Social media use, social comparisons and mental health in adults during the COVID-19 pandemic

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Doctorate in Clinical Psychology thesis (Volume 1), 2024

University College London

UCL Doctorate in Clinical Psychology

Thesis declaration form

I confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Overview

This thesis explores the relationship between social media use and mental health within the adult population, with a particular focus on the role of social comparison processes and inter-individual differences in socioeconomic status. It is divided into three parts.

Part One: Conceptual Introduction. An overview of key constructs (i.e., social media and mental health) is provided, followed by a synthesis of existing research in regard to their association, limitations of this existing evidence base, mechanisms of interest within the social media use-mental health association (including social comparison processes), and finally, limitations in regard to research investigating social comparisons as an underlying mechanism and directions for future research.

Part Two: Empirical Paper. Part two is a quantitative, empirical study involving a secondary analysis which used self-report data on social media use, mental health, online and offline social comparisons, socioeconomic status, and anxiety and depression. Data were analysed using regression, mediation and moderated mediation analyses, in order to investigate the potentially mediating effect of online social comparisons in the social media use-mental health association (whilst controlling for *offline* social comparisons), and in turn, whether or to what extent inter-individual differences in socioeconomic status moderated this indirect effect (i.e., of online social comparisons). Results yielded support for the mediating effect of online social comparisons (over and above *offline* social comparisons) and partial support for the moderating effect of socioeconomic status on this mediating path.

Part Three: Critical Appraisal. Part three is a critical appraisal of the conceptual introduction and empirical project process as outlined in parts one and two. It describes reflections on the various challenges faced throughout producing this thesis and what was learned in the process.

Impact Statement

Social media has grown rapidly since the advent of social networking sites Facebook and MySpace in the mid 2000s, and it has become an integral part of day-to-day life for many. This increased usage has been accompanied by growing interest and concern in regard to the psychological impact of social media. However, the association between social media use and mental health outcomes is incredibly complex, with findings of positive, negative and nonsignificant associations, suggesting that multiple underlying mechanisms – including mediating, moderating and confounding variables – are likely at play within this relationship.

Online social comparisons has consistently emerged as a promising mediator in the association, however, very few studies have controlled for *offline* social comparisons. The empirical paper included in the present thesis did exactly that, and results suggest that there is, potentially, something uniquely harmful about social comparisons made online. This finding supports overarching theories within the field, such as the transformation framework (Nesi et al., 2018), which – in a field where research has been driven by a number of different disciplines and is therefore notoriously fragmented – has the potential to pull together and make sense of a number of complex associations. Further, the findings regarding the mediating role of online social comparisons may support the justification for future research to include more longitudinal elements, which would further the field even more by allowing conclusions surrounding directionality and causality in regard to harmful mental health effects.

Prior research into the role of online social comparisons has also revealed complex associations however (i.e., associations with both positive and negative mental health and well-being outcomes). Researchers have therefore called for further investigation into inter-individual differences which may interact with such underlying mechanisms. The empirical paper included in the present thesis provided preliminary and partial evidence that those from lower socioeconomic backgrounds may be more vulnerable to the harmful effects associated with online social comparisons. Given that other hypothesised moderating variables (e.g., age and gender) have sustained limited empirical support, this finding offers the field a future direction for investigation.

Should these findings prove robust and, importantly, if causal effects are established, they could possess multiple impacts outside of academia. Mental health clinicians may be better equipped to support clients, and teachers in schools more informed to have conversations with pupils, for example, around social media use, online social comparisons, and their harmful mental health effects – particularly with individuals identified as being potentially, especially vulnerable. At a systemic level, such findings could further calls to address longstanding, widening inequalities in society, informing economic and / or political action aimed to address poverty and relative deprivation.

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Acknowledgements

Firstly, a huge thank you to the individuals who completed the UCL COVID-19 Impacts Study, without whom this thesis would not be possible.

I would also like to thank my research project supervisor, Dr Marc Tibber, for sharing his knowledge and expertise, his guidance throughout the greatest (and most challenging) academic accomplishment of my life to date, for his responsive and extremely helpful feedback, and for his understanding, kindness and flexibility when life threw me a curveball (or two).

To Professor Katrina Scior and Dr Kat Alcock, for their support in flexing the goalposts wide enough to fit my evolving context. For taking the time to listen, for their compassion, for encouraging me to put my personal life before my professional one when I needed to, and for all of the creative ways in which they helped make this possible.

To my friends – Lex, Chlo, G and Katie – for taking a genuine interest in this thesis, understanding and respecting its personal significance to me, for cheering me on along the way, celebrating my achievements like they were their own, and for always reminding me of just how much fun there is to be had outside of it.

To my Mum and Dad, who started this journey with me and sadly were not able to witness its completion. I am deeply grateful for how they loved and supported the various versions of me over the years. I am privileged to know just how proud of me they would be.

Finally, to my fiancée, Alex, who has been my anchor throughout it all. For being so incredibly patient and tolerant, for picking up my share outside of work without a single complaint when I couldn't quite manage it all, and for the endless cups of tea and snacks, co-regulation, and words of encouragement when it all felt impossibly difficult.

Part One: Conceptual Introduction

Social media use, social comparisons and mental health in adults during the COVID-19 pandemic

Introduction

This project aimed to further knowledge of the role of social comparisons in the relationship between social media use and mental health. Research investigating the psychological impact of social media use has grown exponentially in recent years. Despite a relatively small, yet consistent, negative association between social media use and mental health, the emerging consensus is that the relationship is highly complex (Meier & Reinecke, 2020; Orben, 2020). Social media use appears to pose both harmful and beneficial effects, and there is an increasing push towards identifying potentially confounding, mediating and moderating variables in addition to inter-individual differences that may help us make sense of such a diverse array of findings (Baker & Algorta, 2016; Keles et al., 2020; Meier & Reinecke, 2020; Tibber & Silver, 2022).

Amongst the many proposed and investigated mechanisms underlying the relationship between social media use and mental health, social comparisons – *"the process of thinking about information about one or more other people in relation to the self"* (Wood, 1996, pp. 520–521) – has retained its plausibility as a mediator in this association in the face of increasing interest and research (Lee, 2014; Tibber et al., 2020). This thesis therefore aimed to test the mediating role of social comparisons further, paying particularly attention to the uniqueness of this relationship to the online social context and the extent to which, if at all, inter-individual differences such as social status (specifically, socioeconomic status), may in turn effect this.

The thesis sought to achieve this via a study of adults during the COVID-19 pandemic, whereby participants self-reported demographic information, social media use, social comparison and mental health outcomes via an online survey. Results were analysed using conditional process / path analysis, allowing the exploration of mediators and moderators between basic associations in the key constructs (Hayes, 2018).

Clarification of the issues raised has the potential to contribute to an evidence base that better informs the public, media, policymakers and clinicians of the true impact of social media use on mental health and the ways in which social media use's harmful effects may be reduced.

This conceptual introduction will outline what is currently known about the relationship between social media use and mental health and factors thought to be significant in this association, with a specific focus on social comparisons and inter-individual differences (i.e., socioeconomic status), and thus the research and theory which has informed the design and methodology of the subsequent empirical paper.

Social media

The term "social media" (SM) first came to fruition in the mid 2000s following the birth of social networking sites (SNS) such as MySpace and Facebook. Technological advancements, in particular the growing availability of high-speed Internet, the development of Web 2.0 and the subsequent rise of User Generated Content (UGC), were all central to this development of modern society (Kaplan & Haenlein, 2010). To define SM therefore, such terms in themselves must first be considered.

At its simplest, Web 2.0 represented a move from Web 1.0 – in which online content was solely created and updated by software developers and end-users – to a more dynamic interface whereby multiple users became able to continuously and collaboratively contribute to modifying such content. Web 2.0 can be considered a development in the functionality of the Internet that gave rise to SM as we know it today. Comparatively, UGC can be considered an umbrella term used to describe the vast range of media content that, as a result of the development of Web 2.0, users of SM became able to produce, consume and exchange. In summary, SM can be defined as any online application or platform that facilitates the creation, consumption and exchange of UGC (Kaplan & Haenlein, 2010).

This definition of SM spans widely different technologies – virtual worlds, SNSs, content communities (such as YouTube), blogs and collaborative projects (like Wikipedia) – each with varying features and functions. Meier and Reinecke's (2020) hierarchical computer-mediated communication (CMC) taxonomy offers a parsimonious yet thorough approach to classifying and conceptualising SM further, grounded in theory and research. CMC can be understood as an umbrella term used to describe social interaction that is mediated by information and communication technology (hence, closely mapping on to the definition of SM).

The hierarchical CMC taxonomy was devised through concept mapping (a technique which draws out conceptual and operational similarities, differences and hierarchies from a number of pre-existing operationalisations of a construct, until theoretical saturation is reached) (Booth et al., 2012). A full outline of their classification is beyond the scope of this introduction. However, at its core, the authors propose that CMC can be broken down in terms of two broad conceptual approaches. Channel-centred conceptualisations of CMC focus on the technological properties and span four levels of analysis – the device (e.g., laptop, phone), type of application (e.g., email, SM, SNSs, online forums), application brand (e.g. YouTube, Instagram), and the brand / application's feature (e.g., status updates, private messages). Communication-centred conceptualisations instead dive into the nuances of interaction and encompass two levels. The interaction level focuses on how users are communicating (e.g., thinking about the function of communication) and who they are communicating with (e.g. individuals versus groups), whereas the message level considers the content and mode of exchanges (e.g., actual utterances, images, videos and emojis shared) (Meier & Reinecke, 2020).

Of all SM, SNSs have arguably become a central part of today's life in addition to having been widely studied. SNS can be defined as applications that foster connection between users via the creation, consumption and exchange of UGC in the form of personal profiles (containing photos, videos, blogs etc.) and instant messages (Kaplan & Haenlein, 2010). To put into perspective how fast-growing and widespread SNS usage is, figures from January 2022 indicate that Facebook, the most popular SNS, had 2.9 billion users worldwide – an increase of approximately 26% from less than three years before, and approximately 71% from the three years before that (Clark et al., 2018; Krause et al., 2021; Statista, 2022b). Further, as of August 2022, worldwide figures show that internet users spend around 147 minutes per day on SM, which is, again, an increase on previous years (Statista, 2022a). The rapid growth in the number of people using SM, particularly SNSs, and the increasing amount of time people are spending on such platforms, speaks to the importance of understanding its psychological impact.

Whilst research in the field of SM and its relationship to mental health has largely focussed on SNSs, this conceptual introduction will adopt a maximally inclusive definition of SM (i.e., it will not focus specifically on a single sub-type of SM). One could challenge that this approach risks collapsing unique effects associated with different sub-types of SM. However, researchers today highlight how most SM applications offer a myriad of different functions, meaning that their characteristics more often overlap with, as opposed to distinguish, one sub-type from another. For example, Whatsapp, which a decade ago may have been considered more akin to traditional digital communication (like e-mail or text message), today involves a 'profile picture' (much like Facebook). In turn, Facebook today facilitates private messaging (much like traditional digital communication). Therefore, researchers have argued that a maximally inclusive definition of SM is best placed when investigating its psychological impact (Nesi et al., 2018).

Mental health

Research in the field of mental health (MH) is often split into two broad perspectives – psychopathology and psychological well-being. Psychological well-being (hereafter referred to as 'well-being') has traditionally been viewed as the absence of psychopathology (such as anxiety and depression). However, it is now widely recognised that well-being and psychopathology are two distinct psychological states, each with their own, independent definitions and contributions to wellness, a concept referred to as the two-continua model of MH (Keyes, 2007; Meier & Reinecke, 2020).

Psychopathology can be defined as "*any pattern of behaviour – broadly defined to include actions, emotions, motivations, and cognitive and regulatory processes – that causes personal distress or impairs significant life functions, such as social relationships, education, work, and health maintenance*" (Lahey et al., 2017, p. 3). Symptoms of psychopathology are measured dimensionally (i.e., on a spectrum), with a set of symptoms constituting different psychological disorders, as defined in diagnostic manuals such as the Diagnostic and Statistical Manual of Mental Disorders (DSM). Such disorders are (compared to symptoms) considered categorical, splitting the population into psychologically 'healthy' (non-clinical) and 'unhealthy' (clinical) populations (American Psychiatric Association, 2013).

Well-being, on the other hand, is a less clear cut concept and an umbrella term used to describe "*the presence of positive indicators and / or the absence of negative indicators of wellness*" (Yang et al., 2021, p. 631). Whilst there are numerous definitions, research in the field of well-being tends to align with one of two perspectives. The hedonic concept defines well-being as the presence of positive affect and a positive, cognitive evaluation (life satisfaction), in addition to the absence of negative affect. The eudemonic concept on the other hand widens the definition to include the presence of meaning, purpose, personal growth, authenticity and excellence. Most researchers assert that hedonia and eudaimonia are complementary psychological functions, and that a combination of both is required for peak wellness (Meier & Reinecke, 2020; Reinecke & Oliver, 2016).

Finally, in conceptualising MH, some have argued that it is important to consider a third component relating to variables that are often misconstrued as direct measures of MH, but are in fact indirectly relevant. These variables are those that are not specifically related to psychopathology or well-being, but are aspects of psychosocial function which may increase or decrease an individual’s susceptibility to psychopathology / well-being. Meier and Reinecke (2020), in their extension of the two-continua model, consider these ‘risk and resilience factors’ and operationalise risk factors as variables such as perceived loneliness and stress, and resilience factors as variables such as social capital and self-esteem. Indeed, low self-esteem, for example, whilst not necessarily indicative of psychopathology or well-being, has long been linked to poor MH outcomes (Fennell, 1998).

Whilst Meier and Reinecke (2020) offer a clear, theory and research driven conceptualisation of MH, it is often a poorly operationalised construct in the field investigating its relationship to social media use (SMU) (Orben, 2020), a point that will be returned to and considered further later on. Thus, this introduction will also adopt a maximally inclusive definition of MH, in line with the definition provided by Meier and Reinecke (2020) (i.e., spanning psychopathology, well-being, and risk and resilience factors). However, whilst some researchers in the field suggest little utility in distinguishing between sub-types of SM when considering its relationship with MH (Nesi et al., 2018), others highlight the importance of distinguishing between sub-types of MH when considering their association with SMU (Meier & Reinecke, 2020).

The association between social media use and mental health

With the amount of people using SM and the time spent on SM increasing year on year, as has already been outlined, research investigating its psychological impact has grown exponentially. This is particularly true of the child, adolescent and emerging adult population, given that this age group spend more time online than any other, in addition to having been the first generation to grow up in a world where internet-based communication is an integral part of daily life (Kim, 2017; Nesi et al., 2018; Orben, 2020). We will now consider what is known, broadly, in regards to the relationship between SMU and MH, before considering the limitations of the field and digging deeper into potential underlying mediators, moderators and mechanisms.

Meta-analyses, systematic reviews and, more recently, meta-reviews within the field indicate a predominantly negative association, trivial to small in size, between SMU and MH (Meier & Reinecke, 2020; Orben, 2020), suggesting that greater SMU correlates with poorer MH outcomes. Such findings provide a deceptively simple overview of what is currently known about the association between SMU and MH. Meier and Reinecke's (2020) meta-review, synthesising results of 34 systematic reviews and meta-analyses (conducted with non-clinical samples), found that around 41% of reviews included suggest a mixed relationship (i.e., negative, positive and non-significant associations between SMU and MH), 32% a predominantly negative relationship, and 18% a predominantly positive relationship (Meier & Reinecke, 2020). Further, and in regards to the predominant finding (i.e., of those suggesting a mixed relationship), this spanned the full spectrum of MH outcomes as per our aforementioned conceptualisation. That is, there is evidence of negative, positive and / or non-significant associations between SMU and symptoms of depression (Baker & Algorta, 2016) and anxiety (Frost & Rickwood, 2017) (i.e., psychopathology), measures of life satisfaction (well-being) (Erfani & Abedin, 2018), and risk and resilience factors (such as self-esteem) (Krause et al., 2021).

Such conflicting results point to a highly complex relationship and a subsequent likelihood that different psychological, social, behavioural and other individual factors play a confounding, mediating or moderating role and require investigation (Baker & Algorta, 2016; Keles et al., 2020; Meier & Reinecke, 2020; Tibber & Silver, 2022). However, what is currently known about the association between SMU and MH, and the potential mechanisms within this relationship, is complicated even further by issues relating to study design and methodology. Given that such limitations permeate research across the field – that is, research investigating the SMU / MH association and subsequent research investigating potential third factors and underlying mechanisms within the association – this introduction will now discuss these in more detail, so as to support the reader in reviewing what is currently known and unknown through a shared, critical lens.

Limitations of the existing evidence base

As interest and research in the field has grown, so too have criticisms of the evidence base, which is arguably saturated with cross-sectional studies, sampling and measurement issues, selective research reporting and an overinterpretation of trivial effects, potentially misinforming policymakers and the public alike (Keles et al., 2020; Meier & Reinecke, 2020; Orben et al., 2019). It is beyond the scope of this conceptual introduction to examine all limitations of the evidence base. However, we will now consider those most relevant to the present thesis – concerns related to cross-sectional data, problems with sampling and measurement issues, which were all held carefully in mind when planning and executing the subsequent empirical study, and interpreting its results.

Design limitations

Many have argued that the field is plagued with cross-sectional studies and that there is a lack of robust, longitudinal research, which poses consequences for inferring causality in the relationship (Best et al., 2014; Dobrean & Păsărelu, 2016; Erfani & Abedin, 2018; Keles et al., 2020; Orben, 2020). Is it that SMU leads to declines in MH, or is it possible that poor MH contributes to increased SMU, or both? The longitudinal research which does exist certainly supports the possibility of reciprocity. For example, one study of 256 university students in China found evidence that SNS usage negatively predicted well-being (measured in terms of life satisfaction and positive / negative affect), but well-being also negatively predicted SNS usage, over the course of one year (Wang et al., 2018).

Relatedly, a further limitation (central but not limited to) cross-sectional research concerns the focus on between-person, as opposed to within-person, effects. One study of 500 participants over an eight year period found that whilst between-person analyses suggested a moderate association between SMU and symptoms of anxiety and depression, within-person analyses of the exact same sample and relationship found no significant association (Coyne et al., 2020). Thus, whilst the between-person analyses certainly support the consensus of prior research (i.e., an overall, negative *association* between SMU and MH), the within-person results challenge the notion of causality within this relationship. Other research has also indicated that the same users may experience positive effects of SM at one point in time and negative effects at another (Frost & Rickwood, 2017; Orben et al., 2019; Orben, 2020). Taken together, such findings suggest that future research would do well to move away from cross-sectional, between-subjects designs, towards closer inspection of within-person effects.

Sampling limitations

Systematic reviews reveal that the majority of research focuses heavily on healthy adolescent populations, particularly students, neglecting other cohorts (Erfani & Abedin, 2018; Keles et al., 2020). Some have argued that future research would do well to investigate the association between SMU and MH amongst the older generations, for example, as there is some (preliminary) evidence to indicate that SMU may relate differently to MH amongst this cohort, specifically, for example, in the case of active versus passive SMU. Active SMU can be defined as all SM behaviour that facilitates interactions with others / content (e.g., messaging, updating a Facebook status), whereas passive SMU is considered such because SM users consume, but do not produce or interact with content (e.g., browsing, scrolling) (Verduyn et al., 2015, 2017).

A number of studies have linked *active* SMU to increases in well-being and *passive* SMU to decreases in the same. For instance, in one study of 702 18-49 year olds (with a mean age of 23.4, *SD* = 6.2), for every one-point increase in passive SMU there was a 33% increase in symptoms of depression. Conversely, for every one-point increase in active SMU there was a 15% decrease in symptoms (Escobar-Viera et al., 2018). However, research on older adults has suggested the inverse. A study of 1,258 older adults, aged 65 and over (mean age = 73.1, *SD* = 7.0) found that passive SMU was associated with a decreased likelihood of depressive symptoms, whereas active SMU was associated with an increased likelihood (Lewin et al., 2022). The authors offer a number of explanations for these findings, including the possibility that age moderates potential mechanisms underlying the SMU and MH association (such as social comparison processes), alongside other potential differences related to the type of SM content consumed and motivations of SMU.

Whilst these studies were correlational in design, thus the previous limitations regarding causality apply, such research does suggest the possibility of something quite different about the relationship between active / passive SMU and MH depending on the sample investigated. Hence, this arguably illustrates the point that future research would do well to not only widen the pools of participants, but also to consider the impact of inter-individual differences, particularly how such may interact with potential underlying mechanisms in the SMU-MH association.

Measurement limitations

Finally, there is the issue of measurement. Starting with the conceptualisation of SMU, a meta-review of 34 reviews spanning 594 studies revealed that of 1,829 CMC indicators (i.e., measures of CMC used within the included studies), more than half (51%) focussed on more than one of the six levels proposed in the hierarchical CMC taxonomy. A first glance at such a finding could lead a reader to evaluate this as a strength of the evidence base, on the logic that such methodology takes into consideration the varying features and functions of SM (i.e., multiple elements that make up a construct) and their relation to MH outcomes. However, as the authors highlight, this finding actually raises concerns because it indicates conflation of analytical levels, whereby multiple levels of analysis are collapsed into one CMC indicator, hence threatening construct validity (Meier & Reinecke, 2020). For example, if a study investigates the impact of scrolling for one hour through a user's TikTok 'for you page' on their smartphone, and locates a negative association between such and life satisfaction, it is impossible to know where the effect lies – is it attributable to the device level (smartphone), the type of application (SNS), the brand of application (TikTok) and its features (the 'for you page'), the interaction level (passive SM use, i.e. scrolling), or the message level (reels consumed)?

On the other hand, the authors discuss how studies in the field typically focus on a single platform (i.e., Facebook), whereas it may be more productive for future research to instead consider features *across* platforms, so as to keep up with the everchanging landscape across applications, hence increasing generalisability of findings (particularly over time). Further, they highlight how the field typically relies on technology-centred measures (those that capture certain aspects of technology use, e.g., time spent on SMU or frequency of use) as opposed to user-centred measures (those that capture more of the psychological-perceptual component of use, e.g., motivations for use or how content is perceived), both of which possess unique strengths and limitations. Taken together, Meier and Reinecke (2020) recommend that future research would do well to utilise a combination of technology-centred and user-centred measures of SMU across all levels of the taxonomy, and which allow the isolation of distinct levels of analysis, so as to support the field to better understand exactly what it is within SMU that relates to certain effects and their underlying mechanisms (Meier & Reinecke, 2020).

Similarly, MH is often poorly operationalised in this field of research (Orben, 2020). In the same meta-review, Meier and Reinecke (2020) also investigated conceptualisations and operationalisations of MH. They found that nearly half (47%) of the 34 reviews spanning 594 studies operationalised MH in terms of risk and resilience factors (e.g., stress, self-esteem, social support and social capital). Research that has studied psychopathology typically focuses on internalising symptoms (e.g., anxiety and depression), largely ignoring externalising symptoms (e.g., aggression, substance misuse). In regards to well-being, there is a focus on the hedonic side, particularly life satisfaction (i.e., the cognitive component), but a lesser focus on positive / negative affect (i.e., hedonia's affective component). Further, eudamonia (the side of well-being related to a sense of meaning, personal growth etc.) has received very little attention at all (Meier & Reinecke, 2020).

In line with the extended two-continua model of MH, each of these elements of MH capture something unique about the construct, yet they have not been equally investigated in their relation to SMU. A potential implication of this could be that the field misses crucial effect patterns. For example, preliminary research indicates that the impact of online social comparisons may depend on the MH outcome measured, including the (largely ignored) eudaemonic well-being component (Meier & Schäfer, 2018).

Thus, it seems reasonable to suggest that future research would benefit from more clearly conceptualising and operationalising both SMU *and* MH. Doing so may possibly progress understanding of the complex association between SMU and MH, via supporting the identification of unique and diverse effects.

Mechanisms of interest in the association between social media use and mental health

A number of potential mechanisms have been explored in attempts to make sense of the inconsistent / conflicting results regarding the association between SMU and MH. It is beyond the scope of this conceptual introduction to consider them all. Given that the focus of the present thesis is on the role of social comparisons in the association between SMU and MH, and given that the research to date concerning social comparisons in this relationship has largely focussed on SM's harmful effects, the subsequent section will discuss possible mechanisms that have been studied specifically in this regard (i.e., we will not consider research on mechanisms underlying the association between SM and beneficial effects).

Displacement or disruption of activities beneficial for well-being

The displacement hypothesis claims that "*by using the Internet, people are substituting poorer quality social relationships for better relationships, that is, substituting* *weak ties for strong ones*" (Kraut et al., 1998, p. 1029). In other words, and applied specifically to SM, this theory proposes that SMU reduces time spent with existing friends and thus the quality of existing friendships, which in turn negatively impacts on MH.

In a cross-sectional study of adolescents, whereby SMU was conceptualised in terms of type of application only (specifically, instant messaging (IM) and chatroom usage) and operationalised at a technology-centred level only (i.e., time spent and frequency of use), and MH was measured in terms of life satisfaction (i.e., the cognitive component of well-being only), limited support for the social displacement hypothesis was found. In fact, the study produced support for the opposite notion – that SMU enhances MH via increasing time spent with friends and the quality of existing friendships (Valkenburg & Peter, 2007). However, this was only true for IM, not for chatroom usage, which the researchers attribute to IM being more typically used to communicate with existing friends (whereas chatroom usage is more typically associated with stranger interactions), arguably underscoring the importance of distinguishing between platform features in future work. A major limitation of the study however was the cross-sectional design, and the authors acknowledge the possibility that, for example, the quality of existing friendships may instead drive SMU.

Relatedly, another argument is that SMU negatively impacts MH via reducing the time an individual has for sleep. Sleep has long been linked to a range of MH problems, with sleep disturbance predicting the onset of depression, for example (Lovato & Gradisar, 2014). In contrast to the aforementioned displacement hypothesis, disruption to sleep as a significant factor in the association between SMU and MH holds somewhat greater plausibility.

In an experimental study of 132 participants aged 18-61, researchers limited SMU amongst the intervention condition to a maximum of ten minutes per day for a period of one week (in contrast to the control group, who were free to utilise SM as much as they wanted). Whilst self-report measures are often criticised for unreliability, this study utilised a more objective measure via obtaining screenshots of participant's battery usage (albeit, a technology-centred measure only, i.e. time spent on SM, with no control for participants accessing SM on other devices). MH was measured via the Warwick Edinburgh Mental Wellbeing Scale (WEMWBS), a commonly used tool for assessment of general MH and well-being. Sleep was measured by a modified version of the four item sleep quality scale, which taps into sleep problems in the last week. The study found that limiting SMU for one week resulted in improvements in MH and sleep quality. Further, mediation analysis revealed support for the notion of sleep as a mediator in the association between SMU and MH. However, it must first be noted that the effect of taking a one-week break from SM on MH was small to medium in size (Cohen's $d = 0.34$, $t(91) = 2.116$, $p = 0.035$). Further to this, the mediation analysis finding was only marginally significant (Graham et al., 2021). Thus, whilst the hypothesis around sleep disruption yields greater support than the displacement hypothesis, it appears that sleep may only in part explain the relationship between SMU and MH.

Passive social media use

Whilst active and passive SMU have been defined in brief in previous sections, we will now revisit this in more detail. Some suggest that active use encompasses all SM behaviour that facilitates interactions with others (Verduyn et al., 2015, 2017). Other researchers make a further distinction, defining active use as the production of (non-directed) content (e.g., updating a Facebook status), and *interactive* use as the production of (directed) content (e.g., direct messaging or commenting on an online communication partner's content), on the basis that the former do not necessarily lead to interactions with others (Yang, 2016). On the other hand, researchers typically agree on a definition of passive SMU, whereby SM users consume, but do not produce, content (e.g., when browsing) (Verduyn et al., 2015, 2017; Yang, 2016).

Active and passive SMU can be considered different types of SM behaviours. In other words, they tap into the user-centred operationalisations of SM (i.e., *how* one engages with SM when they do use it). In recent years, attempts to clarify the complex association between SMU and MH have increasingly turned attention to the study of SM behaviours, such as active versus passive SMU, and their role within this relationship. It has been suggested that passive use is linked to the more negative effects of SMU on MH, whereas active use is linked to the more positive effects. Whilst there is both cross-sectional and longitudinal research indicating that *active* SMU is positively associated with subjective well-being (Kim & Lee, 2011; Wenninger et al., 2014), such findings are inconsistent, with some studies finding non-significant effects (Verduyn et al., 2015) and others finding associations with negative psychological effects, such as loneliness (Yang, 2016).

The evidence regarding passive SMU is stronger, with cross-sectional, longitudinal and experimental studies consistently indicating a negative association with well-being (Frison & Eggermont, 2016; Verduyn et al., 2015, 2017). Verduyn et al. (2015) conducted two studies, both using samples of young adults, and both investigating the relationship between passive SMU and MH. The first study was conducted under laboratory settings and found that participants who passively used SM for ten minutes reported (statistically) significantly lower levels of (affective) well-being at the end of the day, in comparison to those amongst the active SMU condition. The effect of active SMU on well-being was non-significant. Study two sought to replicate these findings in daily life. Further, the second study also measured envy, which researchers hypothesised as the underlying mechanism in the relationship between passive SMU and declines to well-being. The second study replicated the results of the first – passive SMU predicted declines in affective well-being at the end of the day, whilst active SMU did not significantly affect well-being. In addition, the reverse was not significant, i.e., affect did not predict passive SMU. Furthermore, mediation analyses revealed that envy did indeed mediate this relationship and again, ruled out the possibility of the inverse (i.e., of envy predicting passive SMU, in turn predicting affect) (Verduyn et al., 2015). However, the researchers also measured passive and active SMU's effect on cognitive well-being (i.e. life satisfaction), and neither study found significant effects in either regard.

More recent meta-analyses and systematic reviews have yielded limited support for both the active and passive SMU hypotheses. One meta-analysis spanning 63 studies and 144 effect sizes found that neither active nor passive SMU possessed significant effects for either positive or negative indicators of well-being (Yin et al., 2019). A further (scoping) review, of 40 studies and 172 associations of active and passive SMU with well-being (happiness, life satisfaction and positive affect) and ill-being (depressive symptoms and negative affect) found that most studies did not support active nor passive SMU's putative associations with MH outcomes, as well as finding considerable heterogeneity amongst effect sizes (Valkenburg et al., 2022).

Valkenburg et al. (2022) offer a number of different explanations for these findings, including the suggestion that the active versus passive SMU distinction may be flawed. For example, when reading comments or reviewing likes on a Facebook post (i.e., active use), an integral part of this is essentially passive use (that is, consuming and receiving content). This conceptual difficulty in disentangling active and passive use then translates on an empirical level, with some studies categorising 'liking' or 'commenting' (two of the most common SM behaviours) as passive SMU and an equal number categorising them as active SMU. The authors conclude by suggesting that future research move away from the active / passive distinction and toward more nuanced measures of SMU, including those relating to content (i.e., *what* is being actively or passively engaged with) and, importantly, the psychological processes involved in this engagement (Valkenburg et al., 2022).

Social comparisons

Social comparisons, a term initially proposed by Festinger (1954), can be defined as "*the process of thinking about information about one or more other people in relation to the self*" (Wood, 1996, pp. 520–521). Festinger's (1954) social comparison theory claims that humans are innately driven to evaluate their opinions and abilities in order to survive. It is proposed that when there is no objective way of measuring this in the physical world, people turn to how they compare with others. Festinger (1954) argues that people choose 'comparison targets' that possess opinions / abilities not too dissimilar to one's own, on the basis that information yielded from similar others provides more utility than information gained from extremely different others (which simply tells the comparer that their ability is unique) (Festinger, 1954; Wood, 1989).

Central to this original theory is the notion that individuals are predominantly driven to compare for self-evaluative purposes (i.e., a drive to *accurately* decipher their capacities and limitations as they currently stand (Wood, 1989). However, researchers have since argued the presence of other, additional comparison goals, which can be broadly classified as self-improving (that is, a drive to identify how one can develop or grow in regard to an ability or opinion) and self-enhancing (a drive to protect or enhance one's self-esteem, which is inherently more biased than self-evaluative motivations), with different motivations shaping the choice of comparison targets and the direction of comparison (Wood, 1989). For example, it has been suggested that the desire to self-improve can shift comparison targets to someone perceived as superior (upward social comparisons) (Wheeler, 1966), whereas downward comparison theory suggests that individuals, motivated to self-enhance, are more likely compare to someone perceived as inferior (downward social comparisons) (Wills, 1981).

Some have argued that earlier developments in social comparison theory exaggerate deliberate, conscious intention (goals) and selection (of targets), when in fact evidence suggests that some social comparisons are simply encountered, automatic and unconscious (Wood, 1989, 1996). The finding that children with learning disabilities in specialist educational provisions (i.e., surrounded by peers of a similar academic ability) have higher self-esteem than children with learning disabilities in mainstream provisions, irrespective of academic ability (known as the frog-pond effect) is a good example of how some social comparisons can be thrust upon us by our environment (Gerber et al., 2018; Wood, 1989). This phenomenon also highlights the significance of target immediacy and how local information is typically more highly weighted than distant information, something researchers have related to how humans have evolved and survived in small groups (Gerber et al., 2018). Social comparisons, therefore, can arguably be driven by conscious desires to inform one's self-concept and can also be unconsciously imposed by one's social context.

Other evidence has indicated the presence of individual differences in one's tendency to engage in social comparisons at all, known as social comparison orientation (SCO). It appears that those with a high, chronic activation of the self (i.e., publicly and privately self-conscious), those who are more socially oriented, and those who are more prone to experiencing negative affect and a sense of uncertainty in relation to the self are more likely to compare than others (also known as high SCO) (Buunk & Gibbons, 2005; Gibbons & Buunk, 1999).

Whilst social comparisons can differ in their direction (i.e., upward to a 'superior' target and 'downward' to an inferior target), a further important distinction relates to the ideas of 'contrastive' and 'assimilative' cognitive processes that follow. Assimilative comparisons move an individual *toward* the comparison target (i.e., shifting attention toward similarities), whereas contrastive comparisons move an individual *away* from a target (shifting attention to dissimilarities) (Gerber et al., 2018). Gerber's (2018) meta-analysis, spanning 60 years of research in the field, found that (when an individual *is* able to consciously choose a comparison target) upward comparisons were more common than downward comparisons. Further, the study revealed that contrast (versus assimilation) was by far the most dominant psychological response to social comparisons, with individuals more commonly increasing their self-evaluations in response to downward comparison and decreasing them in response to upward comparisons. Thus, taken together, tendencies towards upwards, contrastive comparisons suggest that, for the most part, social comparisons typically lead to negative, i.e. harmful, effects (Gerber et al., 2018).

Social comparisons and the association between social media use and mental health

An argument that has emerged in recent years concerns how SM transforms what is ultimately a social context, and that this transformation has significant implications for both (online) social comparison processes and their psychological effects (Nesi et al., 2018).

Firstly, whereas social comparisons in the 'real world' are naturally limited to in-person interactions with close others, SM widens the pool of potential comparison targets, allowing users to compare to others they may not necessarily be able to in offline, day-to-day interactions (Verduyn et al., 2017; Vogel et al., 2014). Further, the functionality of SM allows users to selectively curate online personas that emphasise desirable traits and idealised versions of the self, something which researchers have argued proliferates superior comparison targets (Vogel et al., 2014; Yang et al., 2021; Yang & Bradford Brown, 2016).

Relatedly, SM enables asynchronous communication, meaning that users have more time to modify the content of any interactions (in socially desirable ways) before delivering these to a recipient (Nesi et al., 2018; Verduyn et al., 2017, 2020). Finally, it has been suggested that SM enables comparisons regarding information that is not typically available offline, such as the qualitative and quantitative features of another person's social network (e.g., the number of friends one has), hence SM arguably facilitates 'social' upward comparisons in addition to 'personal' upward social comparisons (Vogel et al., 2014). Taken together, these features of SM could suggest that it is a fertile breeding ground for upward social comparisons and negative impacts to self-evaluation, and research has indicated that upward social comparison is the predominant form of social comparison on SM (Vogel et al., 2014).

Further, online social comparisons have indeed been linked to harmful effects for MH. In a recent meta-analysis of 13 publications, spanning 22 studies (N = 11,199), researchers found a small to moderate, negative association (r = -.20, 95% CI [-.29, -.11]) between social comparisons (specifically on Facebook) and affect, life satisfaction and self-esteem, supporting the notion that online social comparisons may negatively impact well-being and MH risk factors (Yang et al., 2019). Similar results have been established regarding psychopathology, with a second meta-analysis indicating a small to moderate, positive association between social comparisons (again, specifically on Facebook) and symptoms of depression (r = .23, 95% CI [.12, .34]), and a moderately sized positive association between upward comparisons specifically and symptoms of depression (r = .33, 95% CI [.20, .47]) (Yoon et al., 2019).

Longitudinal research provides further insights into the relationship between SMU, online social comparisons and MH. Wirtz et al. (2021) used an experience sampling design to gather multiple measurements of SMU, MH and online social comparisons from a sample of university students (N = 77) over the course of ten days. Participants' life satisfaction and self-esteem were measured at the beginning and end of the study, whereas SMU, online social comparisons, and positive and negative affect were measured five times per day via email. They found that the more that participants engaged in SMU (measured in terms of multi-site use, i.e. any one of Facebook, Twitter or Instagram) in between random surveys, the more negative affect they reported (B = .16, 95% CI [.05, .26], p = .004), whereas the same relationship for positive affect was non-significant. In addition, greater online social comparison increased negative affect (B = .21, 95% CI [.11, .31], p < .001) and also decreased positive affect (B = -.16, 95% CI [− .25, − .07], p = .001). Given the significant effects of SMU and online social comparisons on negative affect, they then tested a model whereby negative affect was predicted from both SMU and online social comparisons, essentially probing whether online social comparisons could, in part, explain the effects of SMU. They found that online social comparisons continued to predict significant increases in negative affect (B (SE) = .21 (.05), t = 3.91, p < .001, 95% CI [.10, .33]); however, the relationship between SMU and negative affect collapsed. This suggests that online social comparisons may, in part, serve as an underlying mechanism in the relationship between SMU and affective well-being (Wirtz et al., 2021).

It is important to highlight that, in this study, the finding that online social comparisons may, in part, underly the relationship between SMU and well-being was limited to the affective component of well-being only. The researchers failed to find evidence for a relationship between SMU and the cognitive component of well-being (i.e., life satisfaction). On the other hand, researchers *did* find a significant relationship between SMU and self-esteem. Controlling for baseline self-esteem, SMU predicted post-test self-esteem scores. However, when online social comparisons were incorporated into the model, the association between SMU and self-esteem collapsed, whereas the association between online social comparisons and self-esteem remained statistically significant ($B = -.01$, $\beta = -.26$, $t(61) = -$

2.37, p = .02), providing additional evidence that social comparisons may also, in part, explain the relationship between SMU and self-esteem (Wirtz et al., 2021).

Building further on these findings is a study consisting of an online survey, whereby a sample of 809 Facebook users completed measures of Facebook activities, social comparison orientation, self-esteem and symptoms of depression. The study found that *passive* Facebook use was positively associated with social comparisons, negatively associated with self-esteem, and positively associated with symptoms of depression. Further, mediation analysis revealed a significant indirect effect of Facebook use on symptoms of depression via social comparison orientation and self-esteem, suggesting that the negative effect that social comparisons can have on self-esteem in turn can translate into depressive symptoms (β = .040, BC 95% CI [.0240; .0581], p < .001). It should be noted however that this study consisted of correlational data only, meaning that whilst such results indicate an intervening effect, this only means that mediation is plausible, not proven (Ozimek & Bierhoff, 2020).

Limitations and gaps in the existing evidence base regarding social comparisons, social media use and mental health

Whilst the evidence regarding social comparison's role in mediating the relationship between SMU and MH is promising, it is not absent of limitations and consideration of such points to future research directions.

As has already been discussed, there are a number of reasons why SM may be a fertile breeding ground for social comparisons (i.e., how it widens the pool of comparison targets, enables individuals to portray idealised versions of themselves, supports modifying communication in socially desirable ways, and enables comparisons related to one's social networks). However, whilst possible, as of yet there is limited evidence to actually support such claims (Meier & Johnson, 2022) and the vast majority of research in this specific sub-set of the field often fail to control for *offline* social comparisons. This is of particular significance when one considers the evidence regarding offline social comparison's MH effects.

In the 'real world', social comparisons have been shown to impact all three major components of MH (as *per* the extended two-continua model of MH). In regards to psychopathology, individuals with high SCO (i.e., those that are more likely to compare themselves to others) typically have higher levels of depression (relative to those with low SCO) (Gibbons & Buunk, 1999). In the case of well-being, upward social comparisons have been found to induce negative affect (Muller & Fayant, 2010), in addition to having been linked to decreased subjective well-being, with the opposite effect established for downward social comparisons (Wheeler & Miyake, 1992). In relation to risk and resilience factors, downward social comparisons have been linked to increased self-esteem, whereas upward social comparisons have been linked to decreased self-esteem (Morse & Gergen, 1970), and individuals with high SCO typically have lower self-esteem (relative to those with low SCO) (Gibbons & Buunk, 1999).

At the time of writing, and to the best of the author's knowledge, there are very few studies that have compared online and offline social comparisons and their relation to MH. One such study found that whilst comparisons on SM tend to be more negative, participants actually engaged in social comparisons more offline than they did on Facebook. Of particular relevance to this conceptual introduction, the study also found that offline social comparison orientation and direction (i.e., comparing to inferior or superior targets offline) better predicted depressive symptoms than online social comparison orientation and direction, and that even then (i.e. with both processes included), the model only accounted for 25% variance in symptoms of depression (Faranda & Roberts, 2019). A number of researchers have therefore highlighted the need for the field to clarify the extent to which online social comparison's harmful effects really are unique to the online world, i.e., via controlling for offline social comparisons (Meier & Johnson, 2022).

A second area for future study concerning social comparison's role in the relationship between SMU and MH relates to a limitation of the wider field. As highlighted in Orben's (2020) narrative review, the field of research concerning SMU and MH would do well to increase its focus on inter-individual differences, given that much of the research to date has relied upon convenience sampling of largely healthy adolescent populations, particularly students (Erfani & Abedin, 2018; Keles et al., 2020), and given that the highly heterogenous effects of SMU on MH arguably point to the likelihood of a *number* of confounding, mediating and moderating variables (Baker & Algorta, 2016; Keles et al., 2020; Meier & Reinecke, 2020; Tibber & Silver, 2022).

In Meier and Reinecke's (2020) meta-review, moderator analyses yielded limited support for the notion that SMU's harmful effects may be lesser or greater dependent on gender and age. They did however find that 50% of systematic reviews and meta-analyses reviewed reported moderation effects of either culture or country, concluding that culture may be an important moderator, but one that bears complex and unclear effect patterns.

A far lesser studied moderator remains to be socioeconomic status (SES). SES is "*generally defined in terms of an individual's economic position and educational attainment, relative to others, as well as his or her occupation*" (Manstead, 2018). SES has long been linked to adverse mental health outcomes, with a meta-analysis of 60 studies from around the world suggesting that SES (measured in terms of education, income and occupation) is a moderate to strong predictor of depression (Lorant et al., 2003). More recently, research has suggested that SES may exert its MH effects via a related but distinct construct known as subjective social status (SSS) (i.e., how people perceive their status in comparison to others within a social hierarchy) (Madigan & Daly, 2023), with one study finding that perceived income inequality (relative to peers) predicted negative mental health outcomes in adolescents even when controlling for objective family income (Piera Pi-Sunyer et al., 2023).

It is arguably plausible therefore that SES could moderate the association between SMU, social comparisons and MH, in that those from lower SES groups may be even more vulnerable to the harmful effects of online social comparisons. However, and to the best of the author's knowledge at the time of writing, this has not previously been investigated.

Aims of the thesis

This introduction has provided an overview of what is currently known about the relationship between SMU and MH / well-being and factors thought to be significant in this association, with a specific focus on social comparisons, and thus the research and theory which has informed the design and methodology of the subsequent empirical paper.

The association between SMU and MH is highly complex, with research suggesting harmful, beneficial and non-significant effects. This has led to researchers in the field emphasising the importance of identifying potentially confounding, mediating and moderating variables in addition to inter-individual differences, which may clarify SMU's heterogeneous MH impacts. It is likely that a number of mechanisms underlie the association between SMU and MH. Specifically, in regards to SM's harmful effects, social comparisons appears to be a promising mediator. However, we do not know the extent to which the harmful effects associated with online social comparisons are unique to the online world, versus, the extent to which online social comparisons merely act as a proxy for *offline* social comparison processes. Nor do we know how inter-individual differences in SES may influence online social comparison processes and their alleged effects.

The overall aim of this thesis therefore is to further understanding of the role of online social comparisons in the SMU-MH association in two key ways. Firstly, via controlling for *offline* social comparisons and secondly, via investigating the extent to which, if at all, the role of online social comparisons within the SMU-MH association differs for individuals, in part, dependent on socioeconomic background.

Specifically, the following hypotheses will be explored:

(H1) Higher SMU will be associated with higher MH symptoms, as measured using the GAD-7 and PHQ-9.

(H2a) The association described in H1 will be partially mediated by upward social comparisons, and (H2b) this will hold after controlling for offline upward social comparisons.

(H3) The associations described in H1 and H2 will also be moderated by SES, such that the association between upward social comparisons and MH symptoms will be stronger for those from low SES.

The answers to these research questions would provide the public, media, policymakers and clinicians with a better understanding of how SM impacts MH, which would empower individuals to better protect themselves against any putative adverse effects.

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Part Two: Empirical Paper

Social media use, social comparisons and mental health in adults during the COVID-19 pandemic

Abstract

Aims: Online, upward social comparisons (USCs) have garnered increasing attention in recent years as a potential mechanism underlying the association between social media use (SMU) and mental health (MH). However, most previous research has failed to control for *offline* USCs. Further, results regarding online USCs in the SMU-MH association are mixed, suggesting inter-individual differences may be at play. The present study sought to investigate the role of online USC in the SMU-MH association, whilst controlling for offline USCs and investigating potential interactions with socioeconomic status (SES).

Method: A secondary analysis was undertaken, using self-report data on SMU, online and offline USC, SES, and anxiety and depression, originally gathered from a sample of UK adults during the COVID-19 pandemic. Data were analysed using regression, mediation and moderated mediation analyses.

Results: SMU was positively associated with symptoms of anxiety and depression. Online USCs partially mediated the SMU-MH association, even after controlling for offline USCs. SES, when measured via a composite index of low socioeconomic profile (SEP) (but not when measured in terms of level of education), was found to interact with online USCs in the SMU-MH association, with those from a lower SES background experiencing more harmful effects of online USCs; however, this was only the case when extreme scores were removed.

Conclusions: The present study is one of the few that have controlled for offline USCs and one of the first to investigate how inter-individual differences in SES may interact with such, furthering our understanding of how SMU transforms social comparison processes, their associated MH effects, and who in society may be most vulnerable. Further research is needed to replicate and extend the findings, particularly longitudinal research and conclusions around causality.

Introduction

This introduction will provide the reader with a brief overview of what is known, broadly speaking, about the relationship between social media use (SMU) and mental health (MH), before delving deeper into the literature particularly pertinent to the specific focus of the present study. Readers are referred to Part 1 of this thesis (conceptual introduction) for an in-depth introduction to the concepts of SMU and MH, the evidence base regarding their association, and the limitations within the field.

SMU has become a widespread and integral part of day-to-day modern life for many, with research suggesting that over 4.2 billion individuals worldwide use it, equivalent to 53% of the world's total population (Kemp, 2021). Correspondingly, research investigating its association with MH outcomes has grown exponentially in recent years, and whilst the overarching findings suggest a small, negative association, the relationship is extremely complex (Orben, 2020). A recent meta-review indicates that the vast majority of research suggests a mixed relationship (i.e., positive, negative, and non-significant associations between SMU and MH) (Meier & Reinecke, 2020). This has led to many in the field suggesting that a number of underlying mechanisms, including (from a statistical perspective) mediating, moderating and confounding variables, are likely at play and warrant investigation (Baker & Algorta, 2016; Keles et al., 2020; Meier & Reinecke, 2020; Tibber & Silver, 2022). Over the years, social comparisons – that is, *"the process of thinking about information about one or more other people in relation to the self"* (Wood, 1996, pp. 520–521) – have gathered increasing interest in this respect (Meier & Johnson, 2022; Verduyn et al., 2020).

Social comparison theory suggests that the human species is innately driven to compare oneself to those around them in order to inform one's understanding of their relative self-worth, ultimately enabling survival as a social species (Festinger, 1954). Research suggests that social comparisons (generally speaking, i.e., not specific to SMU) can possess potentially harmful effects for psychopathology (Gibbons & Buunk, 1999), psychological well-being (Muller & Fayant, 2010; Wheeler & Miyake, 1992) and risk / resilience factors such as self-esteem (Gibbons & Buunk, 1999; Morse & Gergen, 1970). Upward social comparisons (USC) – those which involve comparing oneself to a comparison target that is perceived, by the comparer, as 'better off' or superior in some way – specifically have been most commonly linked to negative effects (Gerber et al., 2018).

A theory that has emerged in recent years, drawing from research spanning computer-mediated communication, developmental, organisational and media psychology, known in the field as the transformation framework (Nesi et al., 2018), suggests that rather than merely 'mirroring' the offline world, the online world fundamentally changes and shapes what is an inherently social context, with a number of consequences for interpersonal and intrapersonal (i.e., psychological) processes, with potential positive and / or negative implications for mental health.

With respect to *social comparisons*, researchers in the field have suggested that the SM landscape may transform the processes in a number of ways. One suggestion is that SM widens the pool of potential comparison targets and facilitates comparison with others one may never encounter in the offline world. Another pertains to the way in which SM enables asynchronous communication, allowing individuals large amounts of time in which to post a flattering photograph with a clever caption. The sheer volume of information relevant to social comparisons has also been highlighted, with individuals now able to see how many people 'liked' or 'commented' on another's photograph, or how many 'friends' or 'followers' one has. It is suggested that these transformations allow for social comparisons to be made on an unprecedented scale and, compared to offline social comparisons, make *upward* social comparisons (and their associated harmful effects) more likely (Verduyn et al., 2017; Vogel et al., 2014).

Meta-analyses certainly provide promising results in support of these ideas, with one including 13 publications (and a sample of 11,199 participants) finding a small-to-medium association between social comparisons on Facebook and poorer affect / lower self-esteem and life satisfaction (Yang et al., 2019), and a second (spanning five publications and a sample of 2,298) finding a medium sized association between online USC and greater symptoms of depression (Yoon et al., 2019).

In order to robustly test an association between online USCs and MH, however, some have argued for a need to control for *offline* USCs. In Meier and Johnson's (2022) critical review of social comparisons and SMU, the authors highlight that there is insufficient evidence regarding whether SM in fact changes anything about social comparisons (in other words, a gap in the evidence base exists as to whether there *is* something uniquely harmful about online USC, or whether they simply serve as a proxy for social comparisons more generally) (Meier & Johnson, 2022).

Relatedly, Meier and Johnson (2022) also highlight that the extent to which inter-individual differences exist amongst one's tendency to make, and / or be negatively impacted by, online USCs arguably warrants further research. Whilst less common than findings consistent with a harmful effect, some studies, for example, have found that online USCs are associated with *positive* MH outcomes, such as inspiration, which may in turn be associated with beneficial effects on well-being (Meier & Schäfer, 2018). Meier and Schäfer (2018) recommend that future research explore potential moderators of online social comparisons processes, including that of perceived attainability of comparison standards, given evidence suggesting that SM users may experience inspiration in response to online USCs only when they deem themselves capable of achieving comparable success (Lockwood & Kunda, 1997).

Theoretically, the notion that socioeconomic status (SES) may interact in such a way with online USCs is plausible. SES has long and widely been linked to a range of (mental and physical) health outcomes, in that those coming from higher socioeconomic backgrounds tend to have better outcomes and vice versa. For example, research in the US has found a negative association between annual, total household income and an individual's likelihood of dying in a five year period (McDonough et al., 1997), and the World Health Organisation have previously reported a positive correlation between indices of low SES and the prevalence of mental health disorders across seven different countries (World Health Organisation, 2000). Such findings, it has been argued, cannot be explained by absolute deprivation (i.e., lack of means to meet one's basic needs), but rather, *relative* deprivation (i.e., deprived of something that one feels they should be entitled to) (Marmot, 2004; Wilkinson & Pickett, 2010).

There is some evidence to suggest that people may experience greater life satisfaction when their personal SES is higher than their neighbourhood's SES (i.e., *relative* wealth / deprivation), even after controlling for current personal income (i.e., *absolute* wealth / deprivation) (Dittmann & Goebel, 2010). Further, relative deprivation has been associated with possessing a higher social comparison orientation (i.e., tendency to compare oneself to others) (Buunk et al., 2003). Hence, it is possible that those who are positioned towards the lower end of social hierarchies (of which SES is arguably the crudest, but most pervasive indicator) 'compare and despair' online to a greater extent, or experience greater psychological harm in the face of them, than those who possess higher SES. Indeed, one study involving a sample of 619 students aged 12 to 16 found that the association between online SCs and depressive symptoms was stronger for individuals who were considered lower in terms of social status (measured in terms of popularity) (Nesi & Prinstein, 2015).

Aims and hypotheses

The present study sought to contribute to the existing evidence base in two key ways. First, the research aimed to explore what role online USCs hold in the association between SMU and MH whilst controlling for (i.e. over and above) *offline* USCs, hence shedding further light on whether SMU does indeed transform the social context (and related interpersonal and intrapersonal processes) as predicted by the transformation framework (Nesi et al., 2018). Second, it sought to explore the potential moderating role of SES in this putative relationship.

Specifically, the hypotheses tested are as follows:

(H1) Higher SMU will be associated with higher MH symptoms, as measured using the GAD-7 and PHQ-9.

(H2a) The association described in H1 will be partially mediated by upward social comparisons, and (H2b) this will hold after controlling for offline upward social comparisons.

(H3) The associations described in H1 and H2 will also be moderated by SES, such that the association between upward social comparisons and MH symptoms will be stronger for those from low SES.

The present research was conducted using a secondary analysis of data collected during the COVID-19 pandemic (Tibber et al., 2023, 2024), which saw increased usage of digital technology such as SMU (Ofcom, 2021), in addition to highlighting and exacerbating existing inequalities (Blundell et al., 2020; Paremoer et al., 2021). Whilst the long-term impacts on well-being, and health and social inequalities, are not yet known, many experts predict that the lasting effects will be profound, with the most disadvantaged in society weathering the worst of it (McBride et al., 2021). Coupled with statistics revealing the year-on-year growth in the use of SM – even before the pandemic (Kemp, 2021) – this context arguably underlines the importance of furthering understanding of not only whether SMU yields harmful or beneficial effects for MH, but also, how and when it does so (or, for whom are the effects more potent). It is hoped that the present study will contribute to this area of research, which has the potential to better equip policymakers, clinicians and the general public alike.

Method

Ethical approval

The study was approved by University College London (UCL) Research Ethics Committee (Project ID: 18335/001) (Appendix A).

Design

The present study is a secondary analysis of data gathered via an online survey as part of the University College London (UCL) COVID-19 Impacts Study (Tibber, Milne, et al., 2023; Tibber et al., 2024). The original study was longitudinal in design, collecting data from the same sample at two time-points. Hence, as part of the consent process, participants were asked for consent to be contacted at a later time. The present study is a cross-sectional analysis of data collected at the first time-point only.

Participants

Participants were UK adults aged 18 and over who were able to provide informed consent to participate. Aside from age and residing in the UK, there was no other inclusion or exclusion criteria. Participation was entirely voluntary. Participants were recruited via existing UCL research participant databases (Appendix B), social media (SM) posts and online advertisements (Appendix C).

Procedure

The survey was presented using the online, GDPR (General Data Protection Regulation) compliant platform Qualtrics. All data were subsequently stored in the secure environment UCL Data Safe Haven. Data for the present study (i.e., the first wave of data collection only) was gathered from 16th May to 21st July 2020.

Upon opening the online survey, potential participants were first met with a landing page which detailed the participant information sheet and informed consent sheet (Appendix D). Participants were required to confirm that they had read this information, that they were aged 18 or over, and that they provided consent to participate in the study. Participants who did not confirm this were unable to progress further.

Participant email addresses were taken in order to send links to future follow-up surveys and in order to fulfil duty of care requirements (see below). Email addresses were stored separately from participant answers and deleted as soon as the study finished. All data were appropriately pseudonymised in order to achieve anonymity and maintain confidentiality throughout the study.

In order to address the potential risk of inducing distress, participants were made aware of the nature of the questions that would be asked before opening the questionnaire.

They were also informed of their right to discontinue the study without repercussion at any time and how they could do so. Participants were encouraged to contact a member of the research team if they had any questions or concerns, and were advised of contact details to do so. Once participants had submitted their answers, they were provided with a questionnaire debrief, signposting them to support (Appendix E). Participants who scored highly on the MH measures were emailed this directly and encouraged to contact their GP (Appendix F). Participants who expressed suicidal ideation were contacted directly by a clinical psychologist within the research team.

Participants were able to opt-in to a prize draw for one of 50 £10 Amazon gift vouchers at the end of the study, by way of thanking participants for their time. This option was not advertised outside of the survey and it was presented to participants after informed consent had been taken, so as to avoid purely financially motivated participation. Further, participants were reminded of their eligibility to opt-in to the prize draw regardless of their responses (or lack thereof), to ensure that they did not feel pressured to answer questions that they did not want to.

Measures

Demographics

Demographic data were obtained including participant age, gender and ethnicity (Appendix G). Age was measured via multi-categorical responses with the midpoint taken as the value for data analyses. Responses for gender and ethnicity were collapsed into binary categories due to low frequency counts. For gender, this consisted of ‘female’ and ‘male / other’. For ethnicity, this comprised of ‘White’ and ‘other’. Descriptives for the full range of response options across demographic variables are described in the Results section.

Socioeconomic status

Socioeconomic status has long been conceptualised as comprising of two major aspects: resources (absolute indicators, e.g., education, income) and status (which are more relative in nature, e.g., occupational status, social class) (Krieger et al., 1997). Hence, researchers in the field have coined the term ‘socioeconomic profile’ (SEP) to describe the overarching construct. There is no consensus on an ideal or superior measure of SEP, something that can be understood given integral characteristics of it, such as how huge of a (multidimensional) construct it is (spanning individual, household and neighbourhood level factors), how changeable it can be in the face of factors, such as health, at different points in one’s life course, and how different factors intersect with other social characteristics such as ethnicity and gender to produce different effects across groups (Braveman et al., 2005).

In their critical review of SEP measurement in health research, Braverman et al. (2005) compared widely used measures of education and income across high-quality, longitudinal data sources on health and mortality outcomes. Specifically, multivariate regression models were employed to examine associations between demographic variables and 23 health-related indicators whilst controlling for SEP (measured in terms of education and income). Results suggested that, whilst education-income correlations existed, the two are not interchangeable, with slightly different associations found dependent on the measure of SEP included across 10 of the 23 health-related indicators. Further, across 20 of the 23 health-related indicators, model fit was significantly improved via the inclusion of both income and education, suggesting that both should be considered in future research. Further, whilst the review highlighted some limitations on the use of composite SES measures, their utility in terms of SEP classification specifically was highlighted (Braveman et al., 2005).

In line with previous research therefore, the present study sought to measure SEP in terms of both education and income (see Appendix H for full socioeconomic measures). Education was measured via the multi-categorical item ‘What is your highest completed level of education?’. Response options included ‘No qualifications’, ‘GCSEs / O-levels or equivalent’, ‘Post-16 vocational course’, ‘A-levels or equivalent’, ‘Undergraduate degree or professional qualification’, ‘Postgraduate degree’ and ‘Prefer not to say’. For the final sample used for data analyses (further information regarding the final sample can be found in the Results section), there was no missing data for the education measure.

Upon completion of data collection, it was discovered that 9.79% of the final sample had not answered the measure of income. Hence, a low SEP composite index score was created in its place. Drawing from previous research investigating socioeconomic inequalities during the COVID-19 pandemic (Wright et al., 2020), this variable was constructed via counting indicators of low SEP across five socioeconomic measures. This included possessing educational attainment of GCSEs / O-levels or lower, household income of less than £13,000 per year, unemployment (specifically, ‘Unemployed, looking for work’, ‘Unemployed, not looking for work’, ‘Not able to work’), living in council or supported accommodation, and living in overcrowded accommodation (whereby overcrowding was indicated when there was more than one person per room in a household). The variable was constructed in a binary fashion due to low frequency counts, with participants grouped into ‘no indicators of low SEP’ and ‘one or more indicators of low SEP’.

Mental health

Whilst the conceptual introduction reviewed existing research spanning the extended two-continua model of MH (Meier & Reinecke, 2020) (i.e., psychopathology, well-being, and risk and resilience factors), MH was operationalised in the present study in terms of psychopathology only – specifically, via symptoms of anxiety and depression.

Anxiety and depression are considered ‘common mental disorders’, with research from the National Health Service (NHS) commissioned Adult Psychiatric Morbidity Survey in 2014 indicating that around one in six adults in the UK experiences symptoms of a common mental disorder at any given time. The Adult Psychiatric Morbidity Survey provides data on the prevalence of psychiatric disorder in the English population and has been conducted four times to date (1993, 2000, 2007 and 2014). Of significance is the increasing trend in common mental disorders, with prevalence rising by approximately 20% from 1993 to 2014 (Baker & Kirk-Wade, 2024).

Further, figures from the Office for National Statistics (ONS) suggest that the prevalence of moderate or severe symptoms of depression in UK adults rose during the COVID-19 pandemic, from 10% of the population (prior to March 2020) to 21% by March 2021, with those experiencing greater socioeconomic disadvantage subject to particularly elevated rates. Whilst prevalence has since fallen (to around 17% from July to August 2021), levels remain elevated in comparison to before the pandemic (Office for National Statistics, 2021a). Hence, better understanding factors linked to anxiety and depression (including SMU’s putative influence) has arguably never been more important, and that data for the present study were collected during the height of the COVID-19 pandemic holds particular relevance.

Symptoms of anxiety and depression were measured using validated, standardised questionnaires routinely used in adult MH services: the Patient Health Questionnaire (PHQ-9) and the Generalised Anxiety Disorder Scale (GAD-7) (Appendix I).

The PHQ-9 is a nine item, self-administered tool based on DSM-IV diagnostic criteria for depressive disorders and the GAD-7 is a seven item, self-administered tool based on the DSM-IV diagnostic criteria for generalised anxiety disorder (American Psychiatric Association, 2013). Both measures have been found to hold sound psychometric properties, spanning internal reliability, test-retest reliability, construct validity, criterion validity and external validity (Kroenke et al., 2001; Kroenke & Spitzer, 2002; Spitzer et al., 2006).

Responses for both measures are provided using a four-point Likert scale ranging from 0 (not at all) to 3 (nearly every day), with higher scores representing more severe symptoms of depression and anxiety respectively. The total GAD-7 score (ranging from 0-21) and the total PHQ-9 score (0-27) for each participant was used in data analyses.

Social media use

In line with (Meier & Reinecke, 2020)'s channel-centred conceptualisation of computer-mediated communication and in accordance with recommendations from within the field (Nesi et al., 2018), a maximally inclusive approach was taken to operationalising SMU. I.e., the term 'social media use' was employed, allowing broader focus, as opposed to focus on specific platforms (e.g., Facebook, Instagram) or features (e.g., posting). Hence, SMU was measured via the item 'On a typical weekday in the last 2 weeks, approximately how many hours did you spend using social media?'. Responses were taken in a sliding scale format (i.e., participants moved a slider from between 0 and 10 hours, see Appendix J) and therefore treated as a continuous variables in data analyses.

Social comparisons

Social comparison processes were measured via two items adapted from existing research investigating the relationship between SMU and social comparisons (Vogel et al., 2014). The first item stated 'To what extent do you focus on people who are better off than you when comparing yourself to others online?' and the second item stated 'To what extent do you focus on people who are better off than you when comparing yourself to others offline (i.e., in day-to-day interactions)?'. Responses to both were provided using a five-point Likert scale ranging from 0 (not at all) to 4 (a great deal), with higher scores representing greater (upward) social comparisons (Appendix K). Social comparisons were treated as continuous variables in subsequent data analyses, in line with research suggesting the utility of doing so for single item, ordinal variables with five or more categories (particularly for larger sample sizes) (Johnson & Creech, 1983).

Statistical analyses

Descriptive statistics and linear assumption testing

Preliminary data analyses were run using SPSS (version 29). Descriptive statistics were undertaken to describe the sample. The statistical analyses that were to be employed for subsequent hypothesis testing required assumptions of a linear statistical model be met. These included independence of error values, linearity of relationships, homoscedasticity among error values, normal distribution of error values, absence of multicollinearity, and absence of extreme outliers (Field, 2018; Hayes, 2018; Tabachnick & Fidell, 2014).

The Durbin-Watson test was employed to confirm independence of error values. Partial plots were inspected for linearity and homoscedasticity. Histograms and P-P plots were inspected for normal distribution of error values. Pearson correlations and variance inflation factors (VIF) were used to assess for multicollinearity. Bootstrapping was used throughout all statistical analyses in any event, as an additional safeguard against any problems related to distribution of error values and / or homoscedasticity (or the bias of interpreting such visually using the methods described above). Lastly, continuous variables

(SMU, GAD-7 and PHQ-9) were screened for extreme outliers using z-scores of ± 2.58 (Field, 2018). How extreme scores were managed is detailed in each subsequent analyses section.

Regression analyses

The hypothesised association between SMU and MH symptoms (H1 – higher SMU will be associated with higher MH symptoms, as measured by GAD-7 and PHQ-9) was tested in the first instance using simple linear regression with bias-corrected accelerated bootstrapping, whereby SMU was the predictor variable (X) and GAD-7 / PHQ-9 scores were the outcome variables (Y) (run in separate simple linear regression models). Next, the same models were re-run with the inclusion of demographic variables as covariates, in order to control for any potentially confounding effects. Both stages of the analysis (i.e., single and multiple regression models for both GAD-7 and PHQ-9 scores) were run with and without extreme scores included.

Mediation analyses

The hypothesised mediation model (Figure 1) (H2 – the association described in H1 will be partially mediated by USCs) was tested for significance using bootstrapping procedures, whereby random samples with replacement are drawn from the original sample in order to provide the best estimate of a true indirect effect (Preacher & Hayes, 2004).

Initially, SMU was modelled as the predictor (X) variable, online USC as the mediator (M) variable; the model was run twice – once with GAD-7 scores as the outcome variable and a second time for PHQ-9 scores (Y) (Model A1). Next, the same models were re-run with demographic variables incorporated as covariates (Model A2). Finally, offline USC was added to the models as the fourth and final covariate (Model A3) (in order to test

H2b – this association will hold after controlling for offline USCs). Each model (Models A1-A3 for both GAD-7 and PHQ-9 scores) was also run with extreme scores excluded.

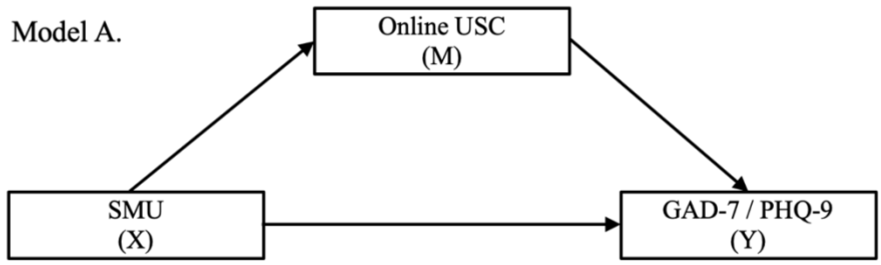

Figure 1. Conceptual model of hypothesised indirect / mediating effect (through online upward social comparisons) of social media use on mental health symptoms.

Using model 4 of the SPSS PROCESS macro (version 4.2), 5,000 bootstrap samples were created to estimate standard errors and 95% percentile confidence intervals for the indirect (mediating) effect of SMU on GAD-7 / PHQ-9 scores through online USC. The indirect effect is deemed statistically significant at p <.05 if zero is not enclosed within the 95% confidence intervals (Hayes, 2018, 2022).

Moderated mediation analyses

The hypothesised moderated mediation models (Figure 2) (H3 – the associations described in H1 and H2 will also be moderated by SES, such that the association between USCs and MH symptoms will be stronger for those from low SES) were investigated using a bootstrapping approach to assess the statistical significance of the indirect (mediating) effect at differing levels of the moderators.

Throughout all models, SMU was the predictor (X) variable and online USC was the mediator variable (M). Every model was run twice, once for GAD-7 scores and then a second time for PHQ-9 scores (Y). The first series of moderated mediation models (Models B1-B3) utilised education as the moderator (W). The second series of moderated mediation models (Models C1-C3) utilised SEP index as the moderator (W). Models B1 and C1 tested the basic moderated mediation models (i.e., the indirect effect of education (B1) and SEP index (C1) on the association between SMU and MH via online USC). Next, the same models were re-run with demographic variables incorporated as covariates (Models B2 and C2). Finally, offline USC was added to the models as the fourth and final covariate (Models B3 and C3). Each model (Models B1-B3 and C1-C3, for both GAD-7 and PHQ-9 scores) was also run with extreme scores excluded.

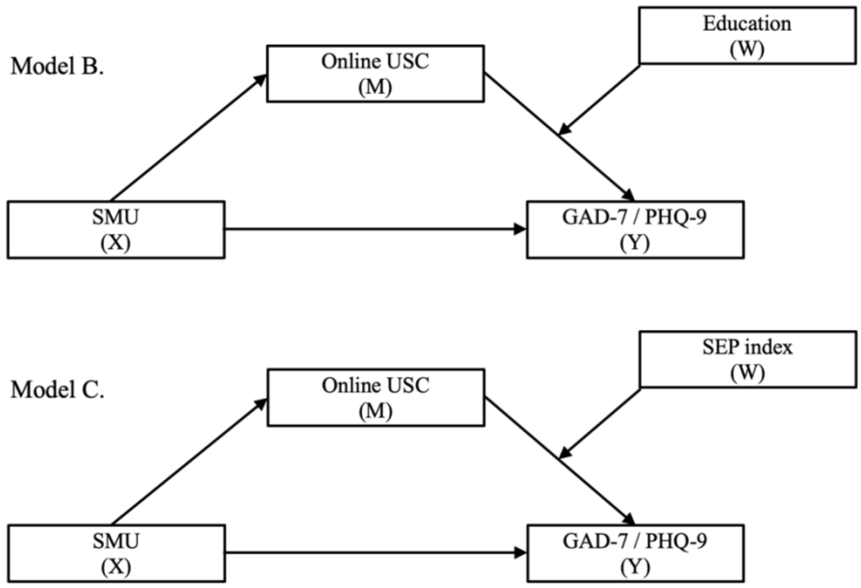

Figure 2. Conceptual model of hypothesised moderated mediation for education (Model B) and socioeconomic profile index (Model C).

Model 14 of the SPSS PROCESS macro (version 4.2) with percentile bootstrap 95% confidence intervals (n = 5,000) was used to test the significance of the indirect (mediated) effects moderated by education / SEP index (i.e., conditional indirect effects). This model explicitly tests the moderating effect of the mediator to outcome variable path (i.e., path b).

An index of moderated mediation was used to test the statistical significance, i.e., the difference of the indirect effects across various levels of the moderator. Statistical significance is indicated by the absence of zero within confidence intervals (Hayes, 2018, 2022).

Sample size and statistical power

Sample size and power calculations at an alpha level of .05 and a power level of .80 were considered. For regression analyses, a power calculation was carried out using the “G*Power 3” computer program, and suggested that in order to detect a small to medium effect size with four predictor variables (SMU, age, gender and ethnicity), a sample size of 244-602 would be required (Faul et al., 2007). Regarding mediation analyses, research involving simulation analyses suggest that in order to detect a small mediation effect using percentile bootstrapping, a minimum sample of 558 is suggested (Fritz & MacKinnon, 2007). Guidelines for moderated mediation analyses are less clear, though many recommend the Monte Carlo simulation-based power analysis approach (Schoemann et al., 2017; Thoemmes et al., 2010; Zhang, 2014).

Results

Missing and excluded data

A total of 632 participants took part in the survey and complete data was obtained in the case of 562 participants (88.92%). Complete case analyses were therefore conducted on the latter. A total of 56 extreme scores (z-score = ± 2.58) were identified across continuous variables (SMU, GAD-7 scores and PHQ-9 scores). In analyses where these extreme scores were excluded, this resulted in n = 518 (GAD-7) and n = 524 (PHQ-9).

Linear assumption testing

The assumption of independence of error values was confirmed by a Durbin-Watson statistic within the acceptable range of 1.5 to 2.5 (Durbin-Watson = 1.98) (Glen, 2022). Linearity between independent and dependent variables and homoscedasticity were both confirmed via inspection of partial plots. Histograms and P-P plots were inspected for normal distribution of error values, revealing distributions deemed normal enough given the robustness of the regression model against non-severe violations of normality (Hayes, 2018). None of the predictors in the model showed a strong correlation ($r > 0.9$) with one another (Field, 2018) and all variance inflation factors (VIF) were below the acceptable limit of 10 (VIF = 1.01-1.72) (Miles, 2005), confirming an absence of multicollinearity.

Sample characteristics

The modal age of the full sample of participants was 40-49 years, representing 34.49% of the sample (n=218). Participants were mostly female (n=534, 84.49%), White (n=544, 86.08%), educated to undergraduate degree level or higher (n=509, 80.54%), and affluent, with 36.71% receiving an annual household income of £64,000 per year or more (n=232). 21.68% (n=137) of participants scored one or more on the low SEP composite index. On average, participants used SM for 2.89 hours per day (*SD*=2.57). In regards to MH, the average scores for GAD-7 and PHQ-9 were 6.40 (*SD*=5.30) and 6.98 (*SD*=5.91) respectively. 29.5% of the sample scored above the clinical cut-off (National Collaborating Centre for Mental Health, 2024) for an anxiety disorder (i.e., indicating the presence of an anxiety disorder) on the GAD-7 measure. 26.5% of the sample scored above the clinical cut-off for depression on the PHQ-9.

Table 1. Summary of individual-level variables, including demographics, social media use, social comparisons, and mental health measures.

Variable		Complete case analysis N = 562	Full sample N = 632
Age, N (%)	18-21	9 (1.60)	11 (1.74)
	22-29	65 (11.57)	70 (11.08)
	30-39	114 (20.28)	127 (20.09)
	40-49	193 (34.34)	218 (34.49)
	50-59	120 (21.35)	132 (20.89)
	60-69	52 (9.25)	62 (9.81)
	70-79	8 (1.42)	11 (1.74)
	80-85	1 (0.18)	1 (0.16)
Gender, N (%)	Female	478 (85.05)	534 (84.49)
	Male	81 (14.41)	92 (14.56)
	Non-binary / third gender	1 (0.18)	1 (0.16)
	Prefer not to say	2 (0.36)	3 (0.47)
Ethnicity, N (%)	White	493 (87.72)	544 (86.08)
	Black	14 (2.49)	17 (2.69)
	Asian	30 (5.34)	38 (6.01)
	Mixed	25 (4.45)	26 (4.11)
	Other	0 (0.0)	7 (1.11)
Level of education, N (%)	GCSE or lower	35 (6.23)	43 (6.80)
	A-level or equivalent	60 (10.68)	71 (11.23)
	Undergraduate degree	236 (41.99)	255 (40.35)
	Postgraduate degree	231 (41.10)	254 (40.19)
	Prefer not to say	0 (0.0)	9 (1.42)
Low SEP index, N (%)	0	446 (79.36)	495 (78.32)
	1+	116 (20.64)	137 (21.68)
Daily SMU, mean (SD)		2.88 (2.54)	2.89 (2.57)
Online USC, N (%)	Not at all	229 (40.75)	253 (40.03)
	Very little	174 (30.96)	185 (29.27)
	Somewhat	101 (17.97)	104 (16.46)
	Quite a bit	46 (8.19)	48 (7.59)
	A great deal	12 (2.14)	12 (1.90)
	Prefer not to say	0 (0.0)	30 (4.75)
Offline USC, N (%)	Not at all	207 (36.83)	226 (35.76)
	Very little	209 (37.19)	217 (34.34)
	Somewhat	102 (18.15)	109 (17.25)
	Quite a bit	37 (6.58)	40 (6.33)
	A great deal	7 (1.25)	8 (1.27)
	Prefer not to say	0 (0.0)	32 (5.06)
GAD-7, mean (SD)		6.30 (5.18)	6.40 (5.30)
PHQ-9, mean (SD)		6.84 (5.81)	6.98 (5.91)

Note. SMU = social media use, USC = upward social comparisons, SEP = socioeconomic position.

Regression analyses

Univariate regression analyses (i.e., before the inclusion of covariates) indicated support for H1 (H1 – higher SMU will be associated with higher MH symptoms, as measured by GAD-7 and PHQ-9) [GAD-7 (*b* = 0.37, BCa 95% CI = 0.21; 0.55, p <.001), PHQ-9 (*b* = 0.43, BCa 95% CI = 0.24; 0.64, p = .002)]. Multivariate regression analyses (i.e., once age, gender and ethnicity were incorporated as covariates) also indicated support for H1 [GAD-7 (*b* = 0.35, BCa 95% CI = 0.18; 0.53, p <.001), PHQ-9 (*b* = 0.41, BCa 95% CI = 0.22; 0.61, p = .002)]. Tables 2 and 3 describe the results in full. Further, findings held upon the exclusion of extreme scores (see Supplementary Tables 1 and 2).

Within the univariate model, SMU accounted for 3% [GAD-7 (F (1, 560) = 19.28, p <.001, R^2 = 0.03)] and 4% [PHQ-9 (F (1, 560) = 20.39, p <.001, R^2 = 0.04)] of variance in MH symptoms. Within the multivariate model, SMU and demographics together described 7% [GAD-7 (F (4, 557) = 11.17, p <.001, R^2 = 0.07)] and 6% [PHQ-9 (F (4, 557) = 8.89, p <.001, R^2 = 0.06)] of variance in MH symptoms.

Table 2. Regression of GAD-7 on social media use, age, gender and ethnicity.

Predictor / covariate	Univariate model		Multivariate model		
	Bootstrap coefficient (*b*) (BCa 95% CI)	*p*-value	Bootstrap coefficient (*b*) (BCa 95% CI)	*p*-value	Standardised coefficient (β)
SMU	**0.37 (0.21; 0.55)**	**<.001**	**0.35 (0.18; 0.53)**	**<.001**	**0.17**
Age	-	-	**-0.07 (-0.11; -0.3)**	**<.001**	**-0.17**
Gender	-	-	**-1.74 (-2.69; -0.79)**	**<.001**	**-0.12**
Ethnicity	-	-	-.33 (-1.56; 1.08)	.67	-0.02

Note. Values in bold denote statistical significance.

Table 3. Regression of PHQ-9 on social media use, age, gender and ethnicity.

Predictor / covariate	Univariate model		Multivariate model		
	Bootstrap coefficient (*b*) (BCa 95% CI)	*p*-value	Bootstrap coefficient (*b*) (BCa 95% CI)	*p*-value	Standardised coefficient (β)
SMU	**0.43 (0.24; 0.64)**	**.002**	**0.41 (0.22; 0.61)**	**.002**	**0.18**
Age	-	-	**-0.07 (-0.11; -0.03)**	**<.001**	**-0.15**
Gender	-	-	-1.00 (-2.27; 0.37)	.13	-0.06
Ethnicity	-	-	-0.44 (-1.94; 1.11)	.59	-0.03

Note. Values in bold denote statistical significance.

Mediation analyses

Mediation analyses were conducted in three stages. First, the mediating effect (through online USC) of SMU on MH symptoms was analysed (Model A1). Next, age, gender and ethnicity were incorporated to the basic model as covariates (Model A2). Then, offline USC was incorporated as a fourth and final covariate (i.e., age, gender, ethnicity *and* offline USC included as covariates) (Model A3). Table 4 (see below) describes the mediating effects across all three models in full.

In regard to Model A1 (i.e., prior to the inclusion of any covariates), support was yielded for H2 (H2 – the association described in H1 will be *partially* mediated by online USC), with both the indirect (mediating) effect [GAD-7 (indirect effect = 0.12, p <.001), PHQ-9 (indirect effect = 0.14, p <.001)] *and* the direct effect [GAD-7 (direct effect = 0.25, p =.002), PHQ-9 (direct effect = 0.29, p =.001)] found to be statistically significant. SMU and online USC combined described 14% [GAD-7 (F (2, 559) = 45.81, p <.001, R^2 = 0.14)], [PHQ-9 (F (2, 559) = 46.09, p <.001, R^2 = 0.14)] of variance in MH symptoms.

Support for H2 was also found in the case of Model A2 (i.e., after the inclusion of covariate variables age, gender and ethnicity), again with both the indirect (mediating) effect [GAD-7 (indirect effect = 0.10, p <.001), PHQ-9 (indirect effect = 0.12, p <.001)] *and* the direct effect [GAD-7 (direct effect = 0.25, p =.002), PHQ-9 (direct effect = 0.29, p =.001)] found to be statistically significant. When demographics were added, total variance explained increased to 15% [GAD-7 (F (5, 556) = 20.15, p <.001, R^2 = 0.15)], [PHQ-9 (F (5, 556) = 18.84, p <.001, R^2 = 0.15)].

In addition, support was found for H2b (H2b – this association will hold after controlling for offline USC) in that, again, both the indirect (mediating) effect [GAD-7 (indirect effect = 0.05, p = .009), PHQ-9 (indirect effect = 0.07, p = .004)] *and* the direct effect [GAD-7 (direct effect = 0.26, p =.002), PHQ-9 (direct effect = 0.30, p =.001)] were found to be statistically significant once offline USC (in addition to demographic covariates) were incorporated (Model A3). With offline USC incorporated into the model, total variance explained increased for GAD-7 scores to 17% (F (6, 555) = 18.97, p <.001, R^2 = 0.17) and remained the same for PHQ-9 scores (F (6, 555) = 16.22, p <.001, R^2 = 0.15).

Each model was also run with extreme scores excluded. The mediating effects retained statistical significance across all three models (Models A1-A3) upon the exclusion of extreme scores (see Supplementary Table 3). Supplementary Figures 1-3 visually describe Models A1-A3 and the unstandardised coefficients for all paths within each model, both with and without extreme scores.

Table 4. **Mediating effect (through online upward social comparisons) of social media use on mental health symptoms across different variations of the mediation model (Models A1-A3)**.

Model		Indirect effect (Bootstrap 95% CI)	Bootstrap *SE*	*p*-value	Standardised coefficient (β) (Bootstrap 95% CI)	Bootstrap *SE*
A1	GAD-7	**0.12 (0.06; 0.20)**	**0.04**	**<.001**	**0.06 (0.03; 0.10)**	**0.02**
	PHQ-9	**0.14 (0.07; 0.22)**	**0.04**	**<.001**	**0.06 (0.03; 0.10)**	**0.02**
A2	GAD-7	**0.10 (0.04; 0.17)**	**0.03**	**<.001**	**0.05 (0.02; 0.08)**	**0.02**
	PHQ-9	**0.12 (0.05; 0.19)**	**0.04**	**<.001**	**0.05 (0.02; 0.08)**	**0.02**
A3	GAD-7	**0.05 (0.02; 0.09)**	**0.02**	**.01**	**0.02 (0.01; 0.04)**	**0.01**
	PHQ-9	**0.07 (0.03; 0.12)**	**0.03**	**.004**	**0.03 (0.01; 0.05)**	**0.01**

Note. Model A1 represents the basic model (i.e., mediating effect (through online USC) of SMU on MH symptoms). Model A2 represents the basic model with age, gender and ethnicity included as covariates. Model A3 represents the basic model with age, gender, ethnicity *and* offline USC included as covariates. *p*-values calculated via Sobel test (*z*-value $= a*b/\mathrm{SQRT}(b^2*s_a^2 + a^2*s_b^2 + s_a^2*s_b^2)$ (Baron & Kenny, 1986; Preacher & Leonardelli, 2024). Values in bold denote statistical significance.

Moderated mediation analyses

Moderated mediation analyses were conducted using a similar sequence to the mediation analyses. First, moderation (by education) of the mediating effect (through online USC) of SMU on MH symptoms was analysed; specifically, testing whether education moderated the *second* step of the mediating pathway (i.e. from online USC to MH) (Model B1; see Figure 2). Next, age, gender and ethnicity were incorporated as covariates (Model B2). Finally, offline USC was incorporated as the fourth and final covariate (Model B3). This sequence (i.e., basic moderated mediation analysis, followed by the introduction of age, gender and ethnicity as covariates, and finally, including offline USCs as a fourth and final covariate) was then replicated, but with SEP index as the moderating variable (Models C1-C3). Next, each of the models (Models B and C) were rerun with extreme outliers removed.

Education

In regard to Model B1 (i.e., prior to the inclusion of covariates), moderated mediation analyses did not yield support for H3 (H3 – the associations described in H1 and H2 will also be moderated by SES (education), such that the association between USCs and MH symptoms will be stronger for those from low SES).

Thus, whilst both the indirect (mediating) effect (see Table 5) and the direct effect [GAD-7 (direct effect = 0.22, p =.01), PHQ-9 (direct effect = 0.23, p =.02)] retained statistical significance, there was no statistically significant difference between the indirect effects at different levels of education (all confidence intervals straddled zero; see Table 6). This remained true once demographic variables (Model B2) (see Tables 5 and 6) [GAD-7 (direct effect = 0.22, p =.01), PHQ-9 (direct effect = 0.23, p =.02)] and offline USC (Model B3) (see Tables 5 and 6) [GAD-7 (direct effect = 0.22, p =.01), PHQ-9 (direct effect = 0.23, p =.02)] were included, and when Models B1-B3 were rerun with extreme outliers excluded (see Supplementary Tables 4 and 5). Hence, there was no evidence of statistically significant moderated mediation via education.

In Model B1, predictors combined (SMU, online USC and education) described 16% of variance in GAD-7 scores (F (8, 553) = 12.69, p <.001, R^2 = 0.16) and 18% of variance in PHQ-9 scores (F (8, 553) = 14.74, p <.001, R^2 = 0.18). In Model B2, predictors combined (SMU, online USC, education, and demographic variables) described 17% of variance in GAD-7 scores (F (11, 550) = 10.21, p <.001, R^2 = 0.17) and 18% of variance in PHQ-9 scores (F (11, 550) = 11.04, p <.001, R^2 = 0.18). In Model B3, predictors combined (SMU, online USC, education, demographic variables, *and* offline USC) described 19% of variance in GAD-7 scores (F (12, 549) = 10.54, p <.001, R^2 = 0.19) and PHQ-9 scores (F (12, 549) = 10.47, p <.001, R^2 = 0.19).

Supplementary Figures 4-6 visually describe Models B1-B3 and the unstandardised coefficients for all paths within each model, both with and without extreme scores.

Table 5. **Mediating effect (through online upward social comparisons) of social media use on mental health symptoms at different levels of the moderator (education) (moderated mediation analyses, Models B1-B3).**

Model	Level of moderator (Education)	GAD-7 Indirect effect (Bootstrap 95% CI)	GAD-7 Bootstrap *SE*	PHQ-9 Indirect effect (Bootstrap 95% CI)	PHQ-9 Bootstrap *SE*
B1	GCSE or lower	**0.16 (0.03; 0.33)**	**0.08**	**0.22 (0.04; 0.42)**	**0.10**
	A-level or equivalent	**0.15 (0.04; 0.27)**	**0.06**	**0.15 (0.03; 0.28)**	**0.06**
	Undergraduate degree	**0.11 (0.04; 0.20)**	**0.04**	**0.13 (0.05; 0.23)**	**0.05**
	Postgraduate degree	**0.13 (0.06; 0.21)**	**0.04**	**0.14 (0.06; 0.24)**	**0.05**
B2	GCSE or lower	**0.14 (0.01; 0.30)**	**0.07**	**0.19 (0.03; 0.37)**	**0.09**
	A-level or equivalent	**0.13 (0.03; 0.25)**	**0.06**	**0.12 (0.02; 0.25)**	**0.06**
	Undergraduate degree	**0.09 (0.03; 0.17)**	**0.04**	**0.11 (0.04; 0.20)**	**0.04**
	Postgraduate degree	**0.10 (0.04; 0.18)**	**0.04**	**0.12 (0.05; 0.21)**	**0.04**
B3	GCSE or lower	0.07 (-0.01; 0.18)	0.05	**0.12 (0.01; 0.25)**	**0.06**
	A-level or equivalent	**0.07 (0.00; 0.14)**	**0.04**	**0.07 (0.01; 0.16)**	**0.04**
	Undergraduate degree	**0.04 (0.00; 0.10)**	**0.02**	**0.06 (0.01; 0.13)**	**0.03**
	Postgraduate degree	**0.05 (0.01; 0.10)**	**0.02**	**0.07 (0.02; 0.13)**	**0.03**

Note. Model B1 represents the basic model. Model B2 represents the basic model with age, gender and ethnicity included as covariates. Model B3 represents the basic model with age, gender, ethnicity *and* offline USC included as covariates. Values in bold denote statistical significance.

Table 6. **Moderating effect of education on the association between social media use and mental health via online upward social comparisons (moderated mediation analyses, Models B1-B3).**

Model	Level of moderator (Education)	GAD-7 Index of moderated mediation (Bootstrap 95% CI)	GAD-7 Bootstrap *SE*	PHQ-9 Index of moderated mediation (Bootstrap 95% CI)	PHQ-9 Bootstrap *SE*
B1	GCSE or lower x A-level or equivalent	-0.02 (-0.19; 0.15)	0.08	-0.08 (-0.27; 0.12)	0.10
	A-level or equivalent x Undergraduate degree	-0.03 (-0.14; 0.07)	0.05	-0.02 (-0.14; 0.11)	0.06
	Undergraduate degree x Postgraduate degree	0.01 (-0.06; 0.08)	0.04	0.01 (-0.07; 0.10)	0.04
B2	GCSE or lower x A-level or equivalent	-0.01 (-0.16; 0.14)	0.07	-0.07 (-0.24; 0.11)	0.09
	A-level or equivalent x Undergraduate degree	-0.04 (-0.13; 0.06)	0.05	-0.02 (-0.13; 0.09)	0.05
	Undergraduate degree x Postgraduate degree	0.01 (-0.05; 0.07)	0.03	0.01 (-0.06; 0.09)	0.04
B3	GCSE or lower x A-level or equivalent	-0.00 (-0.11; 0.10)	0.05	-0.05 (-0.17; 0.08)	0.06
	A-level or equivalent x Undergraduate degree	-0.02 (-0.09; 0.04)	0.03	-0.01 (-0.09; 0.07)	0.04
	Undergraduate degree x Postgraduate degree	0.00 (-0.04; 0.05)	0.02	0.01 (-0.05; 0.06)	0.03

Note. Model B1 represents the basic model. Model B2 represents the basic model with age, gender and ethnicity included as covariates. Model B3 represents the basic model with age, gender, ethnicity and offline USC included as covariates.

Socioeconomic profile index

In regard to Model C1 (i.e., prior to the inclusion of covariates and the exclusion of extreme scores), moderated mediation analyses did not yield support for H3 (H3 – the associations described in H1 and H2 will also be moderated by SES (SEP index), such that the association between USCs and MH symptoms will be stronger for those from low SES).

Whilst both the indirect (mediating) effect (see Table 7) and the direct effect [GAD-7 (direct effect = 0.22, p =.01), PHQ-9 (direct effect = 0.26, p =.01)] retained statistical significance, the index of moderated mediation was not statistically significant, as indicated by confidence intervals straddling zero [GAD-7 (index of moderated mediation = 0.07, bootstrap SE = 0.04, 95% CI = -0.01; 0.16), PHQ-9 (index of moderated mediation = 0.08, bootstrap SE = 0.05, 95% CI = -0.01; 0.17)].

This remained true once demographic variables (Model C2) were included (see Table 7 for mediating effects) [GAD-7 (direct effect = 0.22, p =.01; index of moderated mediation = 0.06, bootstrap SE = 0.04, 95% CI = -0.01; 0.14), PHQ-9 (direct effect = 0.26, p =.01; index of moderated mediation = 0.07, bootstrap SE = 0.04, 95% CI = -0.01; 0.15)] and once offline USC (Model C3) were included (see Table 7 for mediating effects) [GAD-7 (direct effect = 0.23, p =.01; index of moderated mediation = 0.05, bootstrap SE = 0.03, 95% CI = -0.01; 0.10), PHQ-9 (direct effect = 0.26, p =.01; index of moderated mediation = 0.05, bootstrap SE = 0.03, 95% CI = -0.01; 0.11)].

In Model C1, SMU, online USC and SEP index accounted for 17% of the variance MH symptoms [GAD-7 (F (4, 557) = 27.62, p <.001, R^2 = 0.17)], [PHQ-9 (F (4, 557) = 28.09, p <.001, R^2 = 0.17)]. In Model C2, predictors combined (SMU, online USC, SEP index, and demographic variables) described 18% of variance in GAD-7 scores (F (7, 554) = 17.39, p <.001, R^2 = 0.18) and 17% of variance in PHQ-9 scores (F (7, 554) = 16.58, p <.001,

$R^2 = 0.17$). In Model C3, predictors combined (SMU, online USC, SEP index, demographic variables, *and* offline USC) described 20% of variance in GAD-7 scores (F (8, 553) = 17.09, p <.001, $R^2 = 0.20$) and 18% of variance in PHQ-9 scores (F (8, 553) = 14.99, p <.001, $R^2 = 0.18$).

Table 7. **Mediating effect (through online upward social comparisons) of social media use on mental health symptoms at different levels of the moderator (socioeconomic profile index) (prior to the exclusion of extreme scores) (moderated mediation analyses, Models C1-C3).**

Model	Level of moderator (SEP index)	GAD-7 Indirect effect (Bootstrap 95% CI)	GAD-7 Bootstrap *SE*	PHQ-9 Indirect effect (Bootstrap 95% CI)	PHQ-9 Bootstrap *SE*
C1	≥1 indicators of low SEP	**0.18 (0.08; 0.29)**	**0.06**	**0.20 (0.09; 0.32)**	**0.06**
	No indicators of low SEP	**0.10 (0.05; 0.18)**	**0.03**	**0.12 (0.05; 0.20)**	**0.04**
C2	≥1 indicators of low SEP	**0.14 (0.05; 0.24)**	**0.05**	**0.16 (0.07; 0.28)**	**0.06**
	No indicators of low SEP	**0.08 (0.03; 0.15)**	**0.03**	**0.10 (0.04; 0.17)**	**0.03**
C3	≥1 indicators of low SEP	**0.08 (0.03; 0.15)**	**0.03**	**0.10 (0.04; 0.18)**	**0.04**
	No indicators of low SEP	**0.03 (0.01; 0.08)**	**0.02**	**0.06 (0.01; 0.11)**	**0.03**

Note. Model C1 represents the basic model. Model C2 represents the basic model with age, gender and ethnicity included as covariates. Model C3 represents the basic model with age, gender, ethnicity *and* offline USC included as covariates. Values in bold denote statistical significance.

Models C1-C3 were re-run with extreme scores excluded. In regard to Model C1 (i.e., prior to the inclusion of covariates), upon the exclusion of extreme scores, there *was* evidence of moderated mediation (indicated by the absence of zero within confidence intervals) [GAD-7 (index of moderated mediation = 0.12, bootstrap *SE* = 0.05, 95% CI = 0.02; 0.23), PHQ-9 (index of moderated mediation = 0.14, bootstrap *SE* = 0.06, 95% CI = 0.04; 0.25)]. This remained true once demographic variables (Model C2) [GAD-7 (index of moderated mediation = 0.11, bootstrap *SE* = 0.05, 95% CI = 0.02; 0.22), PHQ-9 (index of moderated mediation = 0.13, bootstrap *SE* = 0.05, 95% CI = 0.04; 0.24)] and offline USC (Model C3) [GAD-7 (index of moderated mediation = 0.09, bootstrap *SE* = 0.04, 95% CI = 0.02; 0.18), PHQ-9 (index of moderated mediation = 0.10, bootstrap *SE* = 0.04, 95% CI = 0.03; 0.19)] were included.

The direct effect retained statistical significance at the basic level (Model C1) [GAD-7 (direct effect = 0.33, p =.001), PHQ-9 (direct effect = 0.28, p =.01)], once demographic variables were included as covariates (Model C2) [GAD-7 (direct effect = 0.33, p =.001), PHQ-9 (direct effect = 0.28, p =.01)] and finally once offline USCs were also included (Model C3) [GAD-7 (direct effect = 0.34, p <.001), PHQ-9 (direct effect = 0.28, p =.01)].

The indirect (mediating) effect (through online USC) of SMU on MH symptoms also retained statistical significance across Models C1-C3 (see Table 8 for mediating effects), except for one instance. In the case of all models (Models C1-C3), the indirect (mediating) effect (through online USC) of SMU on MH symptoms was stronger for those with an SEP index score of ≥ 1 compared to those who did not score on the low SEP index. In regard to C3, and specifically GAD-7 scores, the indirect effect was stronger (and statistically significant) for those scoring ≥ 1 on the low SEP index compared to those who did not score on the low SEP index, whereby the mediating path was not statistically significant.

In Model C1, predictors combined (SMU, online USC and SEP index) accounted for 16% of the variance GAD-7 scores (F (4, 513) = 23.72, p <.001, R^2 = 0.16) and 17% of the variance in PHQ-9 scores (F (4, 519) = 25.57, p <.001, R^2 = 0.17). In Model C2, predictors combined (SMU, online USC, SEP index and demographics) accounted for 17% of the variance GAD-7 scores (F (7, 510) = 15.15, p <.001, R^2 = 0.17) and PHQ-9 scores (F (7, 516) = 15.07, p <.001, R^2 = 0.17). In Model C3, predictors combined (SMU, online USC, SEP index, demographics *and* offline USC) accounted for 19% of the variance in GAD-7 scores (F (8, 509) = 14.96, p <.001, R^2 = 0.19) and 18% of the variance in PHQ-9 scores (F (8, 515) = 13.81, p <.001, R^2 = 0.18).

Supplementary Figures 7-9 visually describe Models C1-C3 and the unstandardised coefficients for all paths within each model, both with and without extreme scores.

Table 8. **Mediating effect (through online upward social comparisons) of social media use on mental health symptoms at different levels of the moderator (socioeconomic profile index) (with extreme scores *excluded* from the analysis) (moderated mediation analyses, Models C1-C3).**

Model	Level of moderator (SEP index)	GAD-7 Indirect effect (Bootstrap 95% CI)	GAD-7 Bootstrap *SE*	PHQ-9 Indirect effect (Bootstrap 95% CI)	PHQ-9 Bootstrap *SE*
C1	≥1 indicators of low SEP	**0.20 (0.09; 0.35)**	**0.07**	**0.25 (0.11; 0.40)**	**0.08**
	No indicators of low SEP	**0.09 (0.04; 0.16)**	**0.03**	**0.11 (0.04; 0.19)**	**0.04**
C2	≥1 indicators of low SEP	**0.18 (0.07; 0.31)**	**0.06**	**0.22 (0.09; 0.37)**	**0.07**
	No indicators of low SEP	**0.07 (0.02; 0.13)**	**0.03**	**0.10 (0.03; 0.18)**	**0.04**
C3	≥1 indicators of low SEP	**0.12 (0.04; 0.21)**	**0.04**	**0.15 (0.06; 0.27)**	**0.05**
	No indicators of low SEP	0.03 (-0.00; 0.07)	0.02	**0.05 (0.01; 0.11)**	**0.03**

Note. Model C1 represents the basic model. Model C2 represents the basic model with age, gender and ethnicity included as covariates. Model C3 represents the basic model with age, gender, ethnicity *and* offline USC included as covariates. Values in bold denote statistical significance.

Discussion

Summary of findings

With respect to *a priori* hypotheses, three out of three were partially or wholly supported. Thus, support was found for the first hypothesis (H1 – higher SMU will be associated with higher MH symptoms, as measured by GAD-7 and PHQ-9), with regression analyses indicating that as SMU increased, so too did symptoms of anxiety and depression (a finding that held upon the inclusion of demographic variables as covariates).

Support was also found for the second hypothesis (H2 – the association described in H1 will be *partially* mediated by online USC), with evidence of a statistically significant direct effect (SMU > MH) *and* indirect (mediating) effect (through online USCs), again, after controlling for demographic variables and, in addition, offline USCs also (H2b – this association will hold after controlling for offline USC).

Finally, partial support was found for the third hypothesis (H3 – the associations described in H1 and H2 will also be moderated by SES, such that the association between USCs and MH symptoms will be stronger for those from low SES). There was no evidence of moderated mediation when SES was operationalised in terms of level of education. However, when SES was operationalised in terms of low SEP index, moderated mediation analyses suggested that the indirect (mediating) effect of SMU on depression and anxiety (via online USC) was stronger for those from lower SES backgrounds, with the mediating effect completely collapsing for the higher SES group in the case of anxiety. This was only the case for analyses in which extreme outliers were removed, however (but survived after controlling for demographic covariates – age, gender and ethnicity – and offline USC).

Discussion of findings

Findings of the regression analyses, suggesting that symptoms of anxiety and depression increased with SMU, fall in line with previous meta-reviews within the field, which suggest a predominantly negative association between SMU and MH / well-being (Meier & Reinecke, 2020). A criticism of existing research pertains to the overinterpretation of trivial effect sizes (Keles et al., 2020; Orben et al., 2019), and whilst the association described was indeed highly statistically significant (p <.001), it was also arguably small, with the univariate models (i.e., when MH symptoms were regressed onto SMU, prior to the inclusion of demographic variables) describing just 3-4% of total variance in MH symptoms.

This does not necessarily mean that this finding is unimportant, however. We know, for example, that there is evidence to suggest that certain types of SMU (i.e., active versus passive use) are associated with an increase in MH symptoms for younger generations and a decrease in MH symptoms for older generations (Lewin et al., 2022). Hence, in a relatively large sample like that used in the present study (with an age ranging from 18 to 85), it is plausible that larger effects amongst sub-populations were masked. In addition, that the direct effect of SMU on MH symptoms held across all analyses (i.e., when incorporating mediating (online USC), moderating (education / low SEP indicators) and confounding (demographics and offline USC) variables) arguably says something about the robustness of the direct association between SMU and MH symptoms. At the same time, the proportion of unexplained variance underlines previous research recommendations to investigate the potential underlying mechanisms (and the present study's subsequent analyses).

The results of the mediation analyses, revealing a statistically significant indirect (mediating) effect of SMU on MH symptoms through online USCs, also largely converge with the existing evidence base. For example, one study of 809 Facebook users (aged 16 to

74) found, via sequential mediation analyses, evidence of a statistically significant indirect effect of Facebook use on symptoms of depression through social comparison orientation and self-esteem (Ozimek & Bierhoff, 2020). In making sense of their findings, Ozimek and Bierhoff (2020) also referenced the transformation framework (Nesi et al., 2018), suggesting that users of SM may be frequently exposed to USCs in the online world in a way that they are not offline. However, the authors did not include separate, distinct measures of offline and online comparisons, instead measuring social comparison orientation generally (i.e., potentially confounding the two). Without a measure of offline comparisons, it could be argued that it is not possible to determine whether online USCs are uniquely harmful (or predict additional variance in outcomes), or whether they simply mirror / act as a proxy for offline social comparative processes (Meier & Johnson, 2022). The present study therefore sought to further the evidence base in this regard, via controlling for offline USCs.

That the indirect (mediating) effect of SMU on MH symptoms through online USC reduced in size but retained statistical significance after controlling for offline USCs both fits and contrasts with the limited research previously conducted that has sought to control for and compare offline with online USCs. One cross-sectional study conducted on a sample of 181 individuals aged 18-25 yielded mixed findings when comparing online and offline SCs and their associations with symptoms of depression (Faranda & Roberts, 2019). Faranda and Roberts (2019) found that whilst individuals did not make a greater number of comparisons online (compared to offline), the comparisons that *were* encountered online were typically more negative (i.e., associated with greater feelings of inferiority). However, after controlling for offline SCs, online SCs did not explain unique variance in depressive symptoms. The results of the present study diverge with this, in that online USCs *did* explain unique variance, suggesting that there is potentially something uniquely detrimental to MH about comparisons made on SM.

One possible reason for this discrepancy pertains to the way in which SMU was operationalised, with the present study focusing on cross-platform usage and that of Faranda and Roberts (2019) focusing on Facebook only. Whilst the association between Facebook use and anxiety, depression and other negative MH impacts is well-evidenced (Frost & Rickwood, 2017), it is possible, for example, that some other underlying mechanism (i.e., not related to social comparison processes), predominantly underlies the association between Facebook usage and MH outcomes, given the consensus that a number of mechanisms likely underpin the SMU-MH relationship (Baker & Algorta, 2016; Keles et al., 2020; Meier & Reinecke, 2020; Tibber & Silver, 2022). Further, previous research has indicated that different SM platforms differentially predict outcomes, such as stress (Tibber et al., 2023). Such an idea also falls in line with the transformation framework, which outlines a number of ways in which interpersonal processes differ in the online world (versus offline), referred to as ‘features’, and how such features vary considerably across different types of SM, including across different platforms (Nesi et al., 2018).

To the best of the author’s knowledge at the time of writing, the present research study contributes uniquely to the field via investigating the potentially moderating role of SES in online social comparison processes. Whilst online USCs represent a promising mediator / underlying mechanism in the association between SMU and MH (Meier & Johnson, 2022; Verduyn et al., 2020; Yang et al., 2019; Yoon et al., 2019), their effects are not unequivocal, with some finding associations between online USCs and beneficial effects, such as inspirational motivation (Meier & Schäfer, 2018). Hence, the present study sought to contribute toward a greater understanding of interindividual differences in online social comparison processes.

Several theories surrounding differential effects of online USC have emerged. Whilst social comparisons can vary in their direction – upwards (comparison to a ‘superior’ target) and downwards (to an ‘inferior’ target), we know that this alone does not determine their effects on well-being or MH outcomes. A further distinction relates to that of ‘assimilative’ versus ‘contrastive’ social comparisons, with assimilation shifting one’s attentional focus toward similarities or ways of becoming similar to the target and contrastive comparisons shifting attention toward the differences with the target (Gerber et al., 2018). Previous research has established that upward, *contrastive* social comparisons are typically associated with negative outcomes for well-being and upward, *assimilative* social comparisons are typically associated with more positive outcomes for well-being (Gerber et al., 2018; Meier & Schäfer, 2018).

Some have suggested that online USCs may be more harmful for some than others dependent on factors such as the perceived attainability of comparison standards, with those who deem themselves as lacking the resources or ability required to achieve the comparison standards experiencing greater upward, contrastive comparisons and hence more negative psychological effects than those who perceive those standards to be attainable (Lockwood & Kunda, 1997; Meier & Johnson, 2022; Meier & Schäfer, 2018). Another relevant theory is that of the two-step model of social comparisons, whereby an initial, unconscious / automatic step (typically associated with negative MH effects) precedes a second, more intentional / conscious step in which such effects may be reversed (for example, via more nuanced consideration / cognitive reappraisal) (Buunk & Gibbons, 2007; Tibber et al., 2024).

In the present study, that individuals scoring on a measure indicative of low SES (low SEP index) were found to be more heavily impacted by online USCs in the case of symptoms of both anxiety and depression (and that, in the case of anxiety, the mediating role of online USC in the SMU-MH association collapsed *altogether* for those from higher SES background) may, perhaps, be understood in the context of all of the aforementioned ideas.

Thus, whilst it is possible that anyone can be confronted with USC on SM (i.e., the first stage of the two-step model of social comparisons, typically associated with negative MH effects) due to the breadth of comparison targets available, it is plausible that differential effects follow in regard to the second step dependent on interindividual differences like SES. It is plausible, for example, that those with higher SES are more able to reflect upon ways in which they may achieve the comparison target standards, due to having the resources / status available to them in order to do so (possibly, shifting attention toward assimilation, with subsequent experiences of inspiration). Conversely, those from lower SES may be less able to engage in such reappraisals, due to lacking the physical means (i.e., resources / status). Hence, such individuals may be less able to shift attentional processes from contrastive to assimilative, perceiving the gap between themselves and the comparison target as too large (i.e., unattainable) to bridge, meaning that the initial, harmful effects of online USC cannot be 'reversed' in the same way (as for those from higher SES). Hence, those from lower SES background may be more vulnerable to the harmful effects of SM that operate specifically via online social comparisons processes.

It is however important to note that moderated mediation was not found when SES was operationalised via highest level of education, a commonly used and widely recommended measure of SES (Braveman et al., 2005). Hence, results regarding the moderated mediation analyses in particular of this present study should be interpreted with caution. A plausible explanation for this could relate to the sample used in the present study, which was predominantly highly educated, whereas the low SEP index captured markers of low SES across *multiple* indices and may therefore have been more sensitive in terms of capturing relative disadvantage within the sample.

That evidence of moderated mediation was only found upon the exclusion of extreme scores also requires consideration. One plausible explanation for this is that extreme scores (i.e., on GAD-7 and PHQ-9 measures) may have masked underlying patterns in the SMU-MH association, with MH outcomes for such individuals being more strongly influenced by something more immediate in their life at that time. Given that the data were collected during the COVID-19 pandemic, with an estimated 6.8 million bereavements in the UK from 2020-2021 alone (an additional 750,000 than would have been expected based on the 2015-2019 five-year average) (UK Commission on Bereavement, 2022), it is possible, for example, that some of the more extreme scores on MH measures may have been strongly influenced by factors such as bereavement. It could be speculated, given that evidence of moderated mediation was replicated across both sets of MH measures upon the exclusion of extreme scores, that some such reason is more likely than the results being a spurious association only.

Strengths, limitations and recommendations for future research

A major criticism within the field is that studies have failed to control for variables such as demographics and in particular offline USCs despite evidence suggesting that they may play a confounding role in the SMU-MH association (Nesi & Prinstein, 2015; Orben et al., 2019; Tibber et al., 2020), hence the present study contributes to the evidence base in this regard. Controlling for offline USCs brings a significant strength, addressing an important gap in the evidence base concerning whether or not there is something inherently damaging about comparisons made online over and above offline comparisons (Meier & Johnson, 2022), yielding further support for the transformation framework (Nesi et al., 2018) and the idea that the features and affordances of the online world have a transformative effect in the nature of interpersonal interactions, with potential implications for mental health and well-being. What exactly that is – a wider pool of comparison targets, asynchronous communications, carefully curated (and overly positive) user-generated content – remains a point for further investigation.

Other strengths of the study include the relatively large sample size and the measurement of core constructs, with SMU and MH conceptualised and operationalised in line with the Meier and Reinecke's (2020) extension of the two-continua model of MH and recommended, maximally inclusive definitions of (cross-platform) SMU (Meier & Reinecke, 2020; Nesi et al., 2018). Whilst an advantage to studying individual platforms (e.g., Facebook, Instagram) is increased ability to detect platform-specific effects, a critique of such an approach is that the functions and features of individual platforms change rapidly (Nesi et al., 2018). The results of the present study therefore are likely to have more generalisability and utility over time. Relatedly, previous research has been criticised for conflating indices of MH, well-being and risk (Orben, 2020). The present study's use of valid and reliable measures of anxiety and depression hopefully offers the field a clearer understanding of how online USCs impact MH specifically.

That the present study was cross-sectional in its design represents perhaps the greatest limitation, particularly given how many have called for longitudinal research and experimental studies to enable the determination of causality (Best et al., 2014; Dobrean & Păsărelu, 2016; Erfani & Abedin, 2018; Keles et al., 2020; Orben, 2020). Hence, the present study was not able to clarify whether online USCs *caused* increased symptoms of anxiety and depression (particularly amongst those from low SES backgrounds), or whether individuals with anxiety and depression (again, particularly those from low SES backgrounds) engage with SM differently and make more social comparisons online / are more negatively affected by them, or both. Future research would do well to investigate both the mediating role of online USCs and whether / how SES or other markers of disadvantage may interact with such in the SMU-MH association in longitudinal research.

Whilst there were aspects of measurement that could be considered strengths of the present study (as highlighted above), there were also several aspects that could be considered weaknesses. One such issues relates to the measurement of SMU via a single item. Further, this single item measured time spent on SMU, and previous research has criticised such methods, arguing that time spent online does not reveal anything meaningful about *what* exactly SM users are doing online (Meier & Reinecke, 2020). Hence, future research would do well to replicate the present findings using a multi-item SMU measure, particularly one that captures information on both channel-centred and communication-centred conceptualisations of CMC (i.e., in line with the hierarchical computer-mediated communication (CMC) taxonomy) (Meier & Reinecke, 2020).

A final limitation pertains to the measurement of online and offline USCs, which were captured via a single-item, ordinal variable. That said, previous research has highlighted acceptable levels of validity and reliability of many single-item measures in MH research (McKenzie & Marks, 1999), particularly in regard to effects that are known to be robust and reliable (such as in the case of USCs and the SMU-MH association) (Verduyn et al., 2020). Future research may do well to measure such on a sliding scale and / or via the use of multiple items, such as the Iowa-Netherlands Comparison Orientation Measure (INCOM) (Gibbons & Buunk, 1999) and INCOM-F (Steers et al., 2014).

Conclusions and implications

The present study sought to clarify the role of online USCs in the relationship between SMU and MH, specifically investigating the extent to which putative associations with MH impacts are unique to the online world (as opposed to simply serving as a proxy for comparisons made offline) and the extent to which interindividual differences in SES may further influence such associations, if at all.

The findings of the present study suggest that online USCs are, somehow, different to those made offline, with potentially damaging implications for MH (assuming one particular direction of causality), and that this experience may be greater for those who suffer from higher levels of relative disadvantage in society. As stated, these findings are not without their limitations, however, and should be interpreted with caution, and the field of research investigating the SMU-MH association would do well to seek to replicate them in longitudinal designs. This would sustain greater confidence in the results of this piece of research, including those relating to potentially causal effects.

If these findings are replicable, they offer promising scientific and clinical implications. At a scientific level, a number of underlying mechanisms in the SMU-MH association have been studied over the years, driven by research from different disciplines, arguably resulting in a fragmented evidence base (Orben, 2018). Replication of these findings could propel the field toward greater integration and justify delving even deeper into online USCs as a mechanism and the ways in which inter-individual differences like SES interact with such.

At a clinical level, the findings could support clinicians to identify clients for whom opening up conversations around SMU may be particularly helpful (i.e., individuals suffering with symptoms of anxiety and depression, and perhaps especially, those from lower SES background who may be most vulnerable to the harmful effects associated with online USC). When asking about a client's SMU, the results of the present study may help guide those conversations to themes or aspects of SMU that may be most relevant, such as *how* individuals use SM – specifically, the extent to which they find themselves comparing with others online. Research suggests that some social comparisons are encountered, automatic and unconscious (Wood, 1989, 1996), hence supporting a client to develop greater awareness of their own online social comparison processes could represent a significant first step. Psychoeducation may be helpful, for example, informing clients around what is known about the potential harms of online USCs. Drawing on a cognitive-behavioural approach, clinicians could, for example, map out a cross-sectional formulation, supporting clients to explore the impact of an online USC on their thinking, their mood and their behaviour, before supporting the client to challenge particular cognitions experienced in response to an online USC. For a client who goes online, views a friend's recent post about having just been on a luxurious holiday, and experiences the thought 'other people have it better than me', a clinician could support the client to develop a more critical, nuanced appraisal, for example. Such ideas are not entirely new, but nor do they contrast too greatly with existing ideas within the field (Tibber & Silver, 2022).

Should the findings prove robust, and particularly if causal effects are established, they could support the call for more stringent regulation within the social media industry, as well as highlighting specific aspects of SM to focus on. For example, sites like TikTok now have features that prompt a user after a certain amount of time spent on the app to consider taking a break from the platform. The present study's findings in regard to online USCs, if replicable and robust, could support the development of other features, such as a similar prompt designed to elicit reflection upon online social comparison processes. At a more systemic level, establishing causality – particularly in regard to the impact of relative deprivation and inequality – could highlight a need for political / economic interventions to alleviate the negative effects of poverty in society.

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Part Three: Critical Appraisal

Introduction

This critical appraisal is a reflective account of my experiences of undertaking this research project, which I have completed as part of the Doctorate in Clinical Psychology. I begin by describing my background prior to commencing clinical training, in the hopes that this provides the reader with an initial context within which my reflections may be understood. I then go on to reflect on the different stages and phases of the research project, where I have continued to describe my context at that time and how I understand it to have shaped or impacted the research process and the decisions I made. My intention behind this critical appraisal is mainly to describe the challenges I faced, how I understood them, how I approached them and why I did so, and what was learned in the process.

Background and selection of research project

Prior to commencing clinical training, my clinical experience namely spanned working with children, young people and families. I was in a privileged position to have been able to leave an unhappy job in administration to volunteer in a number of schools, searching for relevant experience that might help me get a foot in the door to a field that seemed, at that time, somewhat impenetrable without a vocational qualification. I started working as a teaching assistant for one of those schools (an educational provision for autistic children and young people), then as an assistant to the in-house therapy team, supporting occupational therapists, speech and language therapists, and a clinical psychologist. My conversations with those colleagues sparked my interest in clinical psychology over and above educational psychology (which is where I initially thought / hoped I may build a career). Following that, I volunteered with The Samaritans, worked as a clinical support worker in a local adolescent inpatient unit, and then as an assistant psychologist in a local child and adolescent mental health team. I was then fortunate enough to gain an interview for UCL's DClinPsy course, and even more fortunate to receive a place on the course in 2019. I have felt consistently drawn to working with children, young people and families over the years, something I think was initially sparked by my own experiences of childhood, adolescence and family life, and both a driving force and a consequence of my cumulative experiences prior to training and throughout training.

When it came to selecting a research project during the initial stages of training, it seemed an incredibly daunting task, in part due to the commitment to immerse oneself in a certain field of research for the first three years of one's career as a clinical psychologist (and in part, due to reckoning with the realisation that I would, in fact, have to conduct a research project). My highest level of education prior to training was my undergraduate degree, where I had won an award for the highest marked dissertation of the cohort, something I have repeatedly tried to reassure myself with throughout the research project process. Despite this achievement (and my somewhat successful attempts at self-(re)assurance), I ultimately questioned my ability to write a thesis – an insecurity which has hummed in the background of every stage of the project and every draft I have written, something which has also been perpetuated by personal experiences that have shook my confidence along the way. So, when it came to 'choosing' a project, I considered both what I was interested in, which project might capitalise on the research knowledge and skills I *did* have, and which supervisor I might feel most able to ask for help.

In terms of interest, I felt drawn to a research project investigating social media use and its association with mental health outcomes in young people for a number of reasons. I felt excited by this relatively new and rapidly developing field (Kim, 2017). I thought back to my experiences working with children and young people. That social media use may have beneficial impacts for some (Erfani & Abedin, 2018), including for, example, those with autism spectrum conditions (Mazurek, 2013), fitted with my anecdotal experience of working with children and young people across multiple settings. I was reminded of conversations on the inpatient unit I worked on, where access to mobile phones and whether such should be perceived as a right or a privilege, helpful or harmful for recovery, could be a topic of debate and uncertainty. I thought back to my own experiences, as an individual who grew up in an era both before social media and smartphones (with memories of ambivalently being given a bulky Nokia ‘in case of emergency’ as a child / young teen) and once both became commonplace. I also reflected on my own complicated feelings in the here-and-now as to what I share on social media, why, who it is for, and how I feel impacted by the content I consume and my own types of social media use.

The research proposal, research governance, and the change of plan

The initial stages of planning the research project were somewhat overwhelming. Specifically, attempting to formulate a series of specific research questions rooted in what is currently known and unknown within a field, having very limited knowledge of said field of research, felt like a colossal task. Hence, the initial few weeks marked the beginning of ‘immersing oneself within the literature’. I can remember doubting my ability to retain, recall and synthesise the results of a handful of papers, let alone those across an entire research field, which feels starkly contrasted with now – nearly five years later – being able to (albeit, *very* vaguely) call to mind a specific paper, detailing a specific study, supporting a specific idea / highlighting a specific issue. This is a great reminder of the sheer volume of research that I have consumed within the process, how much I have learned about social media use and mental health’s association, and the skills that I have been able to hone throughout this entire process (specifically, those related to synthesising information and holding multiple, complex and sometimes contrasting ideas in mind at once).

What I have come to call ‘Plan A’ for my research project involved exploring the association between social media use and mental health with a specific focus on the underlying mechanisms that may help to explain this association – namely, social comparisons (Festinger, 1954; Vogel et al., 2014), aspirational style (Ryan & Deci, 2000), and active versus passive use (Verduyn et al., 2015) – ultimately considering (through the lens of the interpersonal-connections-behaviours-framework (ICBF) (Clark et al., 2018) whether certain patterns of use may leave individuals more susceptible to the disconnecting, as opposed to the possibly connecting, effects of social media. Plan A involved a longitudinal design with a sample of 16-18 year olds attending an NHS delivered mental health and well-being workshop delivered across schools – hence, also facilitating the exploration of possible causal or bidirectional effects, which represented a significant gap in the evidence base at the time (Orben, 2020). I felt particularly excited about several aspects of the study, including being actively involved from the outset, able to shape its design to fit mine and my research supervisor’s evolving ideas and interests, the focus on young people’s mental health and well-being, and the possibility to draw conclusions in regard to causality or bidirectional effects.

As I embarked on the process of applying for ethical approval, the COVID-19 pandemic hit, and at the same time, I experienced a devastating loss in my personal life. Having successfully gained UCL Research Ethics Committee (REC) approval shortly after, I learned that changes within the NHS Trust in which we planned to collect the data meant that the UCL REC approval was no longer sufficient and an application to an NHS REC was required. As the study design meant that data collection could only take place during specific times of the school year, delays in applying for NHS REC approval would have significant consequences for the project. Additionally, my personal context meant that I needed some time away from the course. Hence, my research supervisor and I considered alternative options.

We discussed and agreed on a Plan B, where I would join an existing research study and complete a secondary analysis of the data, allowing me to step back from my research project and prioritise my personal life for a while. Whilst I felt deeply disappointed about deviating from Plan A – and doing so represented another loss to me, personally, at the time – I felt assured in knowing that I had gained the experience of writing a successful ethics application (even if I did not use it).

Conceptual introduction

I ended up taking an extended break from my thesis as a result of ongoing personal challenges and further losses. When I fully came back to my thesis, so much time had passed that I felt out-of-touch with the field and the research project / process. I decided to focus most of my attention on Part 1, for a number of reasons, but largely as a way of refamiliarizing myself with the evidence base. I chose to complete a conceptual introduction over a systematic review for two main reasons. Firstly, I struggled to find a topic where a systematic review had not been completed already nor was registered, and topics that would contribute to gaps in the evidence base yielded so few papers that there just wasn't enough to review. Secondly, whilst I was somewhat nervous about the prospect of reviewing a much broader landscape (and in a much less strategic or structured way), I genuinely wanted to develop a broad understanding of the field. This desire was likely driven by my personal nature and because I thought (rightly or wrongly) that having this knowledge would better enable me to make sense of whatever results I may find within the wider context of what is currently known (and unknown) regarding social media's association with mental health once I completed my data analysis.

When I was researching for my conceptual introduction, I became increasingly confused and frustrated by the limitations in the evidence base. Specifically, I found that it was sometimes quite difficult to pinpoint exactly how researchers had operationalised core constructs (i.e., mental health and social media use). Some papers simply stated a 'well-being measure', yet there was no outline of exactly what this measure was nor of its validity and reliability. Sometimes, when it was clear, I was not satisfied that the measure that had been used appropriately mapped on to said constructs (or perhaps more so, to the conclusions that were subsequently drawn). For example, I found that in some papers, mental health had been measured in terms of self-esteem or loneliness. Of course, whilst such variables are related to mental health, and no study can measure mental health in every which way possible, I felt that what was sometimes lacking was an acknowledgement of the limitations of said measure. I found this to be problematic given that, in my view, a number of papers offered quite bold interpretations of their research findings and, as has been said by others also, arguably have overinterpreted what were trivial effect sizes (Orben, 2020).

A number of researchers have highlighted this issue, but I thought that Meier and Reinecke's (2020) meta-review clearly offered a resolution to the field, specifically outlining how these constructs can and should be operationalised in research moving forward, consistently and thoroughly backed up by theory and research. Subsequently, I felt strongly that this was something I wanted to embed throughout my thesis. I wanted to present to the reader in very clear, simple, transparent terms a rigorous conceptualisation and operationalisation of constructs, an acknowledgment of the limitations of such / the research study design more generally speaking, and to highlight to the reader what the implications of this were (i.e., what conclusions could and – at least to me, perhaps more significantly – could not be drawn).

Ironically then, I recall a particular meeting with my research supervisor a few months into writing my conceptual introduction (and a few months after I set my intentions towards nuance and parsimony) where I explained that I was feeling incredibly stuck. Through our discussion, I came to realise that I had been taking on too big of a task in trying to find a way to integrate all of the findings in the entire field, and essentially simplify what is an incredibly complex association. On reflection, I think that as I consumed more research (and learned of more and more conflicting results), the more uncertainty there was, the more difficult it became to synthesise, the more anxiety-inducing and colossal the task felt, and the more I sought certainty and drifted from what I can best describe as synthesising to reconciling. This was a humbling experience and one that I held onto throughout the project, in that noticing an urge for certainty when writing became a gentle reminder that I was drifting from the task at hand.

Empirical paper

I was able to contribute to the UCL COVID-19 Impacts Study (Tibber et al., 2024; Tibber, Milne, et al., 2023) primarily through supporting with the design and delivery of the follow-up survey (for the second wave of data collection) and through ‘cleaning’ the T1 dataset, the T2 dataset, and then merging the two into one datasheet. Initially, I thought this would be relatively straightforward. I had not envisaged what a time-consuming task getting the data ready for analysis would be. The database held an enormous amount of demographic information in addition to individual item scores for a number of measures. Further, a number of the measures had not been coded / stored in the correct format, and sometimes, not even in numerical format (but rather, as text, for example). Getting to grips with the measures, the response options, and going back and forth between these and the dataset, manually recoding a number of the measures and identifying gaps in the dataset took much longer than anticipated. However, doing this really helped in terms of familiarising myself with the study and the data, which was imperative as I headed into the data analysis.

One of the challenges encountered related to the creation of the low socioeconomic profile index. I had really hoped to be able to use income and education as indices of socioeconomic status, within the context of my own intentions to robustly conceptualise and operationalise core constructs and given that both are commonly used and widely accepted in health research (Braveman et al., 2005). The finding that there was incomplete data for income was concerning. I considered multiple options, including whether I could reduce the sample used for statistical analyses down to those with complete data across all measures (including income). However, doing so would represent a significant loss of data (9.79%) and thus statistical power.

Creating the low socioeconomic profile index represented a compromise in this trade-off, but was not without complications. The study that I drew from for this idea (Wright et al., 2020) had measured indices of socioeconomic profile slightly differently in a number of ways. For example, their cut-off for low socioeconomic status in terms of annual household income was £16,000, whereas the data I had at hand was ordinal with different brackets (i.e., less than £13,000, followed by £13,000-£18,999). I tried to establish via my own research the level of annual household income in the UK which is considered indicative of low socioeconomic status, however found that there was no clear-cut answer. I decided to use the lower threshold (£13,000) as a cut-off rather than the higher threshold (£18,999) ultimately based on judgment and my belief that being conservative and not finding a statistically significant result was preferable to the inverse (i.e., finding a statistically significant moderating effect which was questionable in integrity / validity).

I encountered numerous other dilemmas / issues in terms of measurement, including those that raised ethical concerns for me. Whilst ethnicity had been collected in accordance with recommendations implemented routinely by the NHS (Office for National Statistics, 2021b), upon initial analysis of sample characteristics, I found that the sample was predominantly White and the frequency counts for all other ethnicities were extremely low in comparison. After discussion with my research supervisor, I proceeded to collapse ethnicity into 'White' and 'other' groups for statistical analysis. With some awareness of the limitations of treating those from minority ethnic groups as a monolith in mental health research (Esie & Bates, 2023) (in addition to the various harms caused by such narratives more generally speaking) this felt incredibly problematic. However, from a statistical point of view, I could not locate an alternative solution. I also returned to the aims of the empirical paper, which were to shed light on the putative additional negative impacts sustained through social media use in those experiencing relative disadvantage in society, and continued with the hopes that despite this ethical flaw, the results of the study may serve to underscore the need for greater equality and anti-oppressive interventions at a systemic level in the UK.

Conducting the statistical analyses was by far the most challenging part of this thesis. Mediation, moderation and moderated mediation analyses was something that my undergraduate degree had certainly not covered, and that the statistical teaching on the DClinPsy touched upon, namely theoretically. I found using the SPSS PROCESS macro (Hayes, 2022) to be relatively simple. However, learning how to interpret the results was more difficult. Whilst Hayes's work (Hayes, 2018; Preacher & Hayes, 2004) was a helpful introduction and an initial guide, the many statisticians and fellow research students posting tutorials to YouTube and Q&As on ResearchGate was invaluable.

One of the most helpful pieces of advice that I received in this respect was from my research supervisor (who, I suspect, at this point in our supervisory relationship had gotten a sense of my tendency to get lost in the detail). The suggestion that I simply make a start and play around with the PROCESS plug-in (rather than endlessly trying to familiarise myself with the theory behind it and understand how to interpret the output beforehand) hugely helped me in terms of getting to grips with the program and its output.

Other reflections

This present thesis – and indeed, my clinical training generally speaking – has been vastly different in contrast to what I initially thought and hoped it would be, as I imagine is the reality for a number of trainees, particularly those who have completed their training during a worldwide pandemic, or in tandem with challenging life circumstances, and for those who were unable to complete their thesis within the typical timelines.

That the COVID-19 pandemic hit the UK six months into the start of my cohort's training, moving our teaching online and limiting opportunity to mingle during breaks and at the end of teaching days, had a huge impact on my ability to form working relationships with other trainees. In addition, I largely completed my thesis once my wider cohort had already completed theirs. Previous research has highlighted the importance of peer support during clinical psychology training (Kuyken et al., 2003) and at times, I have found writing this thesis to be a lonely experience, and I wonder whether I would have felt more confident, skilled or reassured at various stages had I been able to (more frequently) turn to a fellow trainee and connect over a similar challenge or share learning in regard to overcoming particular obstacles.

Further, as I approach the end of this chapter and I reflect on my hopes at the beginning of writing this thesis and my clinical training more widely, I feel a wave of grief for what could have been. The experience was not what I had imagined it would be, and at times, the constraints of my personal life made it feel difficult to get as much out of (or put as much into) my training, and writing a thesis, as I would have liked. That said, given the competing demands (i.e., lectures, seminars, case reports, exams, clinical work, mid and end-point placement reviews, self-directed study, BABCP pathway, not to mention writing a thesis) and the many hats (student, clinician, researcher, advocate / activist, team member / colleague) that need to be worn during training, I think it likely that I may have felt similarly had my personal circumstances not played out in the same way (perhaps just not with the same intensity).

I also think that this was an invaluable learning experience that has shaped me, for the better, as a clinical psychologist. I am the sort of person who prefers to immerse themselves in one thing at a time, and who likes to do anything they are tasked with to the best of their ability. Whilst such characteristics (or, dependent on the lens through which you view such, coping strategies or 'rules for living') have served me very well over the years, I found that they no longer worked the same / I was not able to draw on them in the same way throughout the course and writing a thesis. I found it difficult to change gears and this could mean that on the days dedicated to my thesis I would swing between two ends of the spectrum, either working for far longer into the evening than I had planned or struggling to get started on it due to an underlying belief that there wasn't enough time in the day to get back into it. Having extended periods (e.g., a week at a time) set aside purely for the thesis really helped in this respect, as did having a logbook which served as a snapshot reminder of where I got up to last.

Ultimately though, there was a huge and beneficial learning curve for me in terms of adjusting my expectations of myself in regard to how thoroughly I could approach a task or how much time I could spend on it. A conversation with my research supervisor comes to mind – a discussion around focusing on what is 'good enough' – and a lecture I attended during training on perfectionism, which has been linked to burnout specifically amongst trainee clinical psychologists (Richardson et al., 2020). I really believe that the DClinPsy course taught me an awful lot in terms of holding on to perfectionistic standards a little more loosely, prioritising what matters most, aiming for 'good enough', being able to tolerate that and, over time, learning that nothing terrible happened as a result – a learning experience that has undoubtedly facilitated adjusting to and coping with a full-time, post-qualified role in a notoriously overstretched and underfunded public service like the NHS.

Reflecting on the research project element of the course specifically, I am comforted by the fact that research is an integral part of being a clinical psychologist – whether that is in terms of consumption or production – and I am reminded that I am only just getting started within this career and that this need not be my only experience of conducting research. Whilst composing this thesis did not go as I had planned, I have learned so much through doing it – skills and experience which I have no doubt would provide me with a good enough foundation, should I wish to conduct further research later on.

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Appendices

Appendix A: Ethical Approval

From: **VPRO.Ethics** ethics@ucl.ac.uk
Subject: APPROVED with PROVISOS: COVID ethics application 18335/001
Date: 15 May 2020 at 15:48
To: [redacted]
Cc:

V

<u>Notification of Ethics Approval with Provisos</u>
<u>Project ID/Title: 18335/001:</u>
<u>Environmental Effects on Development and Wellbeing</u>

Further to your satisfactory responses to the Committee's comments, I am pleased to confirm on behalf of the UCL Research Ethics Committee (REC) that your study has been ethically approved by the UCL REC until **<u>15th May 2022.</u>**

However, if a participant withdraws part way through the survey, the data that (s)he has provided up to that point should be withdrawn too. That is the REC's usual expectation.

Also, in view of the fast developments of the pandemic, the numerous projects being initiated and the constantly changing framework, please provide us with regular updates **every 3 months** regarding the ethical aspects of your project and the specific problems (if any) that you have encountered. At the end of the study, as part of the final report you have to submit to the UCL REC, please include alongside a brief outline of the research outcomes, any experiences which would be valuable for informing the fast-track COVID review process, and in turn subsequent fast-tracked studies.

With best wishes for the research, Helen

Helen Dougal
UCL Research Ethics Co-ordinator
Office of the Vice-Provost (Research)
University College London
2 Taviton Street, London, WC1H 0BT
Email: ethics@ucl.ac.uk

Appendix B: Recruitment Email

Dear Parent/Carer,

University College London's Child Vision Lab is inviting all adults on our database to take part in a new online research study: The UCL COVID Social Impacts Study. This a voluntary online survey that will help us understand how families are being affected during the lockdown, for example due to social isolation and home-schooling.

We will ask you to answer a 20 to 30 minute online survey with questions about you and your family, and two shorter follow-up surveys in the next year. The questionnaire will ask about lifestyle, health and wellbeing, and daily routine, amongst other things.

You do not have to take part, and can stop at any time by simply closing the survey browser at any point during the questionnaire.

If you would like to take part in this study:
Please follow this link [__________] to access the questionnaire and further information about the study. You will need to confirm you have read the information before you can start the questionnaire.

The survey is open to anyone over the age of 18 living in the UK, so feel free to share the link above with friends and family who you think might be interested in contributing.

Best Wishes,

The UCL Child Vision Lab

https://www.ucl.ac.uk/ioo/research/research-labs-and-groups/child-vision-lab
www.facebook.com/ChildVisionLab
www.twitter.com/ChildVisionLab

Important GDPR notice: UCL only collects personal data for tasks in the public interest. Under the General Data Protection Regulation (GDPR) (EU) 2016/679, we have a legal duty to protect any information we collect from you from third parties. For further information, please contact data-protection@ucl.ac.uk.

Appendix C: Online Advertising

<u>Facebook and Twitter Adverts</u>

How is COVID-19 affecting your family?

Help us understand how COVID-19 is affecting families in the UK. Click here to learn more.

How is social distancing affecting your wellbeing?

Help UCL scientists understand how individuals and families in the UK are coping with the COVID-19 crisis, by filling out this questionnaire. Click here to learn more.

<u>Newsletter Advert</u>

Every family is different, but all are affected by COVID-19. UCL is inviting all adults in the UK to complete a survey that investigates how adults and children across the country are coping as the pandemic unfolds. This will improve understanding where most support may be needed.

Appendix D: Participant Information Sheet and Consent Form

Welcome to the UCL COVID Social Impacts Study

This study will help inform understanding of how families in the UK are coping with the COVID crisis. It will 20-30 minutes to complete.

We will also invite you to take part in two optional shorter surveys over the course of the next year.

The following page includes some important information about the study. Please take your time to read this information before deciding whether you would like to take part.

Participation Information Sheet for Adults

UCL Research Ethics Committee Approval ID Number: 18335/001

Title of Study: Environmental Effects on Development and Wellbeing, The UCL COVID Social Impacts Study
Department: UCL Division of Psychology and Language Sciences
Researchers: Dr Tessa Dekker, Dr Marc Tibber, Professor Peter Fonagy, Georgia Milne, Greg Cooper
Contact details: ioo-cvl@ucl.ac.uk

Isolation Impacts Questionnaire
You are being invited to take part in a research project about the effects of COVID-19 and related social isolation measures on family wellbeing. The following information will tell you more about the study, and what taking part will involve. It is important that you read this information carefully before deciding whether you would like to take part. If would like to ask any further questions, please contact the researchers via email at ioo-cvl@ucl.ac.uk

What is the project's purpose?
Research shows that our social and physical environment plays an important role in health and wellbeing. This study aims to inform our understanding of how COVID-19-related lifestyle changes, such as social isolation and home schooling, may be affecting the wellbeing of families. This may assist in supporting adults and children during the COVID-19 pandemic, and may also have more general implications for education and social care, as well as for future responses to similar crises should they occur.

Can I take part?
Participation is open to adults over the age of 18 living in the UK. You do not have to be a parent, or currently be in isolation to take part.

Do I have to take part?
Participation is completely voluntary. You do not have to take part, and you can stop any time without any consequences or needing to explain why.

What will taking part involve?
This study will involve answering a 20-30 minute online survey now, and two shorter follow-up surveys over the course of the next year. These will include questions about your and your family's living situation, daily routines, health, and mood.

What are the possible disadvantages and risks of taking part?
Some of the questions asked in this survey will relate to mood and mental health. You do not have to answer these questions if you find them distressing and can simply indicate "prefer not to say" or skip to the next page. We will provide useful information about resources and services that are available to you at the end of the questionnaire if you feel concerned or affected by any of the subjects raised in the questionnaire.

What are the possible benefits of taking part?
Whilst this research will not provide immediate benefits for those taking part in the study, it is hoped that the findings will serve the public good by improving our understanding of the effects of the COVID-19 pandemic on families, and informing how best to handle these impacts.

What if I have concerns?
If you have any concerns about the study or would like to withdraw your data, you can contact the research team at ioo-cvl@ucl.ac.uk. If you feel your concerns have not been handled satisfactorily, you can contact the Chair of the UCL Research Ethics Committee at ethics@ucl.ac.uk. Please note that we will remove any information that could identify you from the data before analysing it, at which point even we can no longer see which answers were yours. It may therefore not be possible to remove your data from the study.

Will my taking part in this project be kept confidential?
Some data that we will collect relating to health, ethnicity, or postcode may be considered sensitive data. We only ask for this information to understand how various groups may be impacted. All the information we collect about you will be kept strictly confidential and stored at high security. We will never share your email address and postcode will any others, they will be removed from the rest of your answers, and deleted as soon as the study finishes. This means that your data will be completely anonymous, and that nobody will be able to identify you after this. We will only use your email address to invite you for follow-up surveys, send you information you have asked for, or to meet our duty of care. If at any point you do not want to be contacted, you can let us know by emailing opt-out to ioo-cvl@ucl.ac.uk.

Limits to confidentiality
Confidentiality will be strictly adhered to throughout the study. In the unlikely case of possible harm/danger to you or others, our duty of care may require us to share some information with relevant agencies, but this will never happen without contacting you first.

What will happen to the results of the research project?
The fully anonymised results of this study will be published in scientific journals and repositories, and presented to governmental bodies. Please let us know if you would like to receive updates for this study by selecting the corresponding option at the end of this questionnaire. This report will not be directly linked to the answers you give in this survey.

Local Data Protection Privacy Notice
The controller for this project will be University College London (UCL). The UCL Data Protection Officer, Alex Potts, provides oversight of UCL activities involving the processing of personal data, and can be contacted at data-protection@ucl.ac.uk

This 'local' privacy notice sets out the information that applies to this particular study. Further information on how UCL uses participant information can be found in our 'general' privacy notice: For participants in health and care research studies, click here

The information that is required to be provided to participants under data protection legislation (GDPR and DPA 2018) is provided across both the 'local' and 'general' privacy notices.

The lawful basis that will be used to process your personal data are: 'Public task' for personal data. Your personal data will be processed so long as it is required for the research project. If we are able to anonymise or pseudonymise the personal data you provide we will undertake this, and will endeavour to minimise the processing of personal data wherever possible.
If you are concerned about how your personal data is being processed, or if you would like to contact us about your rights, please contact UCL in the first instance at data-protection@ucl.ac.uk

Who is organising and funding the research?
This research is organised by researchers at the UCL Division of Psychology and Language Sciences, and funded by UCL.

Contact for further information

If you would like any further information about this study, please contact any of the researchers named above by emailing ioo-cvl@ucl.ac.uk

Thank you for reading this information and for considering taking part in this research study.

Consent

I understand that:

• My participation is completely voluntary.
• I will need to provide an email address so that I can be sent the future surveys to answer. However, this email address will not be passed to any third parties and will be removed from my answers before any analysis takes place, so the information I provide will be anonymised.
• Due to this anonymisation it may not be possible to withdraw my answers after they have been submitted, but I can withdraw from future surveys at any point.
• The data gathered in this study will be stored securely and it will not be possible to identify me in any outputs from this research.

☐ I confirm that I am at least 18 years old, have read the information about the experiment, and voluntarily agree to take part in this study

☐ I agree to providing personal data, including an email address to be contacted by for follow-up surveys.

Appendix E: Questionnaire Debrief

INFORMATION ON MENTAL HEALTH SUPPORT FOR ADULTS AND CHILDREN

If you feel that you have been affected by any of the issues raised in this questionnaire, or if you are concerned about your mental health or that of your child, please follow the advice below.

What should I do if I am concerned about my own safety or my child's safety and it's an emergency?
Call 999 or go to your local A&E. This can be located at: www.nhs.uk/service-search/other-services/Accident-and-emergency-services/LocationSearch/428

What should I do if I feel like I just need to talk to someone (day or night)?
Call 116 123 for the Samaritans, or email: jo@samaritans.org for a reply within 24 hours. Text "SHOUT" to 85258 to contact the Shout Crisis Text Line.

What should I do if I need urgent mental health support, but it's not an emergency?
If you have already been given a Crisis Team number to use, ring this number. Otherwise, contact your local urgent mental health helpline, which can be located at: www.nhs.uk/service-search/mental-health/find-an-urgent-mental-health-helpline Alternatively, **call 111** and you will be directed to the appropriate service. During working hours you can also book an urgent appointment with your local GP.

What should I do if I would like to access mental health support, but it is not urgent?
Book an appointment with your GP. They will be able to refer or signpost you to appropriate services. For further information on available mental health support, visit: www.nhs.uk/using-the-nhs/nhs-services/mental-health-services/how-to-access-mental-health-services/

What should I do if I would like to access mental health support for my child?
Book an appointment with your GP. They will be able to refer or signpost your child to appropriate services. For further information on mental health services for young people visit: www.nhs.uk/using-the-nhs/nhs- services/mental-health-services/child-and-adolescent-mental-health-services-camhs/

For ideas and strategies about how to cope during a crisis, please visit: www.mind.org.uk/need-urgent-help/what-can-i-do-to-help-myself-cope/

Appendix F: Follow-up Email (PHQ-9, item 9)

Dear respondent,

Thank you for taking part in our UCL COVID impact survey. Your answers indicate that you may be feeling very sad or low, and we advise you to contact your GP or your Local IAPT Service or another health professional about this. Below we provide some further information that you may find useful.

Warm regards, Dr. Tessa Dekker

Attached: Questionnaire Debrief

Appendix G: Demographic Measures

What is your age?

☐ Under 18

☐ 18 – 21

☐ 22 – 29

☐ 30 – 39

☐ 40 – 49

☐ 50 – 59

☐ 60 – 69

☐ 70 – 79

☐ 80 – 85

☐ 86 or older

What is your gender?

☐ Male

☐ Female

☐ Non-binary / Third gender

☐ Other

☐ Prefer not to say

What is your ethnicity?

☐ White: British / Irish / Any other White background

☐ Mixed: White and Black Caribbean / White and Black African / White and Asian / Any other Mixed background

☐ Asian or Asian British: Indian / Pakistani / Bangladeshi / Chinese / Any other Asian background

☐ Black or Black British: Caribbean / African / Any other Black background

☐ Any other ethnic group

☐ Prefer not to say

Appendix H: Socioeconomic Measures

What is your highest completed level of education?

☐ No qualifications

☐ GCSEs / O-levels or equivalent

☐ Post-16 vocational course

☐ A-levels of equivalent

☐ Undergraduate degree or professional qualification

☐ Post graduate degree

☐ Prefer not to say

What was your employment status before COVID-19 (1st of March)?

☐ Employed full-time

☐ Employed part-time

☐ Interning

☐ Self-employed/Freelancing

☐ Studying full-time

☐ Studying part-time

☐ Homemaker

☐ Military/Forces

☐ Retired

☐ Unemployed, looking for work

☐ Unemployed, not looking for work

☐ Not able to work

☐ Other

☐ Prefer not to say

What was your approximate yearly household income before COVID-19 (1st of March)?

☐ Less than £13,000 per year

☐ £13,000 - £18,999 per year

☐ £19,000 - £25,999 per year

☐ £26,000 - £31,999 per year

☐ £32,000 - £47,999 per year

☐ £48,000 - £63,999 per year

☐ £64,000 - £95,999 per year

☐ More than £96,000 per year

☐ Prefer not to say

Which best describes your current living situation?

☐ Owned House

☐ Rented House

☐ Owned apartment

☐ Rented apartment

☐ House share

☐ Temporary accommodation

☐ Council or supported accommodation

☐ Other – please specify

☐ Prefer not to say

How many people are living in your home?

How many rooms are in your home (not including bathrooms)?

Appendix I: Mental Health Measures

GAD-7 anxiety (Spitzer et al., 2006)

Over the last two weeks, how often have you been bothered by any of the following problems?

1. Feeling nervous, anxious, or on edge
   ☐ Not at all (0)
   ☐ Several days (1)
   ☐ More than half the days (2)
   ☐ Nearly every day (3)

2. Not being able to stop or control worrying
   ☐ Not at all (0)
   ☐ Several days (1)
   ☐ More than half the days (2)
   ☐ Nearly every day (3)

3. Worrying too much about different things
   ☐ Not at all (0)
   ☐ Several days (1)
   ☐ More than half the days (2)
   ☐ Nearly every day (3)

4. Trouble relaxing
   ☐ Not at all (0)
   ☐ Several days (1)
   ☐ More than half the days (2)
   ☐ Nearly every day (3)

5. Being so restless that it's hard to sit still
   ☐ Not at all (0)
   ☐ Several days (1)
   ☐ More than half the days (2)
   ☐ Nearly every day (3)

6. Becoming easily annoyed or irritable
   ☐ Not at all (0)
   ☐ Several days (1)
   ☐ More than half the days (2)
   ☐ Nearly every day (3)

7. Feeling afraid as if something awful might happen
   ☐ Not at all (0)
   ☐ Several days (1)
   ☐ More than half the days (2)
   ☐ Nearly every day (3)

PHQ-9 - depression (Kroenke et al., 2001)

Over the last two weeks, how often have you been bothered by any of the following problems?

1. Little interest or pleasure in doing things
   ☐ Not at all (0)

☐ Several days (1)
☐ More than half the days (2)
☐ Nearly every day (3)

2. Feeling down, depressed, or hopeless
☐ Not at all (0)
☐ Several days (1)
☐ More than half the days (2)
☐ Nearly every day (3)

3. Trouble falling or staying asleep, or sleeping too much.
☐ Not at all (0)
☐ Several days (1)
☐ More than half the days (2)
☐ Nearly every day (3)

4. Feeling tired or having little energy
☐ Not at all (0)
☐ Several days (1)
☐ More than half the days (2)
☐ Nearly every day (3)

5. Poor appetite or overeating
☐ Not at all (0)
☐ Several days (1)
☐ More than half the days (2)
☐ Nearly every day (3)

6. Feeling bad about yourself — or that you are a failure or have let yourself or your family down
☐ Not at all (0)
☐ Several days (1)
☐ More than half the days (2)
☐ Nearly every day (3)

7. Trouble concentrating on things, such as reading the newspaper or watching television
☐ Not at all (0)
☐ Several days (1)
☐ More than half the days (2)
☐ Nearly every day (3)

8. Moving or speaking so slowly that other people could have noticed? Or the opposite — being so fidgety or restless that you have been moving around a lot more than usual
☐ Not at all (0)
☐ Several days (1)
☐ More than half the days (2)
☐ Nearly every day (3)

9. Thoughts that you would be better off dead or of hurting yourself in some way
☐ Not at all (0)
☐ Several days (1)
☐ More than half the days (2)
☐ Nearly every day (3)

Appendix J: Social Media Use Measure

For the following questions, we will ask about your daily routine. Please think about a typical weekday in the past 7 days.

On a typical weekday in the past 7 days, how many hours did you spend using a computer / laptop / tablet / smartphone for social media?

0 hours 10+ hours

Appendix K: Social Comparisons Measures

To what extent do you focus on people who are better off than you when comparing yourself to others online?

☐ Not at all (0)

☐ Very little (1)

☐ Somewhat (2)

☐ Quite a bit (3)

☐ A great deal (4)

To what extent do you focus on people who are better off than you when comparing yourself to others offline (i.e., in day-to-day interactions)?

☐ Not at all (0)

☐ Very little (1)

☐ Somewhat (2)

☐ Quite a bit (3)

☐ A great deal (4)

Supplementary Table 1. Regression of GAD-7 on social media use, age, gender and ethnicity upon the exclusion of extreme scores.

Predictor / covariate	Univariate model		Multivariate model		
	Bootstrap coefficient (*b*) (BCa 95% CI)	*p*-value	Bootstrap coefficient (*b*) (BCa 95% CI)	*p*-value	Standardised coefficient (β)
SMU	**0.47 (0.24; 0.68)**	**<.001**	**0.45 (0.24; 0.63)**	**<.001**	**0.19**
Age	-	-	**-0.06 (-0.09; -0.03)**	**<.001**	**-0.16**
Gender	-	-	**-1.36 (-2.21; -0.46)**	**.01**	**-0.11**
Ethnicity	-	-	-0.50 -1.64; 0.73)	.39	-0.03

Note. Values in bold denote statistical significance.

Supplementary Table 2. Regression of PHQ-9 on social media use, age, gender and ethnicity upon the exclusion of extreme scores.

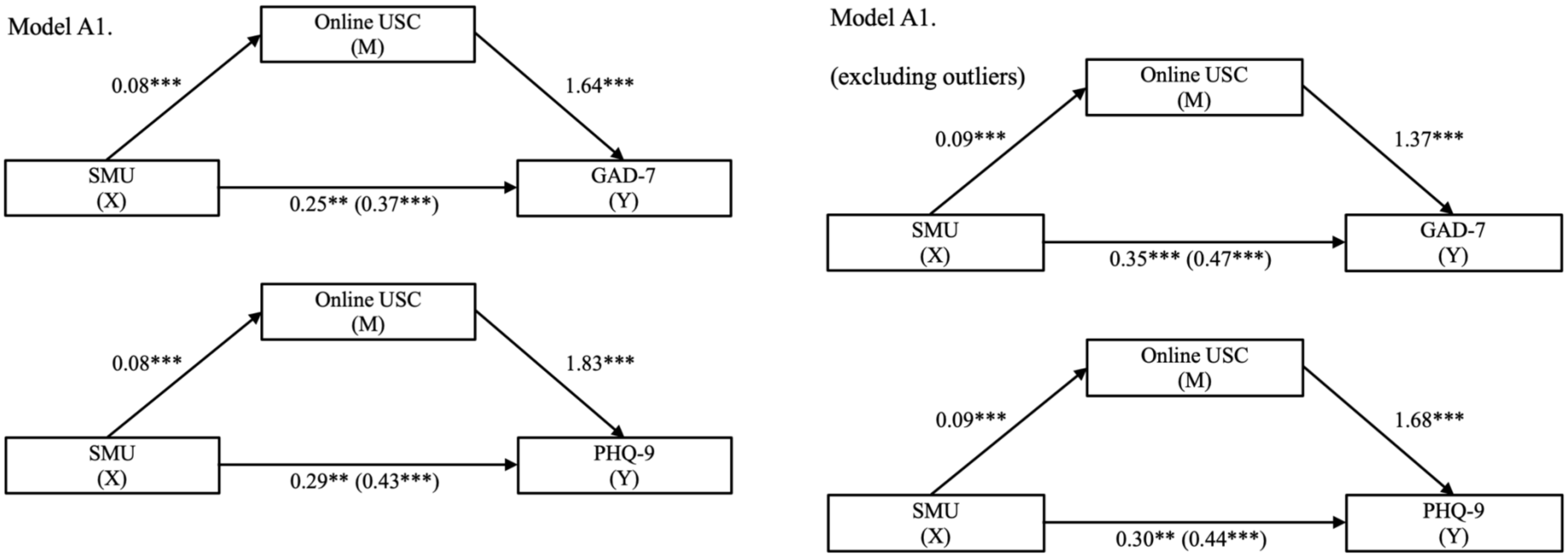
Predictor / covariate	Univariate model		Multivariate model		
	Bootstrap coefficient (*b*) (BCa 95% CI)	*p*-value	Bootstrap coefficient (*b*) (BCa 95% CI)	*p*-value	Standardised coefficient (β)
SMU	**0.44 (0.22; 0.64)**	**<.001**	**0.43 (0.22; 0.65)**	**<.001**	**0.16**
Age	-	-	**-0.05 (-0.08; -0.01)**	**.01**	**-0.10**
Gender	-	-	-1.06 (-2.16; 0.08)	.07	-0.07
Ethnicity	-	-	-0.69 (-2.12; 0.71)	.37	-0.04

Note. Values in bold denote statistical significance.

Supplementary Table 3. **Mediating effect (through online upward social comparisons) of social media use on mental health symptoms across different variations of the mediation model (Models A1-A3), upon the exclusion of extreme scores**.

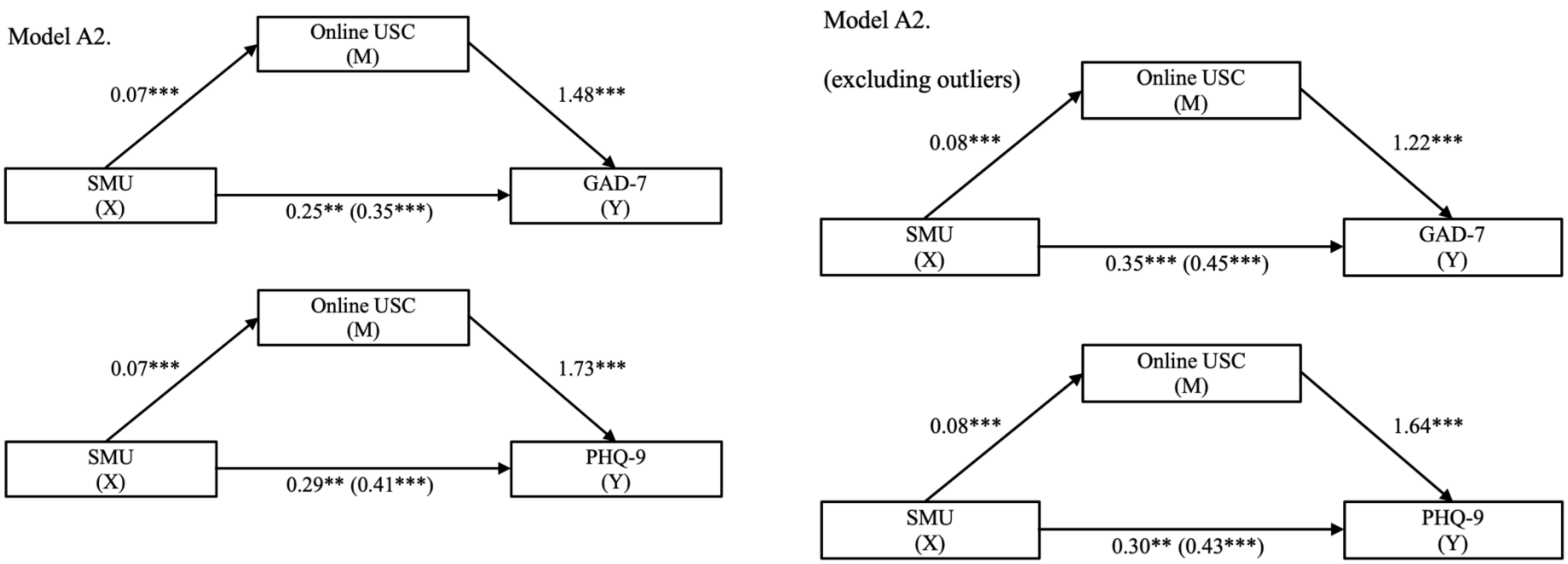
Model		Indirect effect (Bootstrap 95% CI)	Bootstrap *SE*	*p*-value	Standardised coefficient (β) (Bootstrap 95% CI)	Bootstrap *SE*
A1	GAD-7	**0.12 (0.05; 0.20)**	**0.04**	**<.001**	**0.05 (0.02; 0.8)**	**0.02**
	PHQ-9	**0.14 (0.06; 0.24)**	**0.05**	**<.001**	**0.06 (0.02; 0.09)**	**0.02**
A2	GAD-7	**0.10 (0.04; 0.17)**	**0.03**	**.002**	**0.04 (0.02; 0.07)**	**0.02**
	PHQ-9	**0.13 (0.05; 0.22)**	**0.04**	**.001**	**0.05 (0.02; 0.08)**	**0.02**
A3	GAD-7	**0.05 (0.01; 0.10)**	**0.02**	**.02**	**0.02 (0.01; 0.04)**	**0.01**
	PHQ-9	**0.08 (0.03; 0.20)**	**0.03**	**.01**	**0.03 (0.01; 0.06)**	**0.01**

Note. Model A1 represents the basic model (i.e., mediating effect (through online USC) of SMU on MH symptoms). Model A2 represents the basic model with age, gender and ethnicity included as covariates. Model A3 represents the basic model with age, gender, ethnicity and offline USC included as covariates. *p*-values calculated via Sobel test (*z*-value = $a*b/\mathrm{SQRT}(b^2*s_a^2 + a^2*s_b^2 + s_a^2*s_b^2)$ (Baron & Kenny, 1986; Preacher & Leonardelli, 2024). Values in bold denote statistical significance.



Supplementary Figure 1. **Mediation analyses exploring the potentially mediating role of online upward social comparisons in the association between social media use and mental health** (Model A1, i.e., basic model).

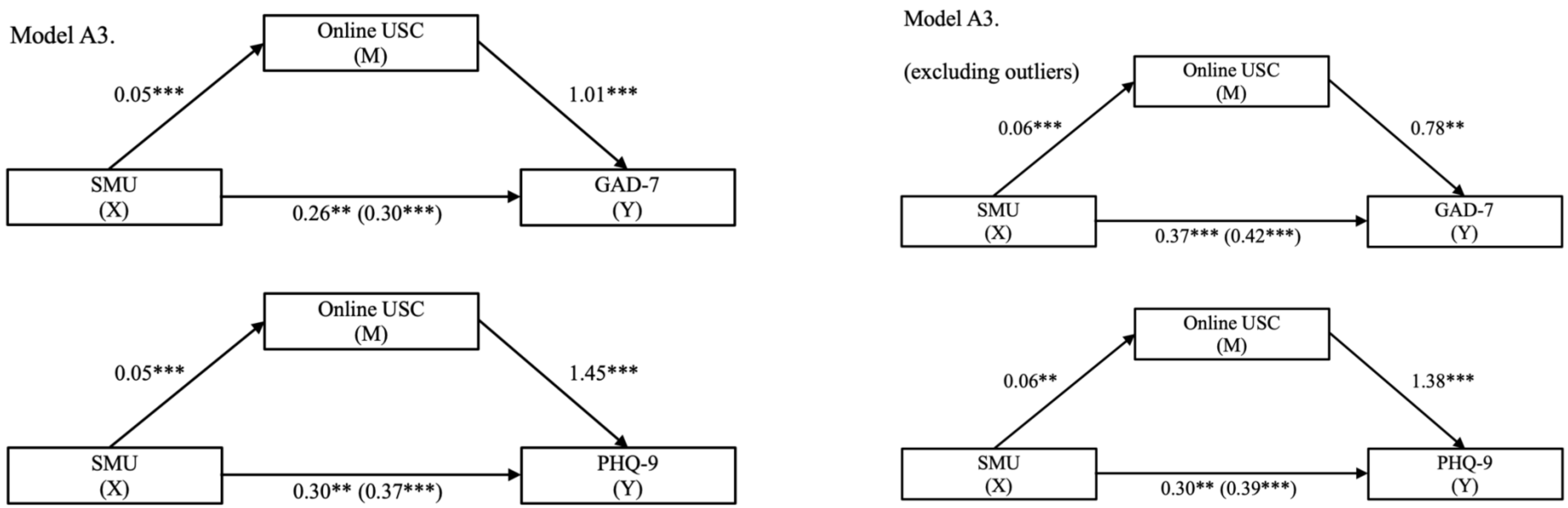
Note. Note, all values represent unstandardised coefficients. Values displayed in brackets denote direct paths in non-mediational models (total effects). *p-value <.05, **p-value <.01, ***p-value <.001



Supplementary Figure 2. **Mediation analyses exploring the potentially mediating role of online upward social comparisons in the association between social media use and mental health, whilst controlling for age, gender and ethnicity** (Model A2, i.e., the same as Model A1 but with age, gender and ethnicity included as covariates).

Note, all values represent unstandardised coefficients. Values displayed in brackets denote direct paths in non-mediational models (total effects).

*p-value <.05, **p-value <.01, ***p-value <.001



Supplementary Figure 3. **Mediation analyses exploring the potentially mediating role of online upward social comparisons in the association between social media use and mental health, whilst controlling for age, gender, ethnicity *and* offline upward social comparisons** (Model A3, i.e., the same as Model A2 but with offline USC included as fourth and final covariate).

Note, all values represent unstandardised coefficients. Values displayed in brackets denote direct paths in non-mediational models (total effects). *p-value <.05, **p-value <.01, ***p-value <.001

Supplementary Table 4. **Mediating effect (through online upward social comparisons) of social media use on mental health symptoms at different levels of the moderator (education) (moderated mediation analyses, Models B1-B3), upon the exclusion of extreme scores**.

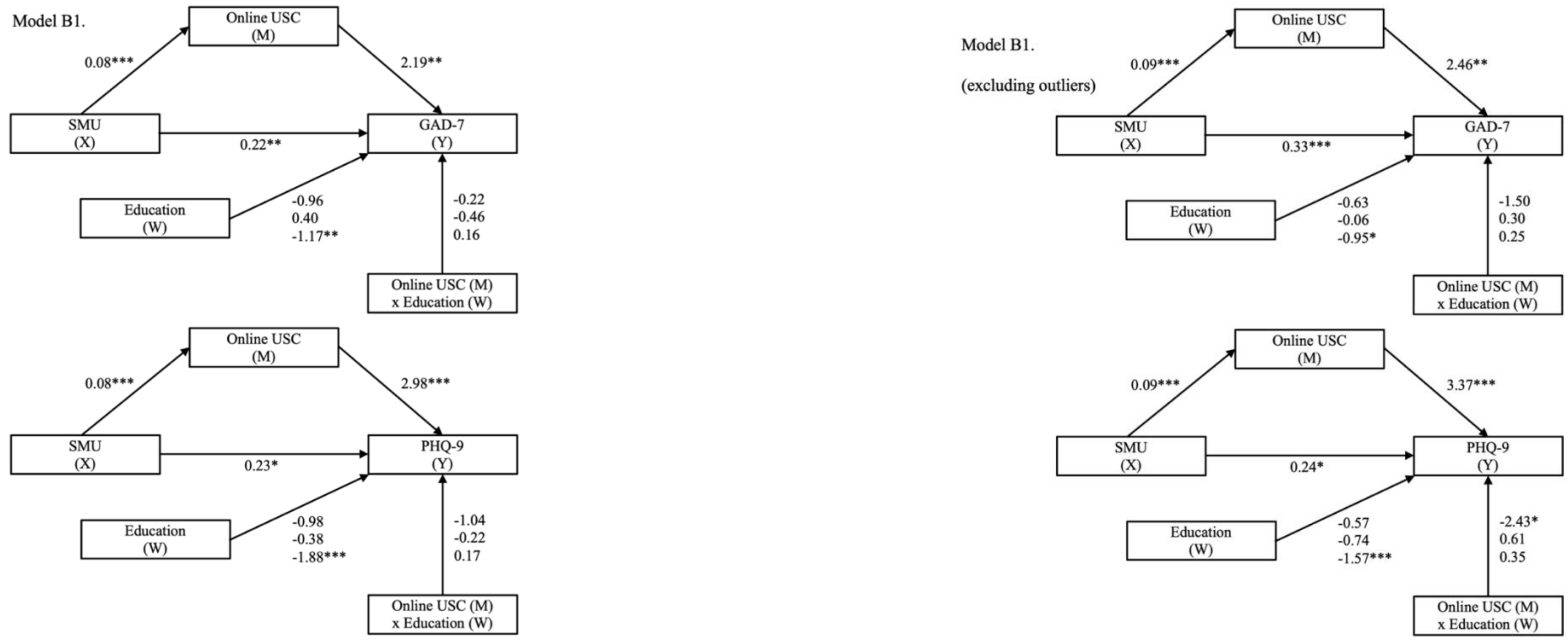
Model	Level of moderator (Education)	GAD-7 Indirect effect (Bootstrap 95% CI)	GAD-7 Bootstrap *SE*	PHQ-9 Indirect effect (Bootstrap 95% CI)	PHQ-9 Bootstrap *SE*
B1	GCSE or lower	**0.21 (0.06; 0.42)**	**0.09**	**0.29 (0.08; 0.53)**	**0.11**
	A-level or equivalent	0.08 (-0.01; 0.20)	0.06	0.08 (-0.04; 0.22)	0.06
	Undergraduate degree	**0.11 (0.04; 0.21)**	**0.04**	**0.13 (0.05; 0.24)**	**0.05**
	Postgraduate degree	**0.13 (0.05; 0.22)**	**0.04**	**0.16 (0.07; 0.28)**	**0.06**
B2	GCSE or lower	**0.19 (0.04; 0.38)**	**0.09**	**0.26 (0.07; 0.48)**	**0.10**
	A-level or equivalent	0.07 (-0.02; 0.19)	0.05	0.07 (-0.03; 0.21)	0.06
	Undergraduate degree	**0.09 (0.02; 0.17)**	**0.04**	**0.12 (0.04; 0.22)**	**0.05**
	Postgraduate degree	**0.10 (0.04; 0.19)**	**0.04**	**0.14 (0.05; 0.26)**	**0.05**
B3	GCSE or lower	**0.12 (0.01; 0.26)**	**0.07**	**0.18 (0.04; 0.35)**	**0.08**
	A-level or equivalent	0.03 (-0.05; 0.11)	0.04	0.04 (-0.04; 0.13)	0.04
	Undergraduate degree	0.05 (-0.00; 0.11)	0.03	**0.07 (0.02; 0.15)**	**0.03**
	Postgraduate degree	**0.06 (0.01; 0.12)**	**0.03**	**0.09 (0.03; 0.18)**	**0.04**

Note. Model B1 represents the basic model. Model B2 represents the basic model with age, gender and ethnicity included as covariates. Model B3 represents the basic model with age, gender, ethnicity and offline USC included as covariates. Values in bold denote statistical significance.

Supplementary Table 5. **Moderating effect of education on the association between social media use and mental health via online upward social comparisons (moderated mediation analyses, Models B1-B3), upon the exclusion of extreme scores**.

		GAD-7		PHQ-9	
Model	Level of moderator (Education)	Index of moderated mediation (Bootstrap 95% CI)	Bootstrap *SE*	Index of moderated mediation (Bootstrap 95% CI)	Bootstrap *SE*
B1	GCSE or lower x A-level or equivalent	-0.13 (-0.33; 0.04)	0.09	-0.21 (-0.46; 0.02)	0.12
	A-level or equivalent x Undergraduate degree	0.03 (-0.09; 0.14)	0.06	0.05 (-0.07; 0.21)	0.07
	Undergraduate degree x Postgraduate degree	0.02 (-0.06; 0.10)	0.04	0.03 (-0.06; 0.12)	0.04
B2	GCSE or lower x A-level or equivalent	-0.11 (-0.31; 0.05)	0.09	-0.19 (-0.41; 0.00)	0.10
	A-level or equivalent x Undergraduate degree	0.02 (-0.09; 0.13)	0.06	0.04 (-0.07; 0.18)	0.06
	Undergraduate degree x Postgraduate degree	0.02 (-0.05; 0.10)	0.04	0.03 (-0.05; 0.12)	0.04
B3	GCSE or lower x A-level or equivalent	-0.09 (-0.24; 0.04)	0.07	-0.14 (-0.33; 0.00)	0.09
	A-level or equivalent x Undergraduate degree	0.02 (-0.06; 0.11)	0.04	0.03 (-0.06; 0.14)	0.05
	Undergraduate degree x Postgraduate degree	0.01 (-0.05; 0.07)	0.03	0.02 (-0.05; 0.09)	0.03

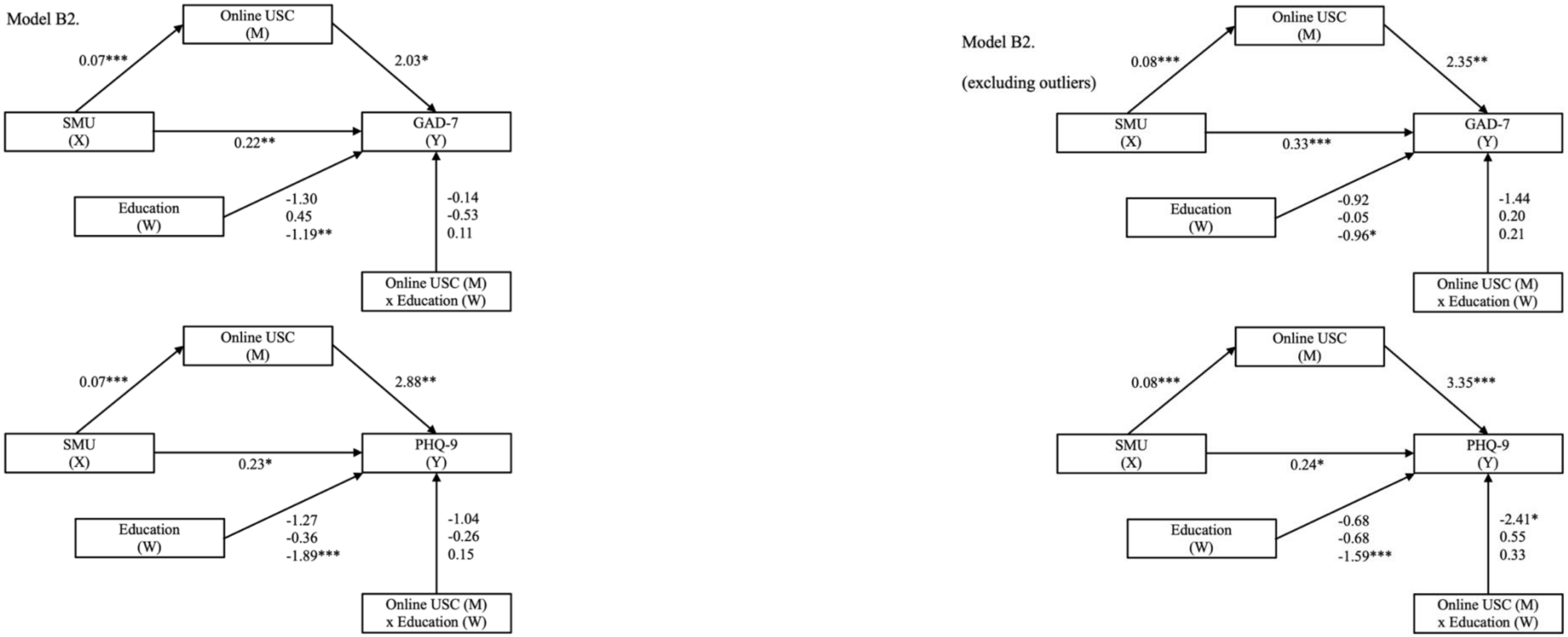
Note. Model B1 represents the basic model. Model B2 represents the basic model with age, gender and ethnicity included as covariates. Model B3 represents the basic model with age, gender, ethnicity and offline USC included as covariates.



Supplementary Figure 4. **Moderated mediation analyses exploring the potentially moderating effect of education on the association between social media use and mental health via online upward social comparisons** (Model B1, i.e., basic model).

Note, all values represent unstandardised coefficients. Values displayed in brackets denote direct paths in non-mediational models (total effects).

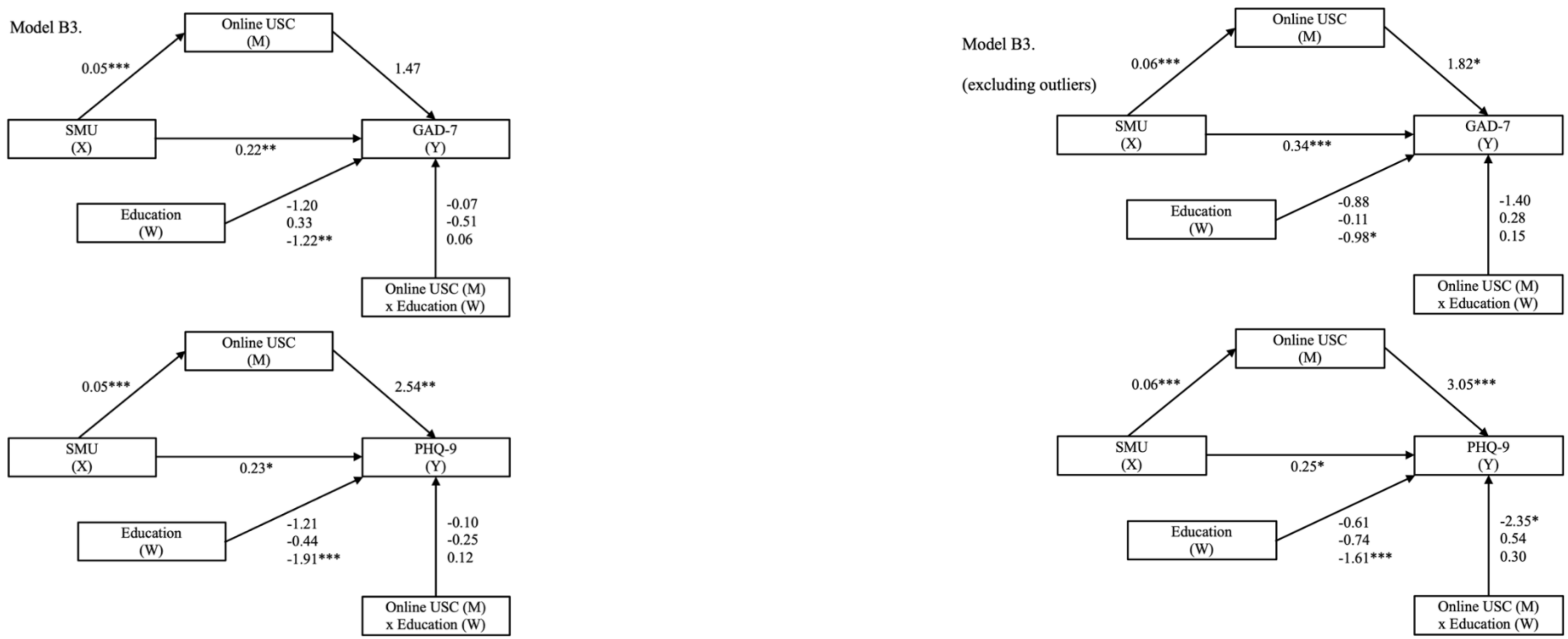
*p-value <.05, **p-value <.01, ***p-value <.001



Supplementary Figure 5. **Moderated mediation analyses exploring the potentially moderating effect of education on the association between social media use and mental health via online upward social comparisons, whilst controlling for age, gender and ethnicity** (Model B2, i.e., the same as Model B1 but with age, gender and ethnicity included as covariates).

Note, all values represent unstandardised coefficients. Values displayed in brackets denote direct paths in non-mediational models (total effects).

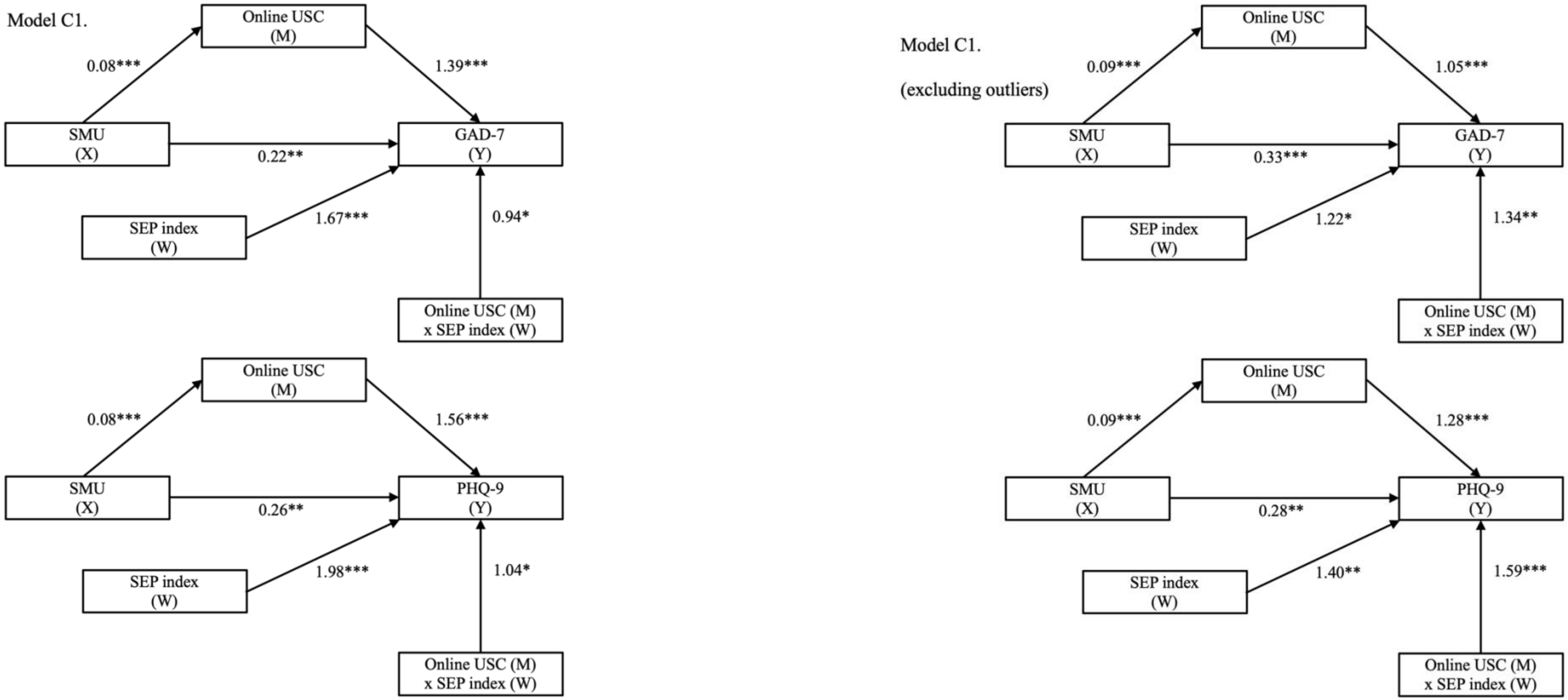
*p-value <.05, **p-value <.01, ***p-value <.001



Supplementary Figure 6. **Moderated mediation analyses exploring the potentially moderating effect of education on the association between social media use and mental health via online upward social comparisons, whilst controlling for age, gender, ethnicity *and* offline upward social comparisons** (Model B3, i.e., the same as Model B2 but with offline USC included as fourth and final covariate).

Note, all values represent unstandardised coefficients. Values displayed in brackets denote direct paths in non-mediational models (total effects).

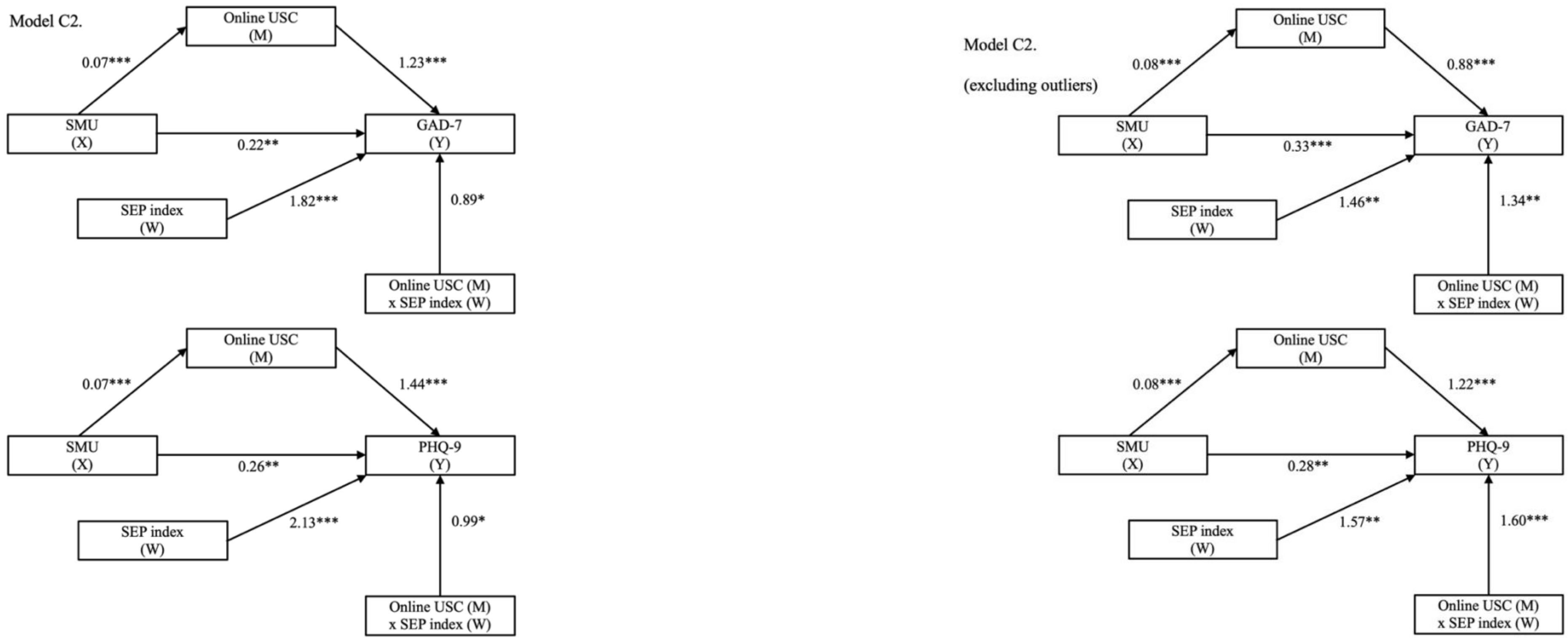
*p-value <.05, **p-value <.01, ***p-value <.001



Supplementary Figure 7. **Moderated mediation analyses exploring the potentially moderating effect of socioeconomic profile index on the association between social media use and mental health via online upward social comparisons** (Model C1, i.e., basic model).

Note, all values represent unstandardised coefficients. Values displayed in brackets denote direct paths in non-mediational models (total effects).

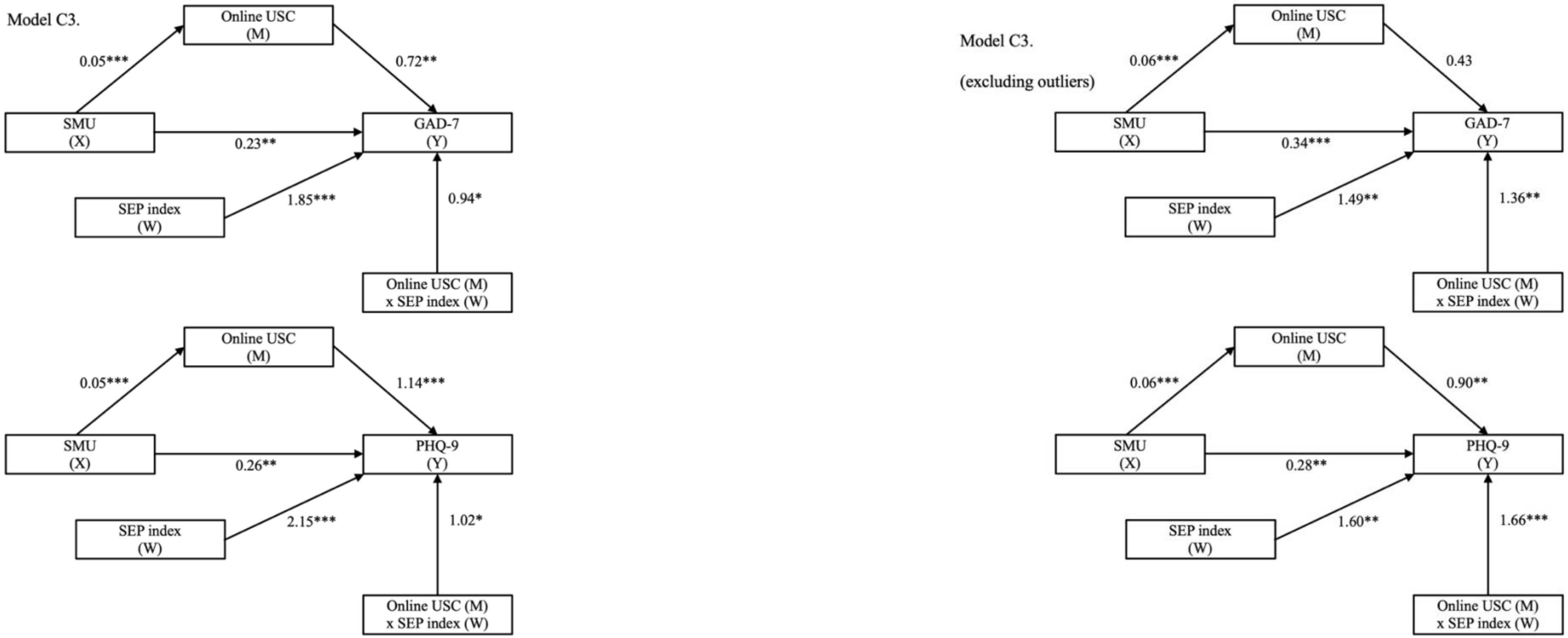
*p-value <.05, **p-value <.01, ***p-value <.001



Supplementary Figure 8. **Moderated mediation analyses exploring the potentially moderating effect of socioeconomic profile index on the association between social media use and mental health via online upward social comparisons, whilst controlling for age, gender and ethnicity** (Model C2, i.e., the same as Model C1 but with age, gender and ethnicity included as covariates).

Note, all values represent unstandardised coefficients. Values displayed in brackets denote direct paths in non-mediational models (total effects).

*p-value <.05, **p-value <.01, ***p-value <.001



Supplementary Figure 9. **Moderated mediation analyses exploring the potentially moderating effect of socioeconomic profile index on the association between social media use and mental health via online upward social comparisons, whilst controlling for age, gender, ethnicity *and* offline upward social comparisons** (Model C3, i.e., the same as Model C2 but with offline USC included as fourth and final covariate).

Note, all values represent unstandardised coefficients. Values displayed in brackets denote direct paths in non-mediational models (total effects).

*p-value <.05, **p-value <.01, ***p-value <.001