychological need satisfaction and latent variable of mental health as moderator

Model 5.0 hypothesised that basic psychological need satisfaction and a more broadly defined latent variable of mental health moderate the relationship between well-being and digital technology use. See Figure 9 for picture of model 5.0. This model was developed as many of the variables which had been conceptualised as being a part of psychological well-being or physical health in previous models can also be defined as being part of mental health, and have been described as such in the research literature. As such, mental health became a latent variable composed of psychological distress, stress, resilience, mindfulness, social support, alcohol use, drug use and sleep. The well-being latent variable was composed of psychological well-being and subjective health measures.

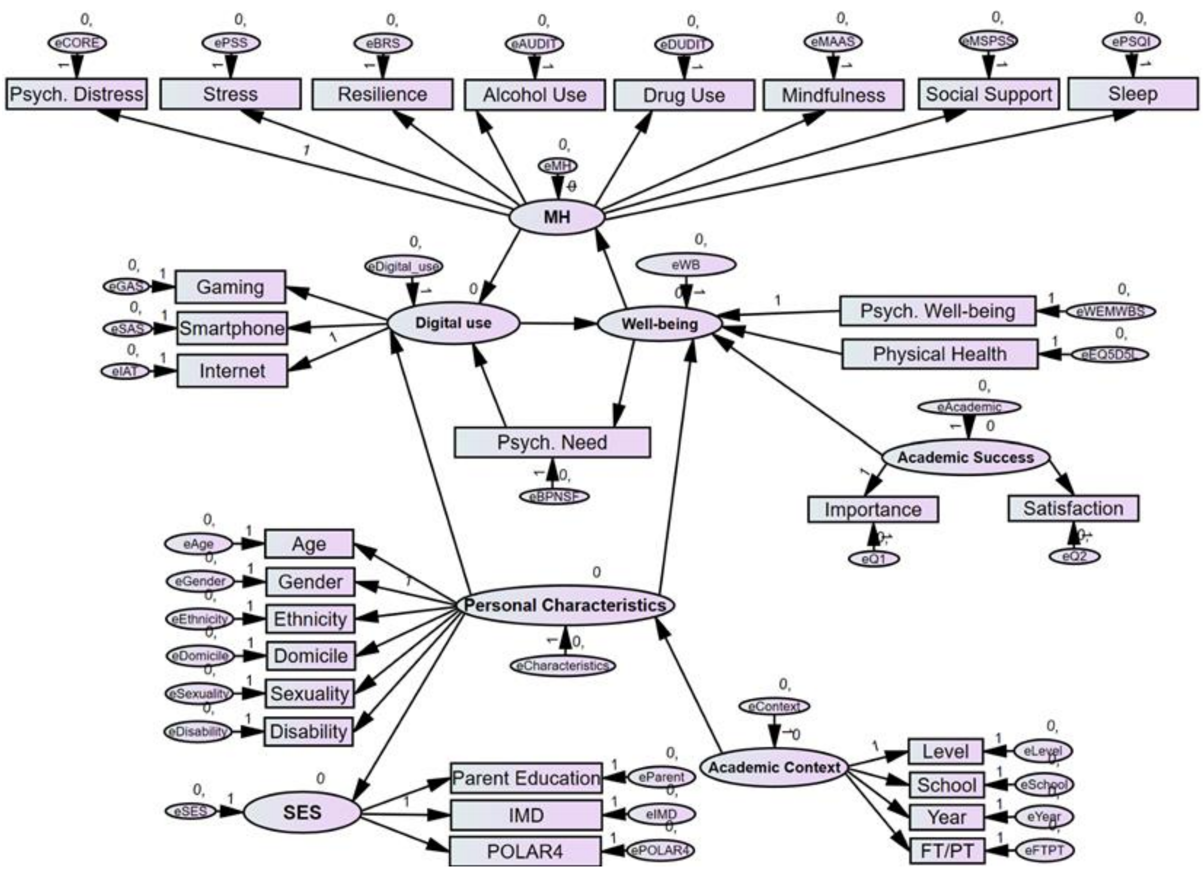

Figure 9 - *Overview of model 5.0*

Assessing model fit and relationships between variables

The following statistics were used to test the fit of each of the models and the relationships between each of the variables in the models (Table 3). All acceptability levels are taken from Schreiber, Stage, King, Nora, & Barlow (2006).

Table 3 - *Summary of statistical measures to indicate model fit and relationships between variables*

Statistical measure	***Description***	***Acceptability level***
Probability level	Measures the validity of the absolute fit of the model.	Values < 0.05
Relative chi-square (CMIN/DF)	Compares the observed covariance matrix to the model's predicted covariance matrix.	Values < 5
Root mean square error of approximation (RMSEA)	Compares the observed covariance matrix to the model's predicted covariance matrix.	Values of < 0.08
Comparative fit index (CFI)	Tests the fit of the specified model compared to an independent model, where all the variables are assumed to be uncorrelated. The CFI value represents the ratio between the discrepancy in the specified model and the discrepancy in the independent model.	Values ≥ 0.95
Akaike Information Criterion (AIC)	Tests the goodness of fit between specified models.	Model which generates the lower value is the better fit
Browne-Cudeck criterion (BCC)	Tests the goodness of fit between specified models.	Model which generates the lower value is the better fit
Standardised regression weight statistics	Assess the direction and strength of the relationships between the variables in each model. Direct effects assessed via path coefficients.	Values < 0.05

Results

Descriptive statistics

Sample characteristics

In total, 544 students completed the online survey representing 1.4% of the University of Leeds student population for the 2019-2020 academic year (University of Leeds Equality Policy Unit, 2020). The majority of participants were female (n=385, 70.8%), aged 21-25 (n=242, 44.5%), heterosexual (n=429, 78.9%), from a white ethnic background (n=366, 67.3%), from the UK (n=439, 80.7%) and did not have a disability (n=469, 86.2%). With regard to the academic context, the majority of participants were full time (510, 93.8%), undergraduate students (n=345, 63.4%) in their first (n=186, 34.2%), second (n=137, 25.2%) or third (n=134, 24.6%) year of study. Table 4 provides a summary of sample characteristics, see Appendix J for a Table detailing the full sample characteristics.

Table 4 - *Summary of sample characteristics*

Variable	***Level***	***n (n=544)***	***%***
Gender	Female	385	70.8
	Male	185	24.8
	Transgender/non-binary	10	1.8
	Prefer not to say	4	.7
	Prefer to self-describe/other	3	.6
	Missing data	7	1.3
Age	21-25	242	44.5
	16-20	165	30.0
	26-29	74	13.6
	30+	59	10.8
	Missing data	4	.7

Variable	*Level*	*n*	*%*
Sexuality	Heterosexual/ Straight	429	78.9
	Bisexual	51	9.4
	Prefer not to say	18	3.3
	Gay man	17	3.1
	Prefer to self-describe/ Other	12	2.2
	Gay woman/ Lesbian	10	1.8
	Missing data	7	1.3
Ethnicity	White	366	67.3
	Asian	83	15.3
	Mixed background	31	5.7
	Black	13	2.4
	Arab	8	1.5
	Prefer not to say	7	1.3
	Prefer to self-describe	6	1.1
	Any other ethnic background	4	.7
	Missing data	26	4.8
Domicile	UK	439	80.7
	International	65	11.9
	EU	38	7
	Missing data	2	.4
Disability presence	No disability	469	86.2
	Yes disability	63	9.7
	Prefer not to say	15	2.8
	Missing data	7	1.3
Level of academic study	Undergraduate	345	63.4
	Postgraduate	197	36.2
	Missing data	2	.4
Year of academic study	1st year	196	36
	2nd year	137	25.2
	3rd year	134	24.6
	4th year	63	11.6
	5th year	10	1.8
	6th year	3	.6
	Missing data	1	.2

Standardised measures

Most participants had average psychological well-being, measured by the WEMWBS (n=395, 72.6%) and some problems with physical health, measured by the EQ-5D-5L (n=417, 76.6%). With regard to psychological distress, measured by the CORE-10, 34.9% (n=190) of participants were below the clinical cut off, 20.6% (n=112) had low levels of psychological distress and 18.4% (n=100) had moderate levels of psychological distress. The majority of participants had a normal level of internet use, measured by the Internet Addiction Test (n=320, 58.8%) and a normal level of gaming use, measured by the Gaming Addiction Scale (n=535, 98.9%). See Table 5 for a full breakdown of descriptive statistics of standardised measures.

Table 5 - *Descriptive statistics for all measures*

	Measure	***Category***	***n (n=544)***	***%***	***Min.***	***Max.***	***Mean***	***95% confidence interval for mean***
Psychological distress	CORE-10	Below clinical cut-off	190	34.9				
		Mild psychological distress	112	20.6				
		Moderate psychological distress	100	18.4				
		Moderate to severe psychological distress	75	13.8				
		Severe psychological distress	62	11.4				
		Total score	539	99.1	0	37	13.92	13.11 – 14.56
		Missing data	5	.9				
Psychological well-being	WEMWBS	Low subjective well-being	77	14.2				
		Average subjective well-being	395	72.6				
		High subjective well-being	70	12.9				
		Total score	542	99.6	40	70	46.13	45.55 - 47.36
		Missing data	2	.4				
	Perceived Stress Scale[1]	Total score	546	98.5	0	30	21.06	20.30 – 21.69
		Missing data	8	1.5				
	Brief Resilience Scale[2]	Total score	538	98.9	6	30	18.04	17.69 – 18.67
		Missing data	6	1.1				

[1] The Perceived Stress Scale scores range from 1-40. Higher scores indicate greater perceived stress.
[2] The Brief Resilience Scale scores range from 6-30. Higher scores indicate greater resilience.

	Measure	Category	n	%	Min.	Max.	Mean	95% CI
	Multidimensional Scale of Perceived Social support	Low support	44	8.1				
		Moderate support	149	27.4				
		High support	344	63.2				
		Total score	537	98.7	1	7	5.35	5.29 – 5.52
		Missing data	7	1.3				
	Mindfulness Attention Awareness Scale[3]	Total score	538	98.9	1	5	3.01	55.56 – 58.23
		Missing data	6	1.1				
	Basic Psychological Need Satisfaction and Frustration Scale	Total psychological need satisfaction score	520	95.6	18	60	44.13	43.45 – 44.87
		Total psychological need frustration score	520	95.6	12	60	31.61	30.67 – 32.38
		Missing data	24	4.4				
Physical health	EQ-5D-5L	Overall health today	542		1	100	72.24	73.35 – 76.27
		Mobility – no problems	479	88.1				
		Mobility – some problems	58	10.7				
		Self-care – no problems	500	91.9				
		Self-scare – some problems	37	6.8				
		Meaningful activities – no problems	363	66.7				
		Meaningful activities – some problems	174	32				

[3] The Mindfulness Attention Awareness Scale scores range from 1-6. Higher scores indicate greater mindfulness

	Category	n	%	Min.	Max.	Mean	95% CI
EQ-5D-5L cont.	Pain or discomfort – no problems	331	60.8				
	Pain or discomfort – some problems	206	37.9				
	Anxiety or depression – no problems	164	30.1				
	Anxiety or depression – some problems	373	68.6				
	Total score	537	98.7	5	23	7.37	7.04 – 7.46
	Total score -no health problems	120	22.1				
	Total score -some health problems	417	76.7				
	Missing data	7	1.3				
Pittsburgh Sleep Quality Index	Good sleep quality	16	2.9				
	Poor sleep quality	498	91.5				
	Global score	514	94.5	3	19	7.98	7.75 – 8.22
	Missing data	30	5.5				
AUDIT-C	No intervention indicated	199	36.6				
	Intervention indicated	344	63.2				
	Missing data	1	.2				
	Total score	543	99.8	0	13	5.40	5.16 – 5.74
DUDIT-C	No intervention indicated	462	84.9				
	Intervention indicated	73	13.4				
	Total score	541	95.4	0	9	.79	.61 - .93
	Missing data	9	1.7				

	Measure	Category	n	%	Min.	Max.	Mean	95% CI
Subjective importance of and satisfaction with academic success	Importance of academic success	Important	529	97.2				
		Neither important nor unimportant	8	1.5				
		Unimportant	6	1.1				
		Total score	543	99.8	1	3	1.04	1.01 – 1.06
		Missing data	1	.2				
	Satisfaction with current academic success	Satisfied	347	63.8				
		Neither satisfied nor dissatisfied	62	11.4				
		Dissatisfied	134	24.6				
		Total score	543	99.8	1	3	1.61	1.53 – 1.68
		Missing data	1	.2				
Digital technology use	Internet Addiction Test	Normal level of internet use	320	58.8				
		Mild level of internet addiction	164	30.1				
		Moderate level of internet addiction	30	5.5				
		Severe dependence on internet	1	.2				
		Total score	515	94.7	0	82	28.35	26.97 – 29.54
		Missing data	29	5.3				
	Gaming Addiction Scale	Normal level of gaming	535	98.3				
		Pathological level of gaming	3	.6				
		Total score	538	98.9	7	28	9.78	9.26 – 10.06
		Missing data	6					
	Smartphone Addiction Scale[4]	Total score	507	93.2	33	174	91.08	88.54 – 93.66
		Missing data	37	6.8				

[4] The Smartphone Addiction Scale scores range from 33-198. Higher scores indicate a greater level of smartphone addiction

Structural equation models fit and estimates

Assessment of fit was measured for each of the seven models. (Table 6).

Table 6 - *Model fit statistics for models 1.0, 1.1, 2.0, 2.1, 3.0, 4.0 and 5.0*

	Model version						
	1.0	**1.1**	**2.0**	**2.1**	**3.0**	**4.0**	**5.0**
Probability Level	<.001	. <.001	. <.001	<.001	<.001	<.001	<.001
CMIN/DF [5]	5.683	5.218	5.131	5.147	5.171	5.111	4.836
RMSEA [6]	.093	.088	.087	.088	.088	.087	.084
CFI [7]	.679	.644	.651	.610	.649	.655	.676
AIC [8]	1683.475	2112.341	2077.073	2082.807	2091.704	2066.596	1971.821
BCC 8	1691.823	2123.569	2088.418	2094.152	2103.049	2078.058	1982.269

Models 1.0 and 1.1

Models 1.0 and 1.1 were the fundamental models where basic psychological need satisfaction was hypothesised to moderate the relationship between mental health and well-being and digital technology use. The models were compared for goodness of fit, to confirm if the 'academic context' latent variable improved model 1.0. Both models reached significance ($p < 0.001$) and so were an appropriate fit for the data. Model 1.1 had a better parsimonious fit and absolute model fit (*CMIN/DF* = 5.218, *RMSEA* = 0.088) than model 1.0 (*CMIN/DF* = 5.683, *RMSEA* = 0.093). However, both models were not more appropriate than equivalent independent models, where all the variables are assumed to be uncorrelated (*CFI:* model 1.0 = 0.679, model 1.1 = 0.644). Furthermore, model 1.0

[5] Used to compare the observed covariance matrix to the models predicted covariance matrix. Values of <5 are considered acceptable.

[6] Used to compare the observed covariance matrix to the models predicted covariance matrix. Values of <0.08 are considered acceptable.

[7] Represents the ratio between the discrepancy in the specified model and the discrepancy in the independent model. Values ≥ .95 are considered acceptable.

[8] Used to test the goodness of fit between specified models, lower values indicate a better fit.

(*AIC* = 1683.475, *BCC* = 1691.823) was a better fit when compared to model 1.1 (*AIC* = 2112.341, *BCC* = 2123.569). See Appendix K for model 1.0 parameter estimates and Figure 10 for model 1.1 parameter estimates.

Model 1.1 included all the variables originally hypothesised as impacting on the relationship between well-being, mental health and digital technology use and it was a better parsimonious and absolute fit than model 1.0. While the increase in AIC and BIC from model 1.0 to model 1.1 could indicate that model 1.0 was a better fit, this is more likely because of the inclusion of the additional variables in the later model. Therefore model 1.1 was used as the fundamental structure for further models and the latent variable 'academic context' was included in all models.

The standardised parameter estimates of model 1.1 (Figure 10) show that mental health and well-being was significantly positively associated with basic psychological need satisfaction ($\beta = 0.69$, $p < 0.001$) and significantly negatively associated with digital use ($\beta = -.25$, $p < 0.001$), while accounting for the proposed moderators. Digital technology use was negatively associated with mental health and well-being ($\beta = -0.06$, $p < 0.100$), although this relationship did not reach statistical significance.

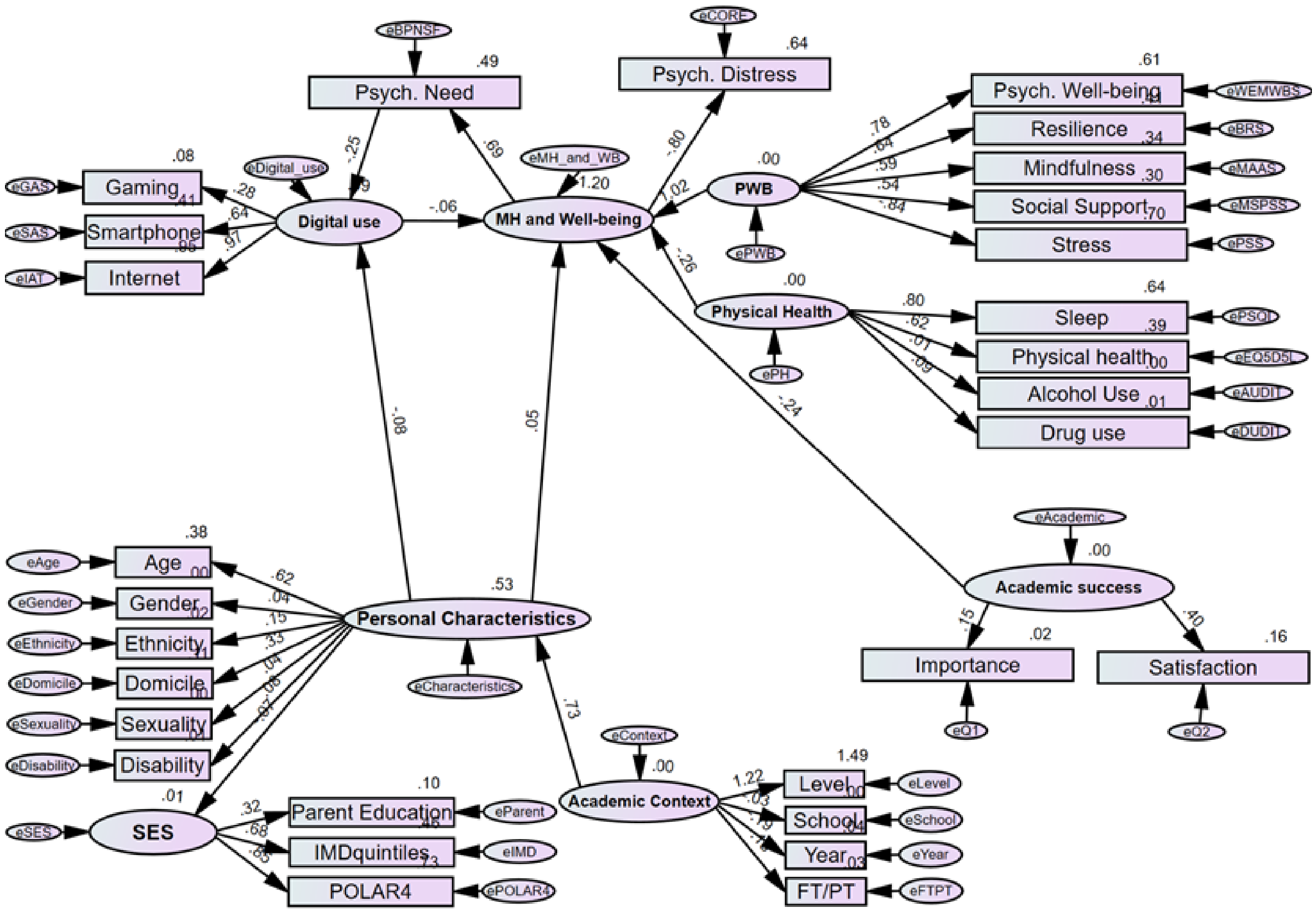

Figure 10 - *Parameter estimates of model 1.1*

Models 2.0 and 2.1

Models 2.0 and 2.1 hypothesised that basic psychological need satisfaction and social support moderate the relationship between mental health and well-being and digital technology use. The models were compared for goodness of fit to test the direction of the relationship between mental health and well-being, social support and digital technology use. Model 2.0 was a better fit across all the model fit measures (see Table 6). As such, the relationship for moderators in further models was hypothesised as going from well-being to digital technology use.

Analysis of model 2.0 showed that mental health and well-being was significantly positively associated with social support ($\beta = 0.50$, $p < 0.001$) and significantly negatively associated with digital technology use ($\beta = -0.15$, $p < 0.001$). Mental health and well-being remained significantly positively associated with basic psychological need satisfaction ($\beta = 0.70$, $p < 0.001$) and significantly negatively associated with digital technology use ($\beta = -0.15$, $p < 0.001$). Digital technology use was significantly negatively associated mental health and well-being ($\beta = -0.09$, $p < 0.05$). However, neither the parsimonious nor absolute fit were at an acceptable level for model 2.0 (C*MIN/DF* = 5.131, *RMSEA* = 0.087), indicating that further refinement/additions of the model were required. See Appendix L for a Figure of model 2.0 parameter estimates and Appendix M for Figure of model 2.1 parameter estimates.

Model 3.0

Model 3.0 hypothesised that psychological distress and basic psychological need satisfaction moderate the relationship between digital technology use and well-being. Model 3.0 was a poorer fit than model 2.0 across all model fit indices (see Table 6). As such, no further interpretation was made on the results of model 3.0. See Appendix N for model 3.0 parameter estimates.

Model 4.0

Model 4.0 hypothesised that basic psychological need satisfaction, psychological distress and social support moderate the relationship between well-being and digital technology use. It was a better fit than any of the previous models on most measures. However, model 1.0 was a better fit (*AIC = 1683.475*, *BCC = 1691.823*) when compared to model 4.0 (*AIC* = 2066.596, *BCC* = 2078.058). It is likely this is due to the complexity of model 4.0 compared to model 1.0.

Analysis of model 4.0 showed that well-being was significantly negatively associated with psychological distress ($\beta = -0.85$, $p < 0.001$) and significantly positively associated with social support ($\beta = 0.51$, $p < 0.001$) and basic psychological need satisfaction ($\beta = 0.71$, $p < 0.001$). Psychological distress was significantly positively associated with digital technology use ($\beta = 0.20$, $p < 0.01$). Social support ($\beta = -0.10$, $p < 0.05$) and basic psychological need satisfaction ($\beta = -0.08$, $p = 0.14$) were negatively associated with digital technology use, although only the relationship between social support and digital use reached statistical significance. Digital technology use was negatively associated with well-being ($\beta = -0.03$, $p = 0.45$), but this relationship did not reach statistical significance. However, neither the parsimonious nor absolute model fit for model 4.0 were at an acceptable level (C*MIN/DF* = 5.111, *RMSEA* = 0.087) indicating that further additions/ adjustments were required. See Figure 11 for model 4.0 results.

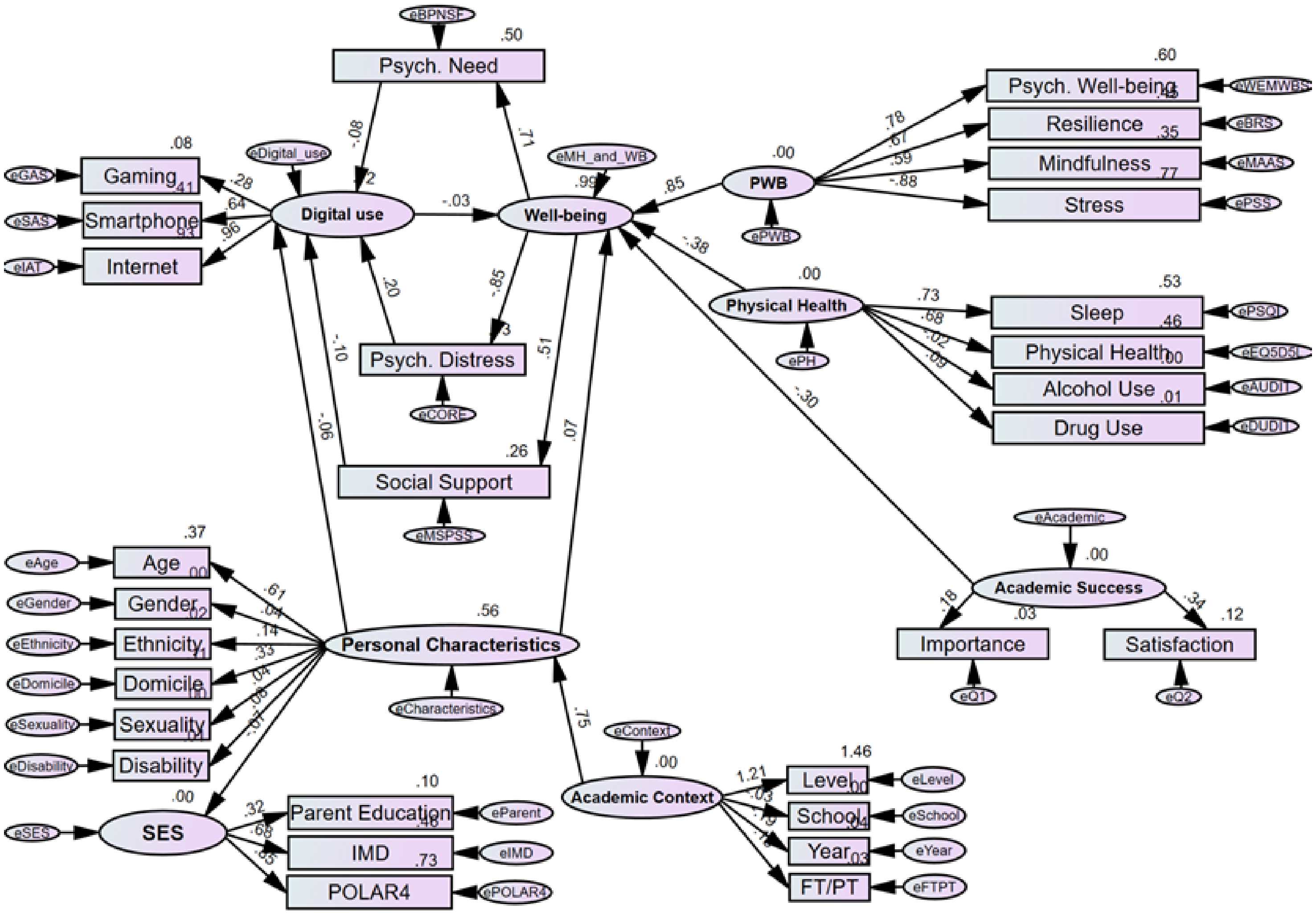

Figure 11 - *Parameter estimates of model 4.0*

Model 5.0

Model 5.0 hypothesised that basic psychological need satisfaction and a latent variable of mental health moderate the relationship between well-being and digital technology use. It was a better fit than other models across most model fit measures. However, model 1.0 remained a better fit when compared to model 5.0 (*AIC* = 1971.821, *BCC* = 1982.269). The parsimonious model fit for model 5.0 was at an acceptable level (C*MIN/DF* = 4.836) but the absolute model fit was not (*RMSEA* = 0.084).

The mental health latent variable was composed of several factors. Psychological distress (β = 0.86) was positively associated with 'mental health', no *p* value was generated as the regression weight for psychological distress was constrained to 1 for analysis. Stress (β = 0.79, $p < 0.001$) and sleep disturbance (β = 0.55, $p < 0.001$) were significantly positively associated with 'mental health'. Social support (β = -0.50, $p < 0.001$), mindfulness (β = -0.55, $p < 0.001$) and resilience (β = -0.58, $p <$ 0.001) were significantly negatively associated with 'mental health'. Alcohol use (β = 0.00, $p = 0.98$) and drug use (β = 0.06, $p = 0.17$) were not significantly associated with the mental health latent variable. In this context, higher mental health scores indicate higher levels of mental health difficulties (higher levels of psychological distress, stress and sleep disturbance and lower levels of social support, mindfulness, and resilience).

Model 5.0 showed that well-being was significantly negatively associated with mental health (β = -0.90, $p < 0.001$) and significantly positively associated with basic psychological need satisfaction (β = 0.75, $p < 0.001$). Mental health was significantly positively associated with digital technology use (β = 0.26, $p < 0.001$). Basic psychological need satisfaction was not significantly associated with digital technology use (β = 0.001, $p = 0.99$). Digital technology use was significantly negatively associated with well-being (β = -0.16, $p < 0.01$). See Figure 12 for model 5.0 parameter estimates.

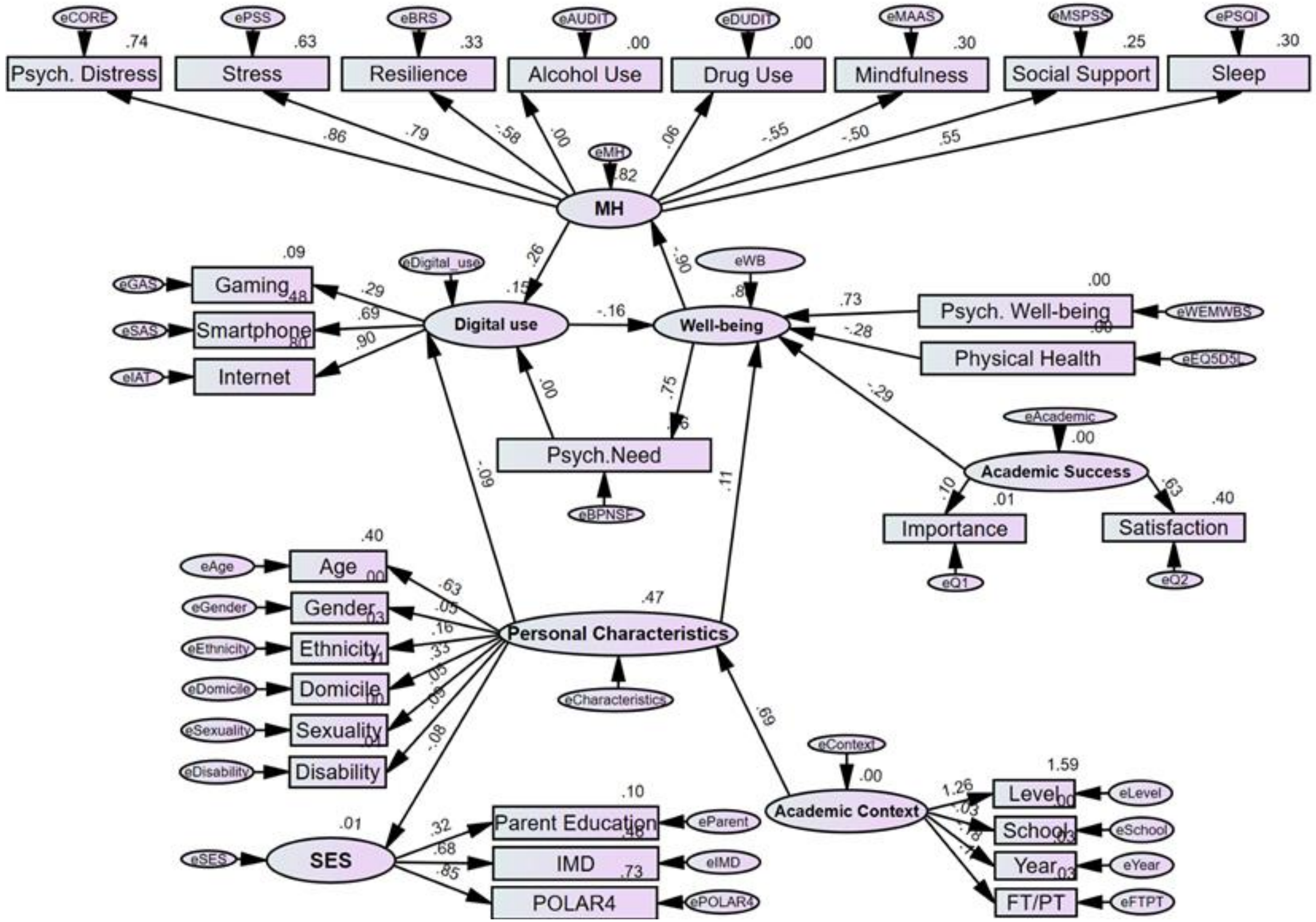

Figure 12 – *Parameter estimates of model 5.0*

Sensitivity analysis – models 6.0 and 6.1

Following analysis of the initial models, two further models were indicated. Model 6.0 was developed to clarify which measures and constructs best align with psychological well-being and which align with mental health. These decisions were based on how these constructs are defined in the literature and which populations the measures were developed for use with.

The psychological well-being latent variable was composed of those constructs that are more often associated with non-clinical populations in the research literature (subjective well-being, resilience, mindfulness, and social support). The mental health latent variable was composed of the constructs that are more relevant to clinical populations in the research literature (psychological distress, alcohol use, drug use and sleep disturbance). It was unclear whether stress sat in the psychological well-being or mental health variable and so stress was tested in both. In model 6.0 stress was within psychological well-being latent variable and in model 6.1 it was within the mental health latent variable. Due to model 5.0 being the best fit of the previous models, it was hypothesised that mental health and basic psychological need satisfaction moderated the relationship between well-being and digital technology use.

Results for models 6.0 and 6.1

Model 6.0 was a slightly better fit across all model fit measures than model 6.1 (Table 7) therefore, the results of model 6.1 were not interpreted further (see Appendix O for model 6.1 results). Model 6.0 was a better fit than models 1.1 to 4.0. However, model 6.0 (*AIC* = 2034.691, *BCC* = 2046.036) was not as good a fit as model 5.0 (*AIC* = 1971.821, *BCC* = 2046.036) and it did not reach an acceptable level for parsimonious or absolute model fit (C*MIN/DF* = 5.016, *RMSEA* = 0.084). Psychological distress was consistently conceptualised as a measure of mental health across models 1.0 to 5.0 but the superior fit of model 5.0 when compared to model 6.0 confirms that stress, alcohol use, drug use, sleep disturbance, resilience, social support and mindfulness are factors which contribute to mental health and moderate the relationship between well-being and digital technology use.

Table 7 - *Model fit statistics for models 5.0, 6.0 and 6.1*

	Model Version		
	5.0	**6.0**	**6.1**
Probability Level	<.001	.000	.000
CMIN/DF [5]	4.836	5.016	5.027
RMSEA [6]	.084	.086	.086
CFI [7]	.676	.662	.660
AIC [8]	1971.821	2034.691	2041.876
BCC [8]	1982.269	2046.036	2053.104

Model 6.0 (Figure 13) showed that well-being was significantly negatively associated with mental health (β = -0.88, $p < 0.001$) and significantly positively associated with basic psychological need satisfaction (β = 0.72, $p < 0.001$). Mental health was significantly positively associated with digital technology use (β = 0.28, $p < 0.001$). Basic psychological need satisfaction was negatively associated with digital technology use, although this relationship did not reach significance (β = -0.08, p =0.23). Digital technology use was negatively associated with well-being, but this relationship did not reach significance (β = -0.08, p = 0.40).

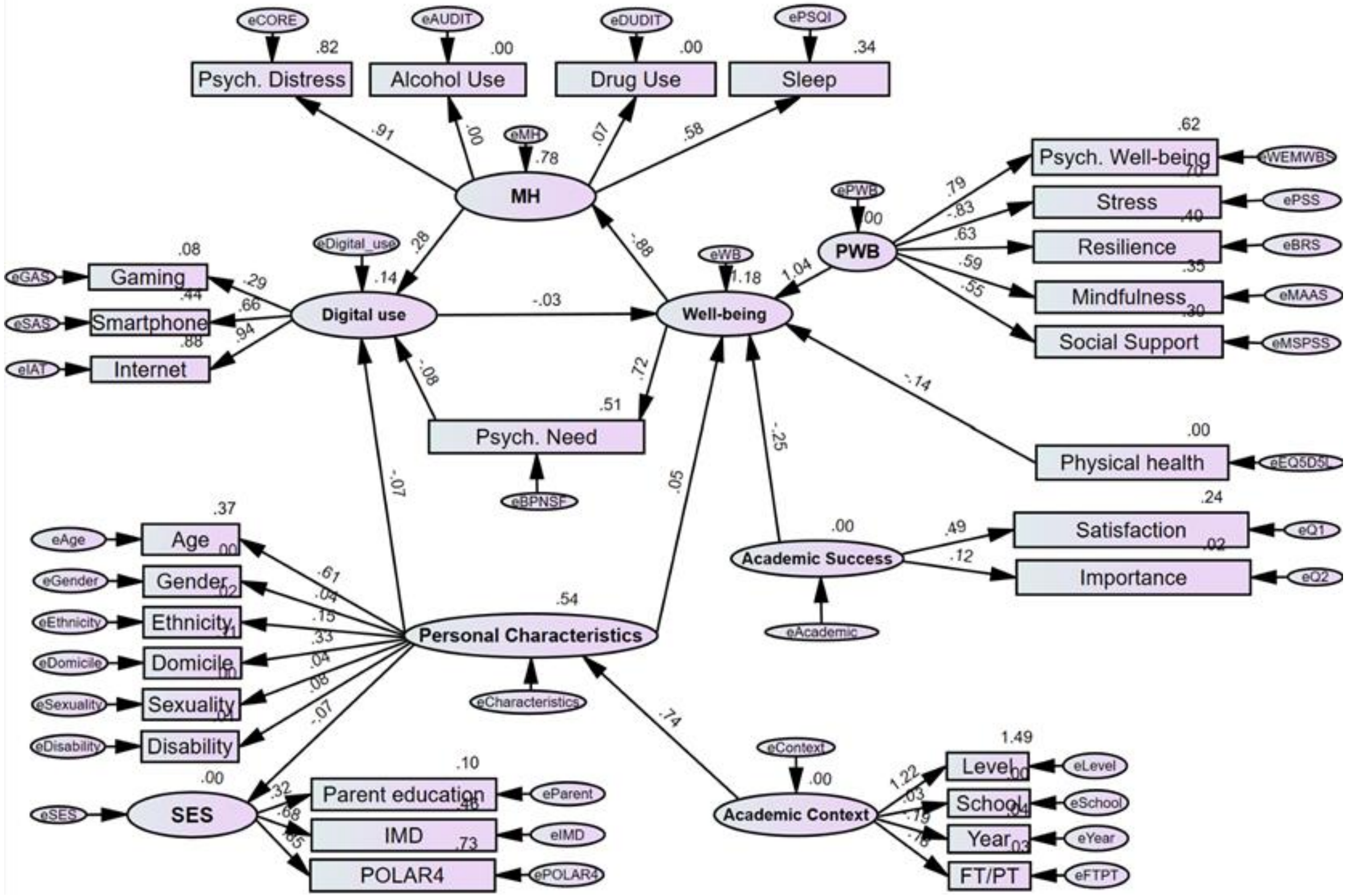

Figure 13 – *Parameter estimates for model 6.0*

Results summary

Model 5.0 was the best fit for the data across all the models tested, therefore models 1.0 to 4.0, 6.0 and 6.1 are rejected. This suggests that mental health is best conceptualised as a multi-faceted construct which is composed of psychological distress, stress, sleep disturbance, resilience, social support and mindfulness. Drug and alcohol use were not significantly associated with the mental health latent variable and therefore should not be considered as an indicator of mental health in this data set. Well-being is conceptualised as a distinct construct which is composed of subjective psychological well-being and physical health in this sample. The parameter estimates of model 5.0 show that digital technology use is negatively associated with well-being and that mental health moderates this relationship.

Discussion

Research rationale and aims

A significant proportion of young people attend higher education in the UK (50.2%, Department for Education, 2019). Research suggests that university can be a time of increased distress (Cvetkovski et al., 2012) and that demand for student well-being support services has increased in recent years (Thorley, 2017). Therefore, understanding and protecting the well-being of university students has become increasingly important to policy makers, universities and support services.

Digital technology use has been identified as one of the factors that impacts on the well-being of university students internationally (Çardak, 2013; Odaci & Çikrikçi, 2014; Ouyang et al., 2017; Rayan et al., 2017; Sultan, 2019; Turel et al., 2018; Ye & Lin, 2015). In addition, much of the research around the impact of digital technology use in student populations has focused on problematic or addictive levels of digital technology use and its relationship with mental health (Bahrainian et al., 2014; Liu, Ni, Yan, & Chen, 2009; Orsal & Sinan, 2013; Younes et al., 2016).

The relationship between digital technology use and well-being is not currently well defined in the UK student population. As such, the current research aimed to understand whether digital technology use is associated with well-being in UK university students and to explore the relationships between digital technology use and the factors that relate to well-being.

Summary of models and results

In all nine models tested, the digital technology latent variable was composed of measures of problematic internet, smartphone and online gaming use. The placement of the measures which related to well-being changed across models depending on the underlying theoretical assumptions. Digital technology was hypothesised as having a relationship with well-being. Basic psychological need satisfaction, social support and mental health were hypothesised to moderate the relationship between well-being and digital technology use.

Of the nine models tested, model 5.0 was the best fit for the data. Model 5.0 hypothesised that well-being was a narrower construct than in other models, measured by subjective psychological well-being and physical health. This model also hypothesised that the relationship between well-being and digital technology use was moderated by basic psychological need satisfaction and mental health. The mental health latent variable in model 5.0 was measured by psychological distress, stress, alcohol use, drug use, sleep disturbance, resilience, mindfulness, and social support. The superiority of model 5.0 suggests that it is most appropriate to conceptualise mental health as a multifactorial variable composed of psychological distress, stress, drug and alcohol use, sleep disturbance, resilience, mindfulness, social support. Well-being is a discrete construct which is composed of subjective psychological well-being and physical health.

Well-being was found to have a significant negative association with mental health, which in turn had a significant positive association with digital technology use. Therefore, mental health moderated the relationship between well-being and digital technology use. Digital technology use was significantly negatively associated with well-being.

This suggests that the negative relationship between digital technology use and well-being is dependent on a person’s mental health. Whereby those with higher levels of mental health difficulties are more likely to have higher levels of problematic digital technology use. Also, that those with higher levels of mental health difficulties are more likely to experience reduced well-being as a result of their problematic digital technology use impacting on their well-being. These results will now be considered in more detail, in relation to the research questions and in the context of the wider literature.

Is digital technology use associated with well-being in university students?

The first research question sought to understand if digital technology use is associated with well-being in the university student population. Previous research has used university student populations to investigate whether specific components of mental health and well-being, such as anxiety or depression, are associated with digital technology use (Bahrainian et al., 2014; Beranuy et al., 2009; Demirci et al., 2015; Hong, Chiu, & Huang, 2012; Lepp et al., 2014; Orsal & Sinan, 2013; Younes et al., 2016).

Others have used a specific measure of psychological well-being to investigate how well-being is associated with digital technology use (Çardak, 2013; Odaci & Çikrikçi, 2014; Ouyang et al., 2017; Rayan et al., 2017; Sacco, 2018; Sultan, 2019; Suphan & Mierzejewska, 2016; Turel et al., 2018; Ye & Lin, 2015). However, little is known about how well-being as a holistic construct with multiple factors is associated with digital technology use in the UK university student population. The current research aimed to address this question, whilst acknowledging the complexity of defining and measuring all the factors which contribute to well-being in university students.

The strength of the relationship between digital technology use and well-being varied across models. This variation occurred because each of the models proposed differing relationships between each of the mental health, psychological well-being, and physical health measures. In all cases the relationship between digital technology use and well-being was negative. In model 5.0, which was the best fit for the data, well-being and digital technology use were significantly negatively associated. Therefore, it is reasonable to conclude that digital technology use is negatively associated with well-being in UK university students, whereby more problematic digital technology use is associated with lower levels of well-being.

What are the relationships between digital technology use and the factors of well-being in university students?

Three moderators of the relationship between well-being and digital technology use were proposed: basic psychological need satisfaction, social support and mental health. The following sections discuss how each of these moderators was found to be associated with well-being and digital technology use.

Does psychological need satisfaction moderate the relationship between well-being and digital technology use?

Self-determination theory posits that we have three basic psychological needs and that satisfying these needs drives our behaviour (Ryan & Deci, 2000). Basic psychological need satisfaction has been shown to be related to digital technology use and well-being in university students (Chen, Vansteenkiste, Beyers, Liesbet Boone, et al., 2015; Cordeiro et al., 2016; Hsu et al., 2009). As such, basic psychological need satisfaction was hypothesised to moderate the relationship between well-being and digital technology use across all models. It was hypothesised that better well-being would lead to greater basic psychological need satisfaction. Also, that those with greater basic psychological need satisfaction would have less problematic digital technology use as they would be less motivated to use digital technology to satisfy their psychological needs.

In the most appropriate model (5.0) basic psychological need satisfaction did not moderate the relationship between digital technology use and well-being. There was a positive, statistically significant relationship between well-being and basic psychological need satisfaction but no statistically significant relationship between basic psychological need satisfaction and digital technology use. Therefore, it can be concluded that better well-being is associated with greater basic psychological need satisfaction in the university student population; a finding consistent with published research (Cordeiro et al., 2016; Sheldon & Bettencourt, 2002). However, it is concluded that basic psychological need satisfaction does not moderate the relationship between digital technology use and well-being in university students.

In the foundation model (1.1) basic psychological need satisfaction did moderate the relationship between well-being and digital technology use. This relationship did not hold as the models became more complex and other moderators were added. This suggests that other factors, such as mental health, are more important than psychological need satisfaction to the relationship between digital technology use and well-being.

It was hypothesised that the less a person feels that their basic psychological needs are satisfied in real-life, the more they feel compelled to use digital technology to satisfy these needs. This was hypothesised in the context of problematic or addictive levels of digital technology use whereby the motivation to satisfy these needs can lead to compulsive and addictive levels of digital technology use. The weak relationship between basic psychological need satisfaction and digital technology use may have been impacted by the lack of problematic or addictive levels of digital technology use in the sample as only 5.7% of the sample had moderate or severe levels of internet addiction (5.5% moderate, 0.2% severe) and only 0.6% had pathological levels of gaming. The relationship between basic psychological need satisfaction and digital technology use may also have been weak in the sample because the models assume linear relationships between variables and this may not be the case in this relationship. For example, the relationship may be more ‘U shaped’ whereby basic psychological need satisfaction is only strongly associated with digital technology use for those who have low levels of basic psychological need satisfaction.

In addition, psychological distress has been found to moderate the relationship between digital technology use and basic psychological need satisfaction (Wong et al., 2014) . It may be that basic psychological need satisfaction only moderates the relationship between well-being and digital technology use for those who have higher levels of psychological distress and problematic digital technology use. Therefore, basic psychological need satisfaction may not have moderated the relationship between digital technology use and well-being as the sample did not have high levels of psychological distress and because the models assume a linear relationship between variables.

Does social support moderate the relationship between well-being and digital technology use?

Social support is widely cited as being linked to both well-being and digital technology use. However, the direction in which this relationship works for UK university students is not clear in the literature. Models 2.0 and 2.1 were developed to test the direction of this relationship. Specifically, whether well-being impacts on social support, which in turn impacts on digital technology use or whether the relationship works the opposite way (with digital technology use as the independent variable). The results of these models suggest that the direction of the relationship is from well-being, to social support and then to digital technology use. Therefore, all further moderator relationships were hypothesised in this direction. As models 2.0 and 2.1 were not found to be a good fit for the data no further interpretation of the findings of these models was made.

In model 5.0 social support was conceptualised as contributing to the mental health latent variable. It had a significant negative relationship with mental health whereby, greater social support was associated with lower levels of mental health difficulties. The relationship between social support and mental health was strong. These results fit with the research around the negative impact that poor social support has on mental health in university students (Hefner & Eisenberg, 2009; Peng et al., 2012; Tajalli, Sobhi, & Ganbaripanah, 2010).

As social support was significantly associated with the mental health latent variable in model 5.0, it can be concluded that social support is an important factor when understanding the relationship between mental health, digital technology use and well-being. These results are consistent with the literature which has established the relationship between social support, well-being and digital technology use in university students (Burke et al., 2010; Chen & Lever, 2005; Fumero et al., 2018; Gülaçt, 2010; Noble et al., 2008; Özcan & Buzlu, 2007; Reifman & Dunkel-Schetter, 1990; Stallman et al., 2018). In summary, it cannot be concluded that social support alone moderates the relationship between digital technology use and well-being. However, the findings of this research show those with better social support have better well-being, less mental health difficulties and less problematic digital technology use.

Does mental health a moderate the relationship between well-being and digital technology use?

Research into the impact of digital technology use often focuses on its relationship with mental health difficulties. More problematic digital technology use has been shown to be associated with anxiety, depression and other indicators of mental health difficulties in university students (Bahrainian et al., 2014; Beranuy et al., 2009; K Demirci et al., 2015; Orsal & Sinan, 2013; Younes et al., 2016). Therefore, it was deemed important to investigate the impact of mental health on the relationship between well-being and digital technology use in the current research.

The way in which mental health was conceptualised changed across models. In its least complex form, it was measured by psychological distress alone (models 1.0 to 4.0). In model 5.0, which was the best fit for the data, mental health was conceptualised as a more complex construct measured by several indicators of psychological health and distress. It was hypothesised that mental health would moderate the relationship between well-being and digital technology use.

In model 5.0 higher levels of psychological distress, stress, drug and alcohol use and sleep disturbance and lower levels of resilience, mindfulness and social support indicated greater mental health difficulties. All the measures, apart from drug and alcohol use, were significantly associated with mental health.

It was hypothesised that drug and alcohol use would be associated with mental health, however drug and alcohol use did not significantly contribute to the mental health latent variable in model 5.0. This is surprising considering previous research has shown that mental health difficulties are associated with drug and alcohol use in university students (Richardson et al., 2016; Sæther et al., 2019; Tembo et al., 2017) and the high levels of potentially problematic drinking levels in the sample (an alcohol intervention was indicated for 63.2% of participants). The discrepancy in these results and the wider literature may be due to the measures of drug and alcohol use used in the current research. The AUDIT-C (Saunders et al., 1993) and DUDIT-C (Berman et al., 2005) were developed to be used as screening tools and further assessment should always be completed to identify problematic drug or alcohol use. As no further assessment of drug and alcohol use was completed in the current research, it is possible that only a small proportion of those for whom an intervention may be indicated would go on to meet problematic levels of drug or alcohol use. As such, the actual level of drug and alcohol use in the sample may not reach the levels that are associated with poor mental health. Again, the assumption of a linear relationship between drug and alcohol use and mental health may have impacted on the strength of the relationship between these variables. In addition, drug and alcohol use may be perceived as a more 'normal' part of university student life than for peers who do not attend university and, in some cases, may not be associated with mental health difficulties.

In model 5.0 mental health was significantly associated with well-being and digital technology use. Whereby, those with lower well-being had higher levels of mental health difficulties and higher levels of digital technology use. Therefore, it can be concluded that mental health moderates the relationship between well-being and digital technology use in that, for those with higher levels of mental health difficulties, digital technology use is more likely to be problematic and to be associated with lower well-being.

Digital technology use has been associated with greater psychological distress, (Al-Gamal et al., 2016; Anand et al., 2018b, 2018a; Beranuy et al., 2009), stress (Deatherage et al., 2014; Wang et al., 2015) and sleep disturbance (Adams & Kisler, 2013; Anderson, 2010; Matar Boumosleh & Jaalouk, 2017) and lower levels of resilience (Kim, H. J., & Sim, 2018; Kim et al., 2014), mindfulness (Calvete et al., 2017; Gámez-Guadix & Calvete, 2016; İskender & Akin, 2011) and social support (Fumero et al., 2018; Özcan & Buzlu, 2007) and the current research is consistent with this literature.

The current results are consistent with the wider evidence that mental health is negatively associated with problematic digital technology use in university students (Al-Gamal et al., 2016; Bahrainian et al., 2014; Beranuy et al., 2009; Kross et al., 2013; Younes et al., 2016). The moderating effect of mental health on the relationship between digital technology use and well-being also fits with the dual continuum model of mental health (Tudor, 2013), which posits that mental health and well-being are two distinct but related concepts. The current results are consistent with conceptualising well-being as distinct from mental health; both mental health and well-being have different relationships with digital technology use but are strongly associated with each other.

Clinical implications

The main findings of this research, that problematic levels of digital technology use have a negative impact on university student well-being and that mental health moderates this relationship, have implications for universities and services that support university students. As universities have a vested interest in promoting the well-being of their students, it is important that they are aware of and consider the impact that problematic digital technology use can have on well-being.

Digital technology is an integral part of everyday life for most university students and is used for both personal and academic reasons. As such, it is likely that it will be difficult to change attitudes and behaviours associated with digital technology use without first building an awareness of the impact it can have on well-being. To build awareness universities should consider providing information to their students about the potential impact that their relationship with digital technology can have on their well-being. Such information should focus on how to recognise when digital technology use might be affecting well-being and how students might change such relationships with digital technology to reduce the negative impact on well-being.

This information should also identify the role that mental health plays in the relationship between digital technology use and well-being and provide students with information on mental health support services. Universities should ensure that this information is easily accessible across campus and embedded into the well-being information routinely given to students.

Services which support university students with their mental health, such as counselling or mental health teams, should also be aware of the association between mental health difficulties, problematic digital technology use and well-being. The findings of this research have identified that those with mental health difficulties are likely to be at risk of greater levels of problematic digital technology use and poorer well-being. It may be helpful to screen for the negative impact of using digital technology when support services are completing assessments with students. It is important that services begin to ask questions about students' relationship with the digital world to build a full picture of the behaviours, beliefs and experiences that impact on their students' mental health and well-being.

In cases where relationships with digital technology are identified as being a part of the 'problem' it is recommended that support services consider specific strategies to address this. Lower levels of mindfulness have been shown to predict internet addiction in university students (İskender & Akin, 2011). Building mindfulness skills may help students to be more aware of their digital behaviours and the emotional impact of using digital technology. The findings of the current research suggest that basic psychological need satisfaction may also have a role to play in motivations to use digital technology. As such, it may be helpful to work with students to identify what psychological needs they may be trying to satisfy by using digital technology and consider other ways in which these needs could be met.

Screening for the impact of problematic relationships with digital technology may also identify students who have problematic or pathological levels of use. Although the UK does not currently diagnose digital addiction, other than gaming disorder, there are evidence based programmes for the treatment of digital addiction. These include Mindfulness-based and Cognitive Behavioural Therapy interventions (Kuss & Lopez-Fernandez, 2016; Li et al., 2017; Pontes, Kuss, & Griffiths, 2015). Trained professionals, such as clinical psychologists and psychotherapists, may consider using effective tools and techniques from such interventions when working with students who report problematic levels of digital technology use.

The current results are particularly pertinent in the context of the current COVID-19 pandemic. With universities closed and social contact in person very limited, students are now required to use digital technology in all aspects of their lives. As such, it is more important than ever that universities disseminate information about signs of a having a problematic relationship with digital technology and how this may impact on well-being. This may be of particular relevance to students identified as having mental health difficulties.

Whilst the results of this research show that digital technology can have a negative impact on well-being, it is important to remember that others have found that digital technology use can have a positive impact on social support, self-esteem and happiness and loneliness (Burke et al., 2010; Y. Chen & Lever, 2005; Ouyang et al., 2017). As such, these recommendations should only be implemented where a student’s relationship with digital technology is considered problematic or where it has a negative impact on their well-being.

Strengths and limitations of the current research

The current research has several strengths and limitations which will now be discussed. Broadly, these are related to the sample size and representativeness of the UK student population, the measurement and collection of data and the analysis of the data.

Strengths and limitations of the sample

It is a strength of the current research that the sample size exceeded what was considered acceptable for the analysis. However, as the sample is a small proportion of the University of Leeds student population (1.4%), generalisations about the findings of this research should be made with caution. In addition, the data was only collected from students at the University of Leeds and therefore the sample may not be representative of student populations at other UK higher education providers. The sample is broadly representative of the University of Leeds student characteristics and included participants from a broad range of faculties and programme levels. However, there are some discrepancies between the sample and the University of Leeds student population. Participants were more likely to be female, from a white ethnic background and a UK resident than those in the University of Leeds population.

The sample shows low levels of problematic digital use (0.6% gaming addiction, 5.7% internet addiction). However, these estimates are broadly in line with findings from other research into the prevalence of digital addiction in UK university students. Estimates range from 3.2% to 18% (Kuss et al., 2013; Morahan-Martin & Schumacher, 2000). As outlined in the discussion in relation to why basic psychological need satisfaction did not moderate the relationship between digital technology and well-being, this may have impacted on the strength of the relationships in the models. As much of the literature used to inform the current research focused on problematic levels of digital technology use the variables hypothesised to moderate the relationship between well-being and digital technology may not hold for a sample with low levels of problematic use.

Due to procedural constraints, outlined in the method, opportunistic sampling was used. Therefore, the sample was open to self-selection bias and the sample may not wholly represent the University of Leeds student population (Bethlehem, 2010). The survey was advertised across the University of Leeds and recruited from a wide range of faculties. However, it is possible that self-selection bias meant that people who were particularly interested in the impact of digital technology use were more likely to participate. Such people are likely to have pre-existing opinions about the relationship between digital technology use and well-being, introducing the potential for bias in their responses. It is not possible to estimate the degree to which this may have impacted on the findings of this research. However, the data was normally distributed on all measures as expected and therefore there is no indication of extreme responses or that responses were skewed by self-selection bias.

Strengths and limitations in collection and measurement of data

All the measures were collected via self-report and therefore may have been influenced by demand characteristics. Whereby, participant responses may have been influenced by the assumption that the researchers hypothesised that digital technology is negatively associated with well-being. To mitigate against the impact of this standardised measures with good psychometric properties were used for all variables, where possible. However, this was not possible for academic success therefore, the data for academic success is likely to be less reliable and valid than other variables.

Data was collected from students across the academic journey but only at one time point. As student well-being fluctuates across time at university (Bewick et al., 2010; Cooke et al., 2006) it is a limitation of the current research that inferences cannot be made about how the relationship between digital technology and well-being changes over time in the sample or about causality in these relationships.

Strengths and limitations in analysis

Structural equation modelling allowed for complex analysis of a large number of variables. The current research was able to test theoretical relationships between digital technology use, factors that influence well-being, academic success, factors that influence mental health, personal characteristics and academic context. It also compared different theoretical models with each other in terms of the fit for the data and was able to identify the model that was the best fit.

However, it was not possible in the scope of the current research to investigate in depth the impact of individual characteristics, such as demographic variables, on the relationship between digital technology use and well-being. Such analysis may have given further insight into the risk factors for problematic digital technology use and led to a better understanding of how to support university student well-being. In addition, structural equation modelling assumes linear relationships between variables, whereby associated variables increase/ decrease at the same rate. However, some of the relationships between variables in the models, such as basic psychological need satisfaction and digital technology use, may not have been linear. The assumption that all relationships between variables are linear may have impacted on the strength of relationships which are not linear and meant that they were statistically weaker than hypothesised.

Future research recommendations

To ensure that the results are more generalisable to the UK student population, future research should aim to yield a bigger and more representative sample. Data collection should also take place at numerous UK universities to highlight any variance in the results based on different student populations. It is also recommended that longitudinal data is collected. This would allow for a greater understanding of how problematic digital technology use impacts on well-being across the university student journey, with the potential to identify the factors that influence this and better understand causality.

In addition, further analysis could be completed on the data collected in this research to identify the personal and contextual factors which increased the risk of digital technology having a negative impact on well-being. Gender has been identified as a factor which influences well-being, mental health and digital technology use (Aljomaa et al., 2016; Morahan-Martin & Schumacher, 2000; Pereira et al., 2019; Thorley, 2017). As such, it would be helpful to further understand the impact of gender on the relationships identified in the current research. Similarly, socio-economic status is strongly associated with many of the factors related to well-being and mental health (Andrews & Wilding, 2004; Cooke, Barkham, & Bradley, 2004; Smith & Naylor, 2005). It has also been associated with digital technology use, although this relationship is not clear from the current literature (Kayri & Günüç, 2016; Lee & McKenzie, 2015). Further analysis on the impact of gender and socio-economic status on the relationship between digital technology use and well-being would allow for more targeted promotion of well-being information and allow clinicians to be more aware of the characteristics that make a person more at risk of a problematic digital use and the negative impact of this on their well-being.

Mental health was found to moderate the relationship between digital technology use and well-being therefore it would be pertinent to disaggregate larger datasets during analysis based on the presence of a diagnosed mental health condition (identified in the disability status questions). This would allow for a more specific understanding of the definition of mental health and identify whether those with diagnosed mental health conditions specifically experience greater levels of problematic digital technology use and poorer well-being.

Greater understanding of how the relationship between problematic digital technology use and well-being changes across time and the risk factors associated with this would increase our ability to recognise the warning signs of problematic digital use. Thus, allowing us to intervene earlier and better protect university student well-being and mental health.

Conclusions

The current research was an exploratory study investigating whether well-being is related to digital technology use in university students and if so, what factors are important to this relationship. Findings indicate that digital technology use has a negative impact on well-being in UK university students and that mental health moderates this relationship. Students who have higher levels of mental health difficulties are more likely to have problematic digital technology use and this problematic use is more likely to negatively impact on their well-being. Mental health was found to be the key moderator, although social support and basic psychological need satisfaction may also play a role.

It is recommended that universities and services which support university students work to increase awareness of the negative impact that digital technology can have on well-being. In addition, support services should include a brief assessment of links between problematic digital technology use and its links with mental health and well-being in their standard assessment practice.

Limitations related to sample size and representativeness, measurement and collection of data and analysis of the data mean that the results are not fully generalisable to the UK university student population. It is recommended that future research address these limitations by increasing sample size and representativeness. Also, that it investigates the risk factors associated with digital technology having a negative impact on well-being and measures the way in which this relationship changes across time.

In summary, digital technology use is related to well-being the UK university student population. Students with mental health difficulties are more likely to have a problematic relationship with digital technology and for their use of digital technology to negatively impact on their well-being.

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Appendix A – *Overview of Systematic Search strategy*

Search run on: 09.09.19

Databases searched: Ovid MEDLINE(R),1946 to August Week 5 2019 and PsycINFO, 1806 to September Week 1 2019.

Search terms:

1. "psychological health".mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

2. (anxiety or depression).mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

3. psychological distress.mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

4. psychological well*.mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

5. "mental health".mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

6. "mental well*".mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

7. (well* or stress).mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

8. 1 or 2 or 3 or 4 or 5 or 6 or 7

9. online behavio?r.mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

10. "internet use".mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

11. "smart phone".mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

12. "digital technology".mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

13. "social media use*".mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

14. "internet addiction".mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

15. "smartphone addiction".mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

16. "digital addiction".mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

17. "social media addiction".mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

18. "gaming addiction".mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

19. 9 or 10 or 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18

20. ((online or internet or "smart phone" or smartphone or digital or "social media") adj2 (addict* or problem* or use* or usag*)).mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh

21. (university or college or student*).mp. [mp=ti, ab, ot, nm, hw, fx, kf, ox, px, rx, ui, an, sy, tc, id, tm, mh]

22. 8 and 19 and 20 and 21

23. limit 22 to English language

24. remove duplicates from 23

Initial results: 887

Refining criteria 1:

- Population: 0=Other, 1= University students, 2=Young people, 3=Unsure).
- Type of well-being investigated: 0=Other, 1=Mental health, 2=Psychological well-being 3=Physical health, 4=Holistic well-being (mental health, physical health and psychological well-being, 5=Unsure.
- Type of technology use investigated: 0=Other, 1=Internet, 2=Smartphone, 3=Gaming, 4=Social media, 5=Mixture.
- To include: 0=No, 1=Yes, 2=Unsure.

Included: University student sample, investigated psychological well-being, any type of technology use.

Refined results: 62 (825 excluded)

Refining criteria 2: Specific measure of psychological well-being used and not measures of mental health or mental distress.

Refined results: 12 (50 excluded).

Read 12 papers in full. Excluded 3 due to not using a measure of psychological well-being.

Final papers: 9 papers (Çardak, 2013; Odaci & Çikrikçi, 2014; Ouyang et al., 2017; Rayan et al., 2017; Sacco, 2018; Sultan, 2019; Suphan & Mierzejewska, 2016; Turel et al., 2018; Ye & Lin, 2015).

Appendix B – ***Table summarising systematic search articles***

Article	*Aims*	*Population*	*N*	*Measures*	*Method*	*Relationship*	*Conclusions*	*Limitations*
(Çardak, 2013)	Relationships between IA and PWB	Undergraduate students Turkey	479	-online cognition scale -Scales of Psychological wellbeing	Paper questionnaires Analysed correlation and regression	Significant negative correlation between internet addiction and psychological well-being. Diminished impulse control, distraction, loneliness/depression & social comfort accounted for 47% of variance in psychological well-being.	Higher levels of internet addiction associated with lower levels of psychological well-being	Convenience sample. Self-report measures.
Odaci (2014)	Association between Pathological internet use, gender, attachment style and psychological well-being	University students Turkey	380	-Problematic Internet Use scale -Relationship Scales questionnaire -Subjective Wellbeing Scale	Paper questionnaires Analysed with correlation and multiple linear regression	Pathological internet use significantly positively correlated with dismissing and preoccupied attachment styles. Pathological internet use significantly negatively correlated with psychological well-being.	Pathological internet use varies according to gender and attachment styles and has a negative effect on wellbeing.	Self-report measures

	Aims	*Population*	*N*	*Measures*	*Method*	*Relationship*	*Conclusions*	*Limitations*
Odaci (2014) cont.						Gender, psychological well-being & dismissing attachment style sig. contribute to pathological internet use. psychological well-being significant negative predictor of pathological internet use. Males have higher pathological internet use scores. Those with secure attachment have lower pathological internet use scores.		
Ouyang et al. (2017)	Differences between intense and less intense male internet users	Male undergraduate students China	1024	-IAT -Online social support scale -Rosenberg SES -Subjective WB Scale	Paper questionnaires Analysed by correlation and SEM	Psychological well-being of intense users sig. lower. Intense users sig. higher levels of online support and sig. lower scores for support from friends/others. No significant diff between the effect of online or real-life social support. Self-esteem a partial mediator between support and psychological well-being.	Online and real-life social support have similar effects on self-esteem. Focusing on alleviating internet addiction might miss out on positive effects of online social support on psychological well-being.	IAT can yield false positive results. Only self-esteem and psychological well-being measured for their effect on internet use, lots of other variables. Also, not just internet use that could be affected (other forms of digital use). Self-report measures.

	Aims	Population	N	Measures	Method	Relationship	Conclusions	Limitations
Rayan et al. (2017)	Prevalence of internet use, advantages and disadvantages and impact on psychological health	University students Palestine	144	Developed from focus groups. Measures of frequency of internet use, advantages and disadvantages of using it and psychological health	Focus groups to develop survey. Analysed using descriptive and ANOVAs	Use of the internet was high. Advantages include updating themselves, help with studying, problem solving. Disadvantages include negative impact on academic work and family relationships	Internet use has a positive and negative impact on educational, social and psychological aspects of students. Advantages higher than disadvantages. Psychological health and family relationships negatively affected by internet use	Self-reported data, convenience sample
Sacco (2018)	The effect of social media and electronic communication on mental health and wellbeing across time and whether rumination is a moderator of this relationship.	University students USA	115	-Health and wellness app. Daily questions about wellness (exercise, diet, mood, social interaction) -Beck Depression Inventory -Positive and negative affect scale -3 items from Psychological Well-Being Scale	Objective phone use data, subjective self-report measures Analysed by correlation and regression	Social communication not correlated to mental health. Frequency of digital use poor predictors of same and next day mental health and psychological well-being. Perceived quality of interactions moderate to strong positive correlation with mental health. Wellbeing on one day predicted social media	The amount of contact is not associated with WB, the quality of the interaction is. Negative affect or Well-being on one day carried over to the next day and meant social interactions were enjoyed	Measurement error and differences between data on different phones. Some self-report measures. Perceived quality of interactions questions ambiguous. No data on the way

	Aims	*Population*	*N*	*Measures*	*Method*	*Relationship*	*Conclusions*	*Limitations*
				-Rumination responses scale -Number of communications made on phone, duration of phone calls and time spent on social media apps.		use on the next. Rumination moderations the relationship between depression and perceived interaction quality (higher rumination = lower quality).	less the next day. Perceptions of relationships are a more useful predictor of mental health than frequency of digital use.	social media apps were used e.g. diff between Facebook and Tinder.
Sultan (2019)	Relationship between intensity/ purpose of social media use and sense of belonging and psychological well-being	Undergraduate students America	298	-Gravitation towards Facebook Scale - Multidimensional Facebook intensity scale -Sense of belonging instrument-Psychological state -Ryff's Psychological Wellbeing Scale -Researcher developed measure of face to face interaction	Online questionnaire. Analysed by multiple regression	Overuse of social media negatively correlated to a sense of belonging and psychological well-being. Self-expression negatively related to sense of belonging. Persistence of use not sig. correlated with face to face interactions. 4 of the 12 social media variables were related to psychological well-being (persistence, overuse, monitoring and learning).	Various types of social media use are associated with a sense of belonging and psychological well-being. Frequency and intensity of Facebook are associated with negative psychological outcomes. Passive use of social media is associated with loneliness and not with psychological well-being.	No prior confirmation that participants used Facebook. Measures don't capture all aspects of Facebook use. No control for other demographics. No measure of other types of social media.

	Aims	*Population*	*N*	*Measures*	*Method*	*Relationship*	*Conclusions*	*Limitations*
Turel et al. (2018)	Does gender and neuroticism moderate the associated between social media and psychological well-being	University students Israel	215	-Bergen Facebook addiction scale -Big Five inventory -WHO 5 item Wellbeing Index -Demographics: Gender, age, number of Facebook friends, frequency of use, education	Online questionnaire. Analysed by hierarchical liner and logistical regression	High levels of social media addiction are related to lower psychological well-being. Higher neuroticism associated with a stronger negative relationship between social media addiction and psychological well-being. High neuroticism magnified negative association between social networking and psychological well-being in women.	Social network addiction can be conceived as a persistent stressor that's associated with reduced psychological well-being. Neuroticism alters the way people interpret and manage this stress. Women differ from men in the way they subjectively associate social media, neuroticism and psychological well-being.	Cross sectional design. No account for possible co-morbidities with social media addiction. Simple set of cut offs used for depression and addiction. Subjective measures.
Ye & Lin (2015)	The effects of online communications on wellbeing, in particular – locus of control, loneliness, subjective well-being, and preference online	Undergraduate students China	260	-Rotter's Locus of Control Scale -Campbell Index of wellbeing -UCLA Loneliness Scale -Preference for online social interaction	Paper questionnaires Analysed by correlation and hierarchical logistical regression.	Positive relationship between external locus of control and preference for online interaction. Those with an external locus of control were more lonely and unhappy. Negative relationship between Psychological well-being and	Those who felt lonelier were more likely to prefer online social interactions.	Participants from one part of China, ore female than male participants. Exploratory study, more in-depth measurement needed.

	Aims	Population	N	Measures	Method	Relationship	Conclusions	Limitations
	social interaction.					preference for online interaction. Loneliness and psychological well-being have a mediating effect between the relationship of locus of control and preference for online social interaction.		
Suphan et al. (2016)	Impact of social media use on well-being and whether there is a boundary between interpersonal online and offline communication spheres. Is there a cultural difference between USA and Germany	American and German university students	685	Items to measure: -positive emotional outcomes of social media use, involvement in social life, perception of exclusion, motives to use social media -SWB limited to positive emotions. 5 items from Mental Health Inventory and Positive and Negative Affect schedule scale.	Questionnaires in person and online. Analysed using SEM, factor analysis, multiple group analysis	Using social media for social grooming sig. increases positive emotional outcomes of social media use. Time spent with friends offline reduced feelings of social exclusion. Well-being influenced by online and offline socialising. Cultural differences between motives for using social media and impact of online socialising on real life socialising.	Online social grooming activities mostly benefit offline social activities and thus well-being. Well-being is increased by time spent with friends and increased by perceived exclusion.	Focused on positive well-being and effects only. Further research needed to investigate other cultures

Appendix C - *Letter of ethical approval*

The Secretariat
University of Leeds
Leeds, LS2 9JT
Tel: 0113 3431642
Email: FMHUniEthics@leeds.ac.uk

UNIVERSITY OF LEEDS

16 May 2019

Miss Azaria Khyabani
Psychologist in Clinical Training
Leeds Institute of Health Sciences
Faculty of Medicine and Health
Clinical Psychology, Level 10, Worsley Building
University of Leeds
Clarendon Way
LEEDS LS2 9NL

Dear Azaria

Ref no: **Investigating the associations between university student well-being and digital use**
Study Title: **MREC 18-082**

Thank you for submitting your documentation for the above project. Following review by the School of Medicine Research Ethics Committee (SoMREC) I can confirm a conditional favourable ethical opinion based on the documentation received at date of this letter *and subject to the following conditions which must be fulfilled prior to the study commencing:*

1. **Please ensure all participant facing documentation has the University of Leeds logo on the top right hand corner**

2. **Please update your Participant Information Sheet (PIS) consent form, survey and other study materials with version numbers**

3. **Please add the text regarding the Research Participant Privacy Notice on the PIS to comply with GDPR requirements – see http://ris.leeds.ac.uk/downloads/download/898/consent_for_questionnaires_and_surveys or the PIS template at http://ris.leeds.ac.uk/downloads/download/212/preparing_your_participant_information_sheet**

The study documentation must be amended as required to meet the above conditions and submitted for file and possible future audit. Once you have addressed the conditions and submitted for file/future audit, you may commence the study and further confirmation of approval is not provided.

Please note, failure to comply with the above conditions will be considered a breach of ethics approval and may result in disciplinary action.

Document Received	*Version*	*Date Received*
Ethics application form	1.0	02/04/2019
Appendix A. – Participant Information Sheet	1.0	02/04/2019
Student Demographics	1.0	02/04/2019
WEMWBS	1.0	02/04/2019
EQ-5D-5L	1.0	02/04/2019
Pittsburgh Sleep Quality Index	1.0	02/04/2019
AUDIT-C and DUDIT-C	1.0	02/04/2019
Gaming Addiction Scale	1.0	02/04/2019
Mindfulness Attention Awareness Scale	1.0	02/04/2019
Academic success	1.0	02/04/2019
Brief Resilience Scale	1.0	02/04/2019
Basic Psychological Need Satisfaction and Frustration Scale	1.0	02/04/2019
Multidimensional Scale of Perceived Social Support	1.0	02/04/2019
Perceived Stress Scale	1.0	02/04/2019

Smartphone Addiction Scale	1.0	02/04/2019
CORE-10	1.0	02/04/2019
Internet Addiction Test	1.0	02/04/2019
Demographics	1.0	02/04/2019
Prize draw information	1.0	02/04/2019
Thank you text	1.0	02/04/2019

Please notify the committee if you intend to make any amendments to the original research as submitted at date of this approval. This includes recruitment methodology and all changes must be ethically approved prior to implementation. Please contact the Faculty Research Ethics Administrator for further information FMHUniEthics@leeds.ac.uk

Ethical approval does not infer you have the right of access to any member of staff or student or documents and the premises of the University of Leeds. Nor does it imply any right of access to the premises of any other organisation, including clinical areas. The SoMREC takes no responsibility for you gaining access to staff, students and/or premises prior to, during or following your research activities.

You are expected to keep a record of all your approved documentation, as well as documents such as sample consent forms, risk assessments and other documents relating to the study. This should be kept in your study file, and may be subject to an audit inspection. If your project is to be audited, you will be given at least 2 weeks notice.

It is our policy to remind everyone that it is your responsibility to comply with Health and Safety, Data Protection and any other legal and/or professional guidelines there may be.

The committee wishes you every success with your project.

Yours sincerely

Dr Naomi Quinton
Co-Chair, School of Medicine Research Ethics Committee

Appendix D - ***Participant information sheet, consent to participate and consent to be entered into prize draw.***

Online surveys

Student well-being and digital use

Survey is Open

Changes may result in lost or corrupted responses.

When creating your survey, we recommend the use of a privacy notice, this should explain to survey respondents about how you plan to use any personal information you collect, and how long you intend on keeping it. Your organisation's data protection officer may be able to provide advice and guidance on creating a suitable privacy notice for your survey.

p. 1 Introduction

Add item

Understanding the well-being of University of Leeds students

This survey asks you questions about well-being, coping and psychological distress.

Everyone who completes the survey and provides an email address will be entered into a prize draw to win **£20** (3 prizes to be won) or **£5** (45 prizes to be won) and the first **100** respondents will receive **£5** cash.

To help you decide whether you would like to complete this survey, further information about this study is provided on the next page.

Add item

p. 2 Participant Information Sheet

Add item

You are being invited to take part in a research project.

Please take the time to read the following information carefully to help you decide whether or not you would like to participate in the study. It is important to understand why the research is being done and what it will involve.

What is the purpose of this study?

The study will investigate if there are links between use of the online world and student well-being and psychological distress.

Why have I been invited to take part?

All students at the University of Leeds have been invited to complete this survey.

What will be involved if I agree to take part in this study?

If you agree to take part you will be asked to complete an online survey. The survey will ask questions about your well-being, your use of the online world, and a little about who you are. The survey should take 25-30 minutes to complete.

If you are one of the first 100 people to complete the survey and provide your contact email, you will receive £5 cash. Everybody who completes the survey can opt to be entered into a prize draw to win £20 (3 prizes to be won) or £5 (45 prizes to be won).

What happens to the information I give?

The answers you give will be stored anonymously on a secure University of Leeds server and will be used in the analysis of this research. After this research has been completed, the data will be kept securely for use in future research by the University of Leeds and their academic collaborators. All of the data obtained will be treated as confidential and stored securely as is required by the Data Protection Act. The data collected will be used as part of a doctoral thesis and may be written up for publication. No identifying information about you will be included in the report. For further information, please see the University of Leeds Research Privacy Notice:

https://dataprotection.leeds.ac.uk/wp-content/uploads/sites/48/2019/02/Research-Privacy-Notice.pdf

What happens if I say yes but then later decide I don't want to take part?

You are able to exit the survey at any time by closing your browser. Any data already submitted on previous pages will already be captured by OnlineSurvey. Once data has been captured you will not be able to withdraw it from the research as the data is stored anonymously.

Do I have to take part in the study?

Taking part in this study is voluntary, participants can withdraw at any time without giving a reason however, any responses already provided will be retained due to anonymity of responses. You do not have to give a reason for not participating and the decision to take part or not will not impact on your studies at the University of Leeds.

Will I be contacted as a result of anything I answer in the survey?

The survey is anonymous therefore you cannot be contacted regardless of what you answer in the survey. If you require health and well-being support please contact one of the support services listed below.

Who has reviewed this study?

This study has been reviewed by the School of Medicine Research Ethics Committee, University of Leeds *(MREC 18-082)*.

How do I take part?

You can take part in this study by completing the consent form on the following page and answering the survey questions.

If I have questions about the study who can I ask?

If you would like further information please contact the Doctoral student who is completing this research, Azaria Khyabani (umakhy@leeds.ac.uk). You can also contact the Lead Supervisor Dr Bridgette M Bewick (b.m.bewick@leeds.ac.uk).

Support

It is possible that you may find some of the questions in this survey distressing. You can exit the survey at any time without giving a reason.

If you feel you require support for your mental health, please contact your GP and book an appointment. You can also contact:

> *Leeds University Student Counselling and Well-being service*: Complete an online referral form at: https://leeds.onlinesurveys.ac.uk/student-counselling-well-being-service-self-referral-form-2018-19
>
> *Leeds University Nightline*: 0113 3801285 (available 8pm- 8am every night of term including weekends).
>
> *Samaritans*: 116 123 (available 24 hours a day, 365 days a year).
>
> *Leeds Improving Access to Psychological Therapies* (email: leedsiapt@nhs.net, phone: 0113 843 4388).

If you feel you are in crisis and are concerned for the immediate safety of you or those around you, please call 999.

To take part in the research please click 'next'.

Add item

p. 3 Consent form

Add item

I confirm that I have read the information on the previous page and understood what I am being asked to do in this research.

I understand that my responses to the survey will remain confidential.

I understand that once my responses have been captured by OnlineSurvey I will be unable to withdraw them.

I understand that my participation is voluntary and I can withdraw at any time without giving a reason.

I give consent to take part in this research and for my anonymised data to be stored and used in the analysis of this and future research.

If you understand the information provided and consent to taking part in the study please click on the next button and go on to complete the survey.

Add item

56 What is the highest level of education achieved by at least one of your parents or carers?

No level of education

Primary school education

High school/ secondary school education

Post-school academic education

Post-school vocational education e.g. apprenticeship

Undergraduate degree

Masters degree

Doctoral degree

Prefer not to say/ Don't know

Show less

Add item

Add item

57 For UK students: What was your postcode when you were 16 years old?

Add item

Add item

p. 20

Add item

58 Is there anything else you feel you need to tell us about your answers to the survey?

Add item

Add item

p. 21 Prize draw information

Add item

To say thank you for completing this survey we will be entering everyone who provides their details below into a prize draw with a chance to win £20 (3 prizes to be won) or £5 (45 prizes to be won). Your email addresses will not be linked to earlier responses.

Add item

59 Would you like to be entered into the prize draw?

Yes, please use the email address given below.

No, I do not wish to be entered into the prize draw.

Add item

Add item

60 Please provide a valid email address.

Add item

Add item

This survey is part of a larger programme of work investigating student well-being. Would you like to receive information on future studies? Your email address will not be linked to your previous responses. Your email will be kept on our mailing list for up to three years. After that time your email address will be removed from our mailing list. Your email will not be shared with third parties. You will only receive information about studies of relevance to student well-being.

Add item

61 Are you interested in being contacted about future research?

Yes, I am interested in receiving information about participation in future studies

No, I am not interested in volunteering for future studies

Add item

Add item

62 If yes, please provide details of the email address we can contact you on:

Please use the email address given above

Please use the email address provided below

Add item

a Please provide a valid email address.

Add item

Add item

p. 22 Thank you

Add item

Thank you for taking the time to complete the questionnaire.

If you are one of the first 100 people to complete the survey we will contact you to arrange for you to collect your £5.

If you are one of the lucky winners of the £20 or £5 prizes, you will be contacted in due course.

If you have been affected by any of the questions in this survey, and/ or wish to seek support please visit your GP or consider one of the following services:

Leeds University Student Counselling and Well-being service: Complete an online referral form at: https://leeds.onlinesurveys.ac.uk/student-counselling-well-being-service-self-referral-form-2018-19

Leeds University Nightline: 0113 3801285 (available 8pm- 8am every night of term including weekends).

Samaritans: 116 123 (available 24 hours a day, 365 days a year).

Leeds Improving Access to Psychological Therapies: email: leedsiapt@nhs.net, phone: 0113 843 4388.

If you feel you are in crisis and are concerned for the immediate safety of you or those around you, please call 999.

Please exit this webpage to end the survey.

Add item

Appendix E - ***Recruitment poster and flyer***

UNIVERSITY OF LEEDS

How much do you use digital technology?

Want to be in with the chance of winning ***£20***?

To get involved, simply scan the QR code or take a link to the online survey. It will take around 25-30 minutes to complete and all answers will be anonymous.

The first 100 respondents will also receive **£5** cash.

Scan me

This research project is being conducted by Azaria Khyabani, as part of a doctoral thesis, and has been reviewed by the School of Medicine Research Ethics Committee (*MREC 18-082*).

Digital use and well-being survey:
https://leeds.onlinesurveys.ac.uk/uol-wellbeing

Digital use and well-being survey:
https://leeds.onlinesurveys.ac.uk/uol-wellbeing

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https://leeds.onlinesurveys.ac.uk/uol-wellbeing

UNIVERSITY OF LEEDS

How much do you use digital technology?

Want to be in with the chance of winning ***£20*?**

The survey will take around 25-30 minutes to complete and all answers will be anonymous.

To get involved, simply scan the QR code or visit:

SCAN ME

https://leeds.onlinesurveys.ac.uk/uol-wellbeing

The first 100 respondents will also receive **£5** cash.

This research is part of a doctoral thesis and is approved by the School of Medicine Research Ethics Committee (MREC 18-082).

Appendix F - *Recruitment email sent directly to students*

Dear student,

There is an opportunity to take part in an online survey about the well-being of University of Leeds students. The survey will take around 25-30 minutes to complete and all responses are anonymous.

To encourage your participation, the first 100 participants who provide their contact details will receive £5 cash and all participants will be entered into a prize draw to win either £20 (3 prizes) or £5 (45 prizes).

This research project is being conducted by Azaria Khyabani, as part of a doctoral thesis, and has been reviewed by the School of Medicine Research Ethics Committee (MREC 18-082).

If you are interested in taking part, simply click the link below:

https://leeds.onlinesurveys.ac.uk/uol-wellbeing

Kind regards,

Azaria

Azaria Khyabani

Doctoral Student

School of Medicine and Health

University of Leeds

Appendix G - *Recruitment email sent to University of Leeds staff and services*

Good morning,

I am a doctoral student conducting research into the relationship between well-being and digital technology use in students at the University of Leeds. I am recruiting students to complete an online survey and wondered if you could please send an email with information about the survey and the link to access it to the students you in your school/ service.

If you would be happy to do so, please just forward the text below in an email:

Dear student,

There is an opportunity to take part in an online survey about the well-being of University of Leeds students. The survey will take around 25-30 minutes to complete and all responses are anonymous.

To encourage your participation, the first 100 participants who provide their contact details will receive £5 cash and all participants will be entered into a prize draw to win either £20 (3 prizes) or £5 (45 prizes).

This research project is being conducted by Azaria Khyabani, as part of a doctoral thesis, and has been reviewed by the School of Medicine Research Ethics Committee (MREC 18-082).

If you are interested in taking part, simply click the link below:

https://leeds.onlinesurveys.ac.uk/uol-wellbeing

Kind regards,

Azaria

Azaria Khyabani

Doctoral Student

School of Medicine and Health

University of Leeds

Appendix H - ***Emails notifying participants they were eligible for one of the 'first 100' £5 prizes or participation prize draw cash prizes.***

Good afternoon,

I'm getting in touch because you completed my thesis survey "University of Leeds student well-being and digital use". As you were one of the first 100 people to complete the survey you are eligible to receive one of the £5 incentive prizes.

I am only able to provide the £5 in cash and will be holding a number of session where participants can come to collect their money. These sessions will all be held in room **10.17** of the **Worsley Building** (level 10). I will just require you to sign a form to confirm that you have collected the money.

Please attend one of the following sessions to collect your prize:

- Wednesday 30th October: 9am - 1pm
- Thursday 7th November: 4:30pm - 5:30pm
- Friday 8th November: 2pm - 5pm
- Wednesday 20th November: 9am - 12:00pm
- Thursday 21st November: 12:30pm - 1:30pm
- Wednesday 11th December - 2:00-4:30pm

Thanks again for your participation.

Kind regards,

Azaria

Azaria Khyabani
Doctoral student
Faculty of Medicine and Health
University of Leeds

Good morning,

I'm getting in touch because you completed my doctoral thesis research questionnaire about the use of digital technology and well-being in UoL students and you are one of the prize draw winners. I'm pleased to let you know that you have won one of the £5 prizes!

I was originally going to give this in cash but of course that's not possible now. The university finance team have agreed that they will do a bank transfer for the £5 and to do so, I will need the following details:

Name:

Address:

Bank Sort Code:

Bank Account Number:

Please can I ask that you reply with these details by **Friday 5th June** so that I can process the payments. Unfortunately, payments for replies after this date will not be processed.

Thanks again for your participation in the questionnaire and I hope you enjoy the prize money!

Kind regards,

Azaria

Azaria Khyabani
Doctoral student
Faculty of Medicine and Health
University of Leeds

Appendix I - ***Table detailing variables and measures collected, response options, scoring of measures and the format for use in analysis***

Measure	***Response options, scoring and cut offs (n = number in data)***	***Categories used in analysis***
Academic school	*Faculty of Arts, Humanities and Culture* • Design *(n=15)* • English *(n=5)* • Fine Art, History of Art and Cultural Studies *(n=6)* • History *(n=2)* • Institute for Medieval Studies *(n=0)* • Inter-Disciplinary Ethics Applied *(n=0)* • Languages, Cultures and Societies *(n=19)* • Media and Communication *(n=28)* • Music *(n=9)* • Performance and Cultural Industries *(n=1)* • Philosophy, Religion, and the History of Science *(n=7)* *Faculty of Biological Sciences* • Biology *(n=25)* • Biomedical Sciences *(n=18)* • Molecular and Cellular Biology *(n=6)* *Faculty of Business* • Accounting and Finance *(n=1)* • Economics *(n=2)* • International Business *(n=2)* • Management *(n=2)* • Marketing *(n=3)* • Work and Employment Relations *(n=1)* *Faculty of Engineering and Physical Sciences* • Chemical and Process Engineering *(n=60)* • Chemistry *(n=31)* • Civil Engineering *(n=3)* • Computing *(n=6)* • Electronic and Electrical Engineering *(n=2)* • Mathematics *(n=6)* • Mechanical Engineering *(n=11)* • Physics and Astronomy *(n=3)* *Faculty of Environment* • Earth and Environment *(n=23)* • Food Science and Nutrition *(n=19)* • Geography *(n=13)* • Institute for Transport Studies *(n=1)* *Faculty of Medicine and Health* • Dentistry *(n=17)* • Healthcare *(n=73)*	Collapsed into seven University of Leeds faculties: • Faculty of Arts, Humanities and Culture • Faculty of Biological Sciences • Faculty of Business • Faculty of Engineering and Physical Sciences • Faculty of Environment • Faculty of Medicine and Health • Faculty of Social Sciences

	• Medicine *(n=44)* • Medicine and Health Graduate School *(n=25)* • Psychology *(n=27)* *Faculty of Social Sciences* • Education *(n=7)* • Education, Social Sciences and Law Graduate School *(n=2)* • Law *(n=3)* • Politics and International Studies *(n=5)* Sociology and Social Policy *(n=6)*	

Measure	***Response options, scoring and cut offs (n = number in data)***	***Categories used in analysis***
Academic programme	• Undergraduate programme *(n=345)* • Master's programme *(n=68)* • Taught postgraduate programme *(n=50)* • Research postgraduate programme *(n=70)*	Collapsed into two categories: • Undergraduate programme • Postgraduate programme
Full-time/ Part-time academic study	• Full time *(n=510)* • Part time *(n=31)*	As survey response categories
Student domicile	• UK student *(n=439)* • EU student *(n=38)* • International student *(n=65)*	As survey response categories
Year of study	• 1st year *(n=196)* • 2nd year *(n=137)* • 3rd year *(n=134)* • 4th year *(n=67)* • 5th year *(n=10)* • 6th year *(n=3)*	Collapsed into four categories: • 1st year • 2nd year • 3rd year • 4th year or higher
WEMWBS	14 items rated on a 5-point Likert scale (1=None of the Time, 2=Rarely, 3=Some of the Time, 4=Often, 5 All of the time). Total score = sum of all items. Higher scores indicate higher well-being. • Low subjective well-being *(n=77)* • Average subjective well-being *(n=395)* • High subjective well-being *(n=70)*	Total score

Measure	***Response options, scoring and cut offs (n = number in data)***	***Categories used in analysis***
EQ-5D-5L	5 items with responses ranging from no problems in that area to extreme problems. A 100-point visual analogue scale used to rate health today. Total score = sum of 5 descriptive items. Lower scores indicate better physical health. • No problems – total score of 5 or less *(n=120)* • Some problems – total score of 6 or more *(n=417)*	Total score
Pittsburgh Sleep Quality Index	10 items rated across 4-point Likert scales. A total score and 7 subscales are measured; subjective sleep quality, sleep latency, sleep duration, sleep efficiency, sleep disturbance, use of sleep medication and daytime dysfunction. Total score = sum of 7 sub scales. Lower scores indicate better sleep quality. • Normal sleep – total score of 0-4.99 *(n=16)* • Poor sleeper – total score of 5 or more *(n=498)*	Total score
AUDIT-C	3 items rated on a 5-point Likert scale (0=Never, 1=Monthly or less, 2=2-4 times per month, 3=2-3 times per week, 4=4+ times per week). Total score = sum of all items. Scores over 5 indicate intervention may be required. Lower scores indicate lower risk alcohol use. • No intervention required – total score of 0-4.99 *(n=199)* • Intervention may be required – total score of 5 or more *(n=344)*	Total score
DUDIT-C	4 items rated on a 4-point Likert scale (0-4). Total score = sum of all items. Scores over 2 for women and 6 for men indicate intervention may be required. Lower scores indicate lower risk drug use • No intervention required – total score of 0-5.99 *(n=462)* • Intervention may be required – total score of 6 or more *(n=73)*	Total score

Measure	*Response options, scoring and cut offs (n = number in data)*	*Categories used in analysis*
Gaming Addiction Scale	7 items rated on a 5-point Likert scale (1=Never, 2=Rarely, 3=Sometimes, 4=Often, 5=Very often). Total score = sum of all items. Higher scores indicate problematic gaming behaviour. • Normal gaming use – 0-2 across all questions *(n=535)* • Pathological gaming use – 3-5 across all questions *(n=3)*	Total score
Mindfulness Attention Awareness Scale	15 items rated on a 6-point Likert scale (1=Almost always, 2=Very frequently, 3=Somewhat frequently, 4=Somewhat infrequently, 5=Very infrequently, 6=Almost never). Total score = mean of all items. Higher scores indicate higher levels of dispositional mindfulness.	Total score
Academic importance and satisfaction	2 items rated on 5-point Likert scales. Academic importance (1=very important, 2=somewhat important 3=neither important or unimportant, 4=somewhat unimportant, 5=very unimportant). Academic satisfaction (1=very satisfied, 2=somewhat satisfied, 3=neither satisfied or dissatisfied, 4=somewhat dissatisfied, 4=very dissatisfied). Higher scores indicate higher importance of and satisfaction with academic success.	Each question collapsed into three categories. Academic importance: • Important • Neither important or unimportant • Unimportant Academic success: • Satisfied • Neither satisfied or dissatisfied • Dissatisfied
Brief Resilience Scale	6 items rated on 5-point Likert scales. Total score = mean of all items. Lower scores indicate higher level of resilience.	Total score
Basic Psychological Need Satisfaction and Frustration Scale	24 items rated on a 5-point Likert scale (1=Not true at all to 5=Completely true). 3 psychological need satisfaction subscales; autonomy, relatedness, and competence satisfaction. 3 need frustration subscales; autonomy, relatedness, and competence satisfaction. Total psychological need satisfaction score = sum of satisfaction subscales. Higher scores indicate higher levels of psychological need satisfaction.	Total psychological need satisfaction score

Measure	***Response options, scoring and cut offs (n = number in data)***	***Categories used in analysis***
	Total psychological need frustration score = sum of frustration subscales. Higher scores indicate higher levels of psychological need frustration	
Multidimensional Scale of Perceived Social Support	12 items rated on a 7-point Likert scale (1=Very Strongly Disagree,2=Strongly Disagree, 3=Mildly Disagree, 4=Neutral, 5=Mildly Agree, 6=Agree, 7=Very Strongly Agree). 3 subscales; Significant other subscale, Family Subscale and Friends Subscale. Total score = mean of all items. Higher scores indicate greater social support. • Low support – total score of 1-2.99 *(n=44)* • Moderate support - total score of 3-5 *(n=149)* • High support – total score of 5.1-7 *(n=344)*	Total score
Perceived Stress Scale	10 items rated on 5-point Likert scales. Total score = sum of all items. Lower scores indicate lower levels of perceived stress.	Total score
Smartphone Addiction Scale	33 items rated on a 6-point Likert scale (1=Strongly disagree, 2=Disagree, 3=Weakly disagree, 4=Weakly agree, 5=Agree, 6=Strongly agree). Total score = sum of all items. Higher scores indicative of smartphone addiction.	Total score
CORE-10	10 items rated on a 5-point Likert scale. Total score = mean of all items. Higher scores indicate greater psychological distress. • Clinical cut off - mean of <10 *(n=190)* • Mild difficulties - mean of 10-14.99 *(n=112)* • Moderate difficulties - mean of 15-19.99 *(n=100)* • Moderate to severe difficulties - mean of 20-24.99 *(n=75)* • Severe difficulties - mean of 25+ *(n=62)*	Total score

Measure	***Response options, scoring and cut offs (n = number in data)***	***Categories used in analysis***
Internet Addiction Test	20 items rated on a 6-point Likert scale (0=Not Applicable, 1=Rarely, 2=Occasionally, 3=Frequently, 4=Often, 5=Always). 6 subscales; Salience, Excessive use, Neglect work, Anticipation, Lack of control, Neglect social life. Total score = sum of all items. Higher scores indicate higher level of severity of Internet compulsivity and addiction. • Normal level of internet usage - total score of 0-30 *(n=320)* • Mild level of internet addiction - total score of 31-49 *(n=164)* • Moderate level of internet addiction - total score of 50-79 *(n=30)* • Severe dependence on the internet - total score of 80-100 *(n=1)*	Total score
Age	• 16 *(n=0)* • 17 *(n=1)* • 18 *(n=15)* • 19 *(n=65)* • 20 *(n=84)* • 21 *(n=70)* • 22 *(n=81)* • 23 *(n=45)* • 24 *(n=26)* • 25 *(n=20)* • 26 *(n=22)* • 27 *(n=24)* • 28 *(n=17)* • 29 *(n=11)* • 30 *(n=14)* • 31 *(n=9)* • 32 *(n=5)* • 33 *(n=4)* • 34 *(n=0)* • 35 *(n=2)* • 36 *(n=5)* • 37 *(n=0)* • 38 *(n=5)* • 39 *(n=2)* • 40 *(n=2)* • 41 *(n=0)* • 42 *(n=3)* • 43 (n=3) • 44 *(n=2)*	Collapsed into four categories: • 16-20 • 21-25 • 26-29 • 30+

Measure	*Response options, scoring and cut offs (n = number in data)*	*Categories used in analysis*
	• 45-51 *(n=0)* • 52 *(n=1)* • 53 *(n=1)* • 54-99 *(n=0)* • 99 years or over *(n=0)* • Prefer not to say *(n=1)*	
Gender	• Female *(n=385)* • Male *(n=135)* • Transgender female *(n=3)* • Transgender male *(n=1)* • Gender non-binary *(n=6)* • Prefer to self-describe/ other *(n=3)* • Prefer not to say *(n=4)* • Free text box for prefer to self-describe/ other *(n=3)*	Collapsed into five categories: • Female • Male • Transgender/ Non-binary • Prefer to self-describe/ Other • Prefer not to say
Country of Origin	List of all countries	Not used in model
Sexuality	• Bisexual *(n=51)* • Heterosexual/ Straight *(n=429)* • Gay man *(n=17)* • Gay woman/ Lesbian *(n=10)* • Prefer to self-describe/ Other *(n=12)* • Prefer not to say *(n=18)* • Free text box for prefer to self-describe/ other *(n=11)*	Collapsed into four categories: • Heterosexual/ Straight • Gay man/ Gay woman/ Bisexual • Prefer to self-describe/ Other • Prefer not to say
Ethnicity	White ethic background: • English/Welsh/Scottish/Northern Irish/British *(n=231)* • Any other White background *(n=25)* • White and Black African *(n=4)* • White and Asian *(n=10)* • Any other Mixed/Multiple ethnic background *(n=10)* Asian ethnic background: • Indian *(n=20)* • Pakistani *(n=13)* • Bangladeshi *(n=2)* • Chinese *(n=21)* • Any other Asian background *(n=10)* Black ethnic background: • African *(n=3)* • Any other Black/African/Caribbean background *(n=2)* Other ethnic background: • Arab *(n=5)* • Any other ethnic group *(n=1)*	Collapsed into four categories: • White ethnic background • Black/ Asian/ Mixed/ Arab/ Other ethnic background • Prefer to self-describe/other • Prefer not to say

Measure	***Response options, scoring and cut offs (n = number in data)***	***Categories used in analysis***
	• Prefer to self-describe/ Other *(n=4)* Prefer not to say *(n=5)*	
Disability	Q1. Do you have a disability? • Yes *(n=53)* • No *(n=469)* • Prefer not to say *(n=15)* Q2. What is the nature of your disability? • Blind/partially sighted *(n=0)* • Deaf/hearing impairment *(n=4)* • Dyslexia *(n=14)* • Mental health difficulties *(n=30)* • Personal care support *(n=0)* • Unseen disability e.g. diabetes, epilepsy, asthma (*n=9)* • Wheelchair user/mobility difficulties *(n=1)* • Other disability *(n=8)* • Prefer not to say *(n=2)*	Q1 used only, as survey response categories
Highest parent education level	What is the highest level of education achieved by at least one of your parents or carers? • No level of education *(n=3)* • Primary school education *(n=3)* • High school/ secondary school education *(n=113)* • Post-school academic education *(n=41)* • Post-school vocational education e.g. apprenticeship *(n=34)* • Undergraduate degree *(n=215)* • Master’s degree *(n=92)* • Doctoral degree *(n=32)* • Prefer not to say/ Don't know *(n=7)*	Collapsed into five categories: • No education • School education • Further education • Higher education • Prefer not to say/ Don’t know
Postcode at 16 (UK students only)	For UK students: What was your postcode when you were 16 years old? Answered via free text box	Transformed into POLAR4 and IMD quintiles. POLAR4: Quintile 1-Lowest participation in HE • Quintile 2 • Quintile 3 • Quintile 4 • Quintile 5-Highest participation HE IMD: • Quintile 1-Most deprived • Quintile 2 • Quintile 3 • Quintile 4 • Quintile 5-Least deprived

Appendix J - ***Table of full sample characteristics***

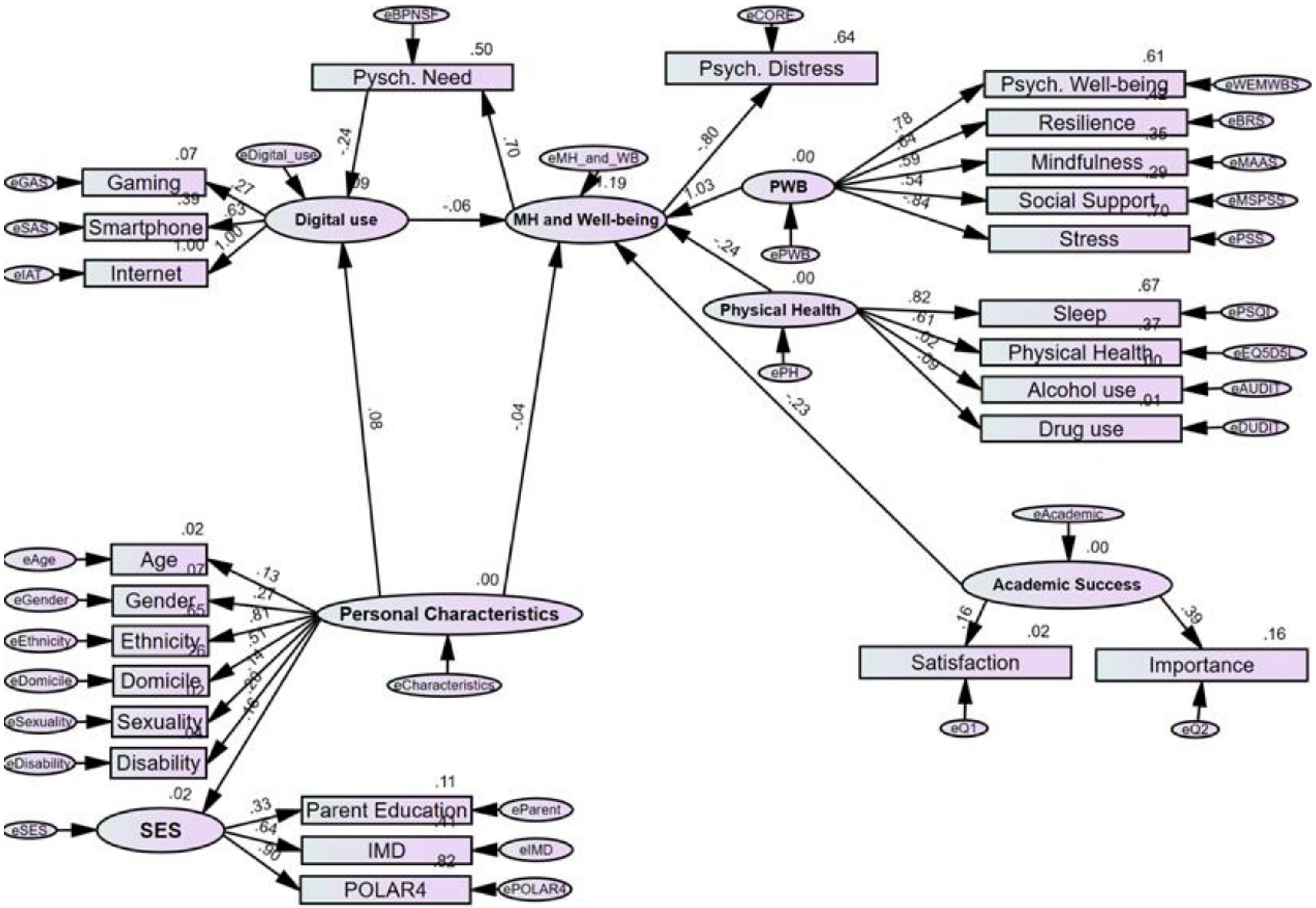
Variable	***Level***	***n (n=544)***	***%***
Gender	Female	385	70.8
	Male	185	24.8
	Transgender/non-binary	10	1.8
	Prefer not to say	4	.7
	Prefer to self-describe/other	3	.6
	Missing data	7	1.3
Age	21-25	242	44.5
	16-20	165	30.0
	26-29	74	13.6
	30+	59	10.8
	Missing data	4	.7
Sexuality	Heterosexual/ Straight	429	78.9
	Bisexual	51	9.4
	Prefer not to say	18	3.3
	Gay man	17	3.1
	Prefer to self-describe/ Other	12	2.2
	Gay woman/ Lesbian	10	1.8
	Missing data	7	1.3
Ethnicity	White	366	67.3
	Asian	83	15.3
	Mixed background	31	5.7
	Black	13	2.4
	Arab	8	1.5
	Prefer not to say	7	1.3
	Prefer to self-describe	6	1.1
	Any other ethnic background	4	.7
	Missing data	26	4.8
Domicile	UK	439	80.7
	International	65	11.9
	EU	38	7
	Missing data	2	.4
Disability presence	No disability	469	86.2
	Yes disability	63	9.7
	Prefer not to say	15	2.8
	Missing data	7	1.3

Variable	Level	n	%
Disability type	Mental health difficulties	30	5.5
	Dyslexia	14	2.6
	Unseen disability	9	1.7
	Other disability	8	1.5
	Deaf/hearing impairment	4	.7
	Wheelchair user/mobility difficulties	1	.2
	Prefer not to say	2	.4
	Blind/partially sighted	0	0
	Personal care support	0	0
Level of academic study	Undergraduate	345	63.4
	Postgraduate	197	36.2
	Missing data	2	.4
Faculty of academic study	Medicine and Health	186	34.2
	Engineering and Physical Sciences	122	22.4
	Arts, Humanities and Culture	92	16.9
	Environment	56	10.3
	Biological Sciences	49	9.0
	Social Sciences	23	4.2
	Business	11	2.0
	Missing data	5	.9
Year of academic study	1st year	196	36
	2nd year	137	25.2
	3rd year	134	24.6
	4th year	63	11.6
	5th year	10	1.8
	6th year	3	.6
	Missing data	1	.2
Full/Part-time academic study	Full-time study	510	93.8
	Part-time study	31	5.7
	Missing data	3	.6
Highest level of either parent's education	Higher education	339	62.3
	School education	116	21.3
	Further education	75	13.8
	Don't know/Prefer not to say	7	1.3
	No formal education	3	.6
	Missing data	4	.7

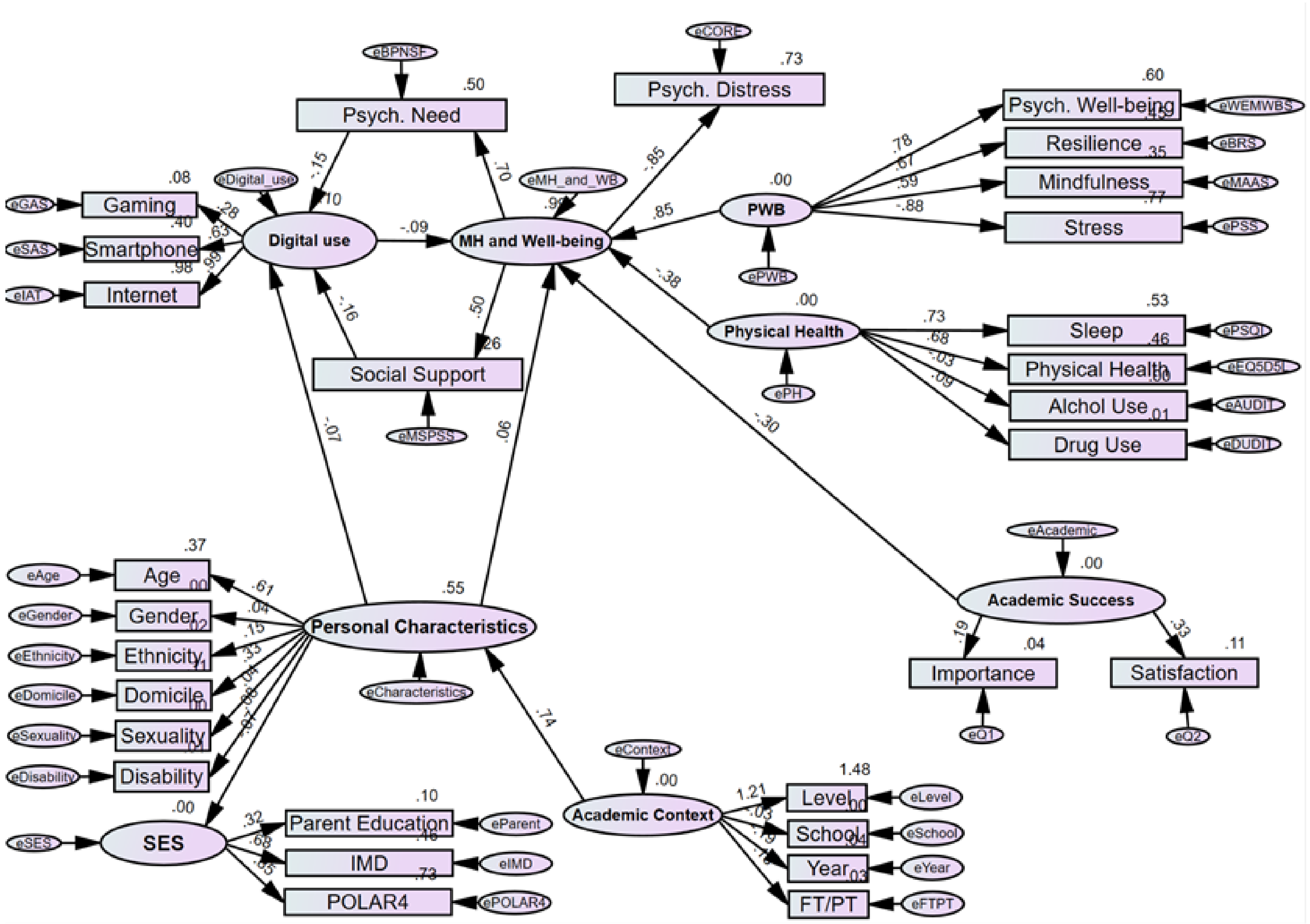
Variable	Level	*n*	%
***POLAR4* (participation rates of young people in higher education by local area).**[9]	Quintile 1 – *least likely to participate in higher education*	40	7.4
	Quintile 2	57	10.5
	Quintile 3	78	14.3
	Quintile 4	86	15.8
	Quintile 5 – *most likely to participate in higher education*	108	19.9
	Missing data (includes non-UK domicile participants)	175	32.2
Index of Multiple Deprivation (relative measure of deprivation by local area). [9]	Quintile 1 – *most deprived*	50	9.2
	Quintile 2	51	9.4
	Quintile 3	74	13.6
	Quintile 4	89	16.4
	Quintile 5 – *least deprived*	106	19.5
	Missing data (includes non-UK domicile participants)	174	32.0

[9] Only applicable to UK participants. Data collected via participant postcode at age 16.

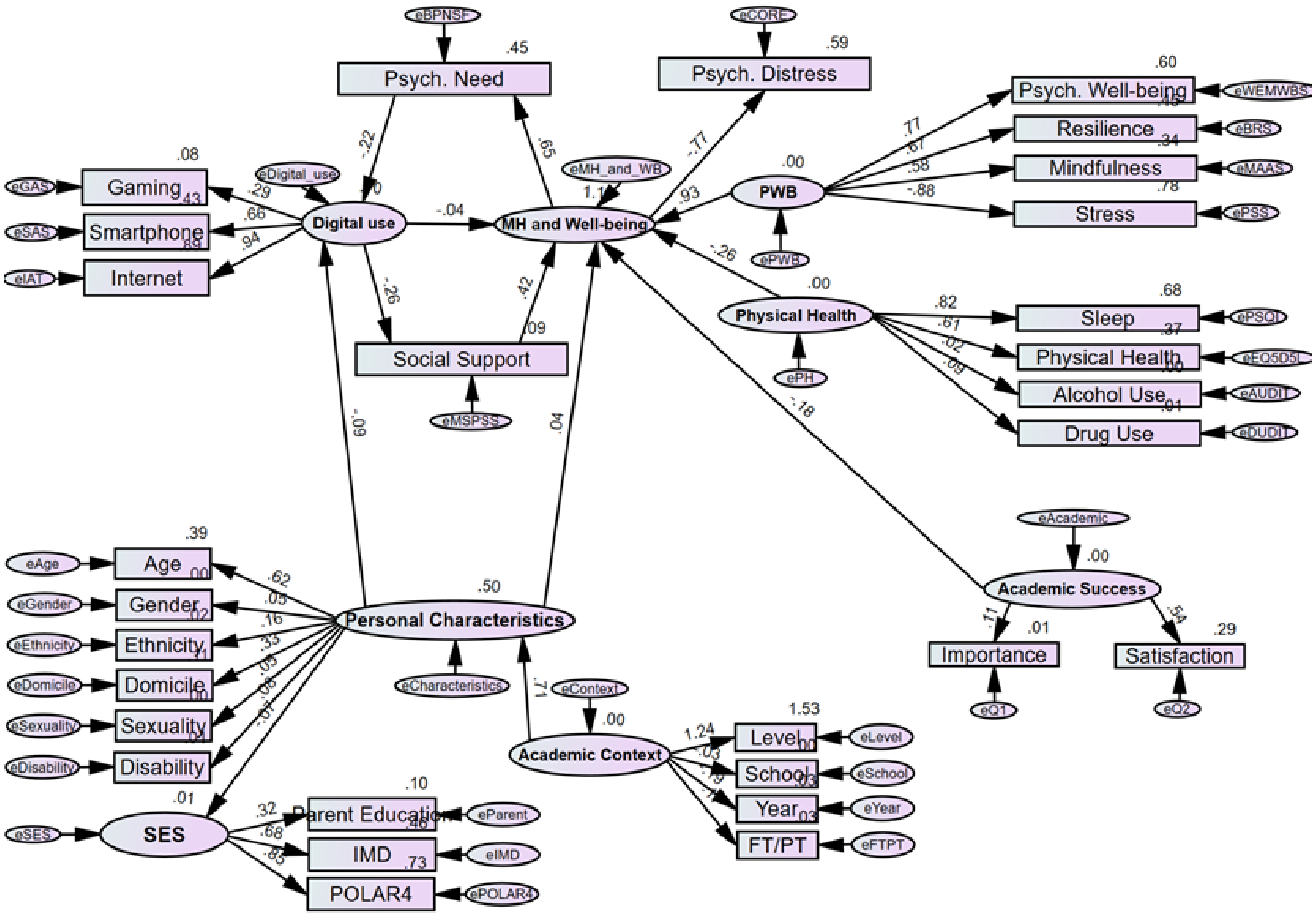
Appendix K – ***Parameter estimates of model 1.0***



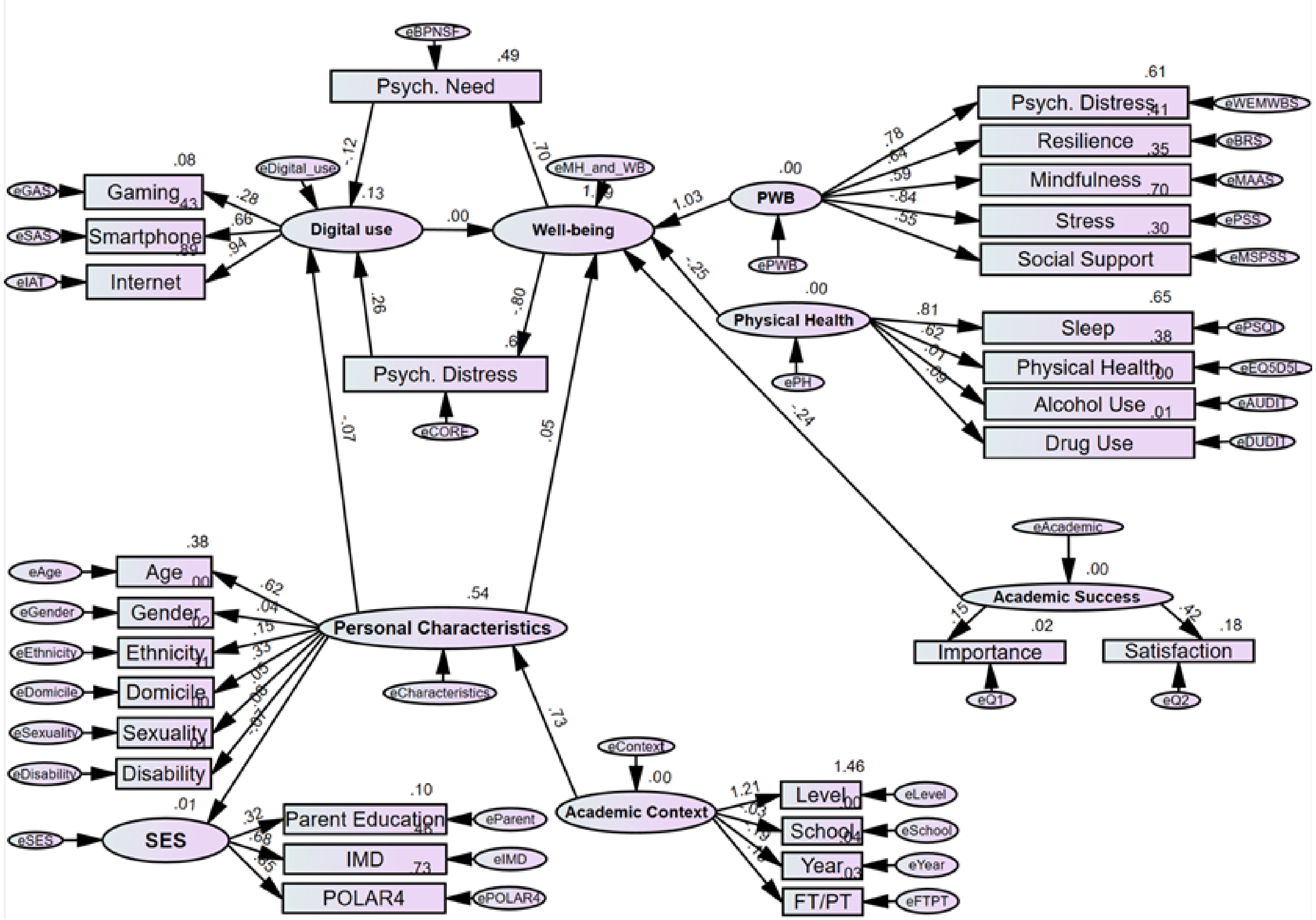
Appendix L – *Parameter estimates of model 2.0*



Appendix M – ***Parameter estimates of model 2.1***



Appendix N – *Parameter estimates of model 3.0*



Appendix O – ***Parameter estimates of model 6.1***