Network analysis of ecological momentary assessment exploring the role of online and offline social comparisons in the mood and wellbeing of undergraduate students

Running head: Social comparisons, mood and wellbeing

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Abstract

Whilst research suggests online social comparisons may be detrimental to wellbeing, little is known about the underlying temporal dynamics. Here we used Ecological Momentary Assessment to sample 100 undergraduate students' experiences five times per day for 21 consecutive days, in conjunction with network analysis, to map dynamic interactions between (upward) online and offline social comparisons and multiple indicators of wellbeing. Contemporaneous, temporal, and between-subjects networks were estimated. Whilst *online* comparisons predicted lower self-esteem in the contemporaneous network, online comparisons predicted *subsequent* increases in positive, and decreases in negative, affect. In contrast, associations between offline social comparisons and poorer wellbeing were seen in all networks, and for multiple indices of wellbeing. Consistent with a two-step model of social comparisons, the findings suggest the effects of online comparisons may operate differently at different times-scales, and further, that offline comparisons may be more strongly related to poor wellbeing, with a potential causal association.

Key words: social media, social network sites, wellbeing, self-esteem, loneliness, affect.

1. Introduction

Interest in the impact of social media (SM)[1] on mental health and wellbeing continues to grow. This is particularly the case with respect to adolescents and emerging adults, who engage most heavily with the technology (GlobalWebIndex, 2023). Interestingly however, in a recent worldwide survey, Generation Z (currently 16-26 years of age) were the only generation whose level of use fell between 2021 and 2023, which was reflected in their self-reported concern for, and active attempt to manage, their use (GlobalWebIndex, 2023). Against this backdrop, some have tried to link increases in mental health difficulties within this age group (McElroy et al., 2022) to the increasing uptake of SM and related screen-based technologies (Kim, 2017).

In parallel, there is growing interest in the mental health and SM habits of university students (Storrie et al., 2010). For example, one cohort study undertaken in the UK found that psychological distress increased upon entry into university (Bewick et al., 2010), and there is evidence to suggest that mental health difficulties in this population is increasing (Sivertsen et al., 2019). Similar patterns are seen in other countries also, including China (Lei et al., 2016), the focus of this study. Once again, links have been made to SM use, with some arguing that university students may be particularly prone to developing problematic patterns of use because of their flexible schedules, high level of free time, and low level of external, i.e. parental or organizational, control (Turel & Qahri-Saremi, 2016). However, greater levels of free time are unlikely to apply to *all* students, e.g., students from lower socioeconomic backgrounds who may need to work part-time alongside their studies, or those with carer responsibilities. The research, however, suggests that the links between SM use and mental

[1] SM = social media; EMA = Ecological Momentary Assessment; RSES = Rosenberg Self-esteem Scale; SCS = social connectedness scale.

health and wellbeing are complex. Whilst potential benefits *and* risks of use are well documented (Tibber & Silver, 2022), systematic reviews and meta-analyses highlight small but relatively consistent negative effects of unknown direction of causality (Valkenburg et al., 2022). In parallel, within the research there has been a move away from dose-response models of SM use (i.e. associations between mental health and *levels* of use) towards a more nuanced perspective that considers the *nature* of engagement, and attempts to identify mediating and moderating factors that drive positive and negative associations with mental health (Nesi et al., 2020; Ngai et al., 2015).

One area of interest is the role of social comparisons. Social comparisons are a fundamental process by which humans attempt to gauge their relative self-worth (ability comparison), and/or how they should think, feel and act (opinion comparison) (Festinger, 1954). The literature typically distinguishes between *upward* social comparisons, in which the comparison target is deemed superior to oneself (in some domain), and *downward* comparisons, in which the target is deemed inferior (Pomery, Gibbons, & Stock, 2012). A common distinction is also often made between *identification*, in which there is a shift (intended and/or actual) *toward* the comparator in some domain, and *contrast*, in which there is a shift *away* from the comparator in some domain (Buunk & Dijkstra, 2017). As a general rule, when there is *identification* with a target, self-image and mood are increased by upward comparisons, and decreased by downward comparisons. When there is *contrast* with a target, self-image and affect are generally decreased by upward comparisons, and increased by downward comparisons. As an illustrative example of upward *identification*, an individual might compare themselves to someone from a similar background who is highly financially successful; as a result, they may be instilled with a sense of hope that one day they may be able to attain a similar level of success if they work hard, with a consequent (positive) impact on mood and sense of self-worth. Conversely, as an example of upward *contrast,* that same individual might compare themselves to another person who is also financially very successful, but from a very different (e.g., cultural and socioeconomic) background, and conclude that such success is unattainable for them, with (negative) consequences for their mood and sense of self-worth.

With the advent of digital technology, a further distinction is now drawn between *online* and *offline* social comparisons, with the former used to differentiate traditional (face-to-face) comparative processes to those mediated by digital communication (Verduyn et al., 2020).

Research into *online* social comparisons has predominantly explored and highlighted associations between higher *upward* social comparisons and poorer wellbeing / mental health (i.e. upward *contrast*) (Verduyn et al., 2020). Thus, online upward social comparisons have been linked to a range of (putative) negative emotions and experiences, including (malicious) envy (de Ven & Zeelenberg, 2020), a fear of missing out (Servidio et al., 2021), a sense of disconnection (Clark et al., 2018), low self-esteem (Tibber et al., 2020), anxiety and depression (McCarthy & Morina, 2020; Tibber et al., 2024). Whilst much of this research is cross-sectional, limited experimental evidence supports these findings in implicating negative effects of online upward social comparisons (Appel et al., 2015; Vogel et al., 2014a, 2015a).

However, it is important to note that online social comparisons have not been *exclusively* linked to negative outcomes; thus, a number of studies have found *positive* associations between upward social comparisons and wellbeing / mental health, presumably reflecting upward identification, e.g., Ruggieri, Ingoglia, Bonfanti, & Lo Coco (2021), as well as the absence of an impact of *downward* comparisons on wellbeing, e.g., Feltman & Szymanski (2018). Thus, it is likely that the full range of upward/downward comparisons and resulting identification/contrast effects occur in the online context, though upward contrast may predominate (Verduyn et al., 2020).

One promising new approach that potentially addresses some of the limitations of such cross-sectional research is network analysis of Ecological Momentary Assessment (EMA) data, which facilitates exploration of moment-by-moment fluctuations in SM use and mental health. EMA (or experience sampling as it is sometimes called) is a data collection method, which allows multi-time-point data harvesting as participants behave in their natural environment, typically by sending participants multiple links to brief surveys throughout the day, usually over a period of several weeks. When coupled with network analysis, a powerful statistical method that allows visualization of these data in the form of a series of networks, such an approach facilitates exploration of complex dynamic processes operating at multiple scales, as well as the directionality of identified paths between variables of interest.

In such analyses *contemporaneous* networks capture correlations between variables (designated edges and nodes respectively within network analysis) within the same timeframe, which are thought to reflect fast-acting processes (Epskamp, Waldorp, et al., 2018). *Temporal networks*, in contrast, capture temporal correlations between variables operating across a defined time-lag, most commonly set to 1, i.e. associations between time-points t and t-1. Finally, *between-subjects* networks capture associations between mean values of included variables. Whilst contemporaneous and between-subjects effects are non-directional and hence cannot speak to underlying directions of causality, edges in temporal networks are directional, and hence address essential criteria of an empirical association and temporal order.

Whilst several studies have used this approach to examine SM / MH links more generally [see (Aalbers, McNally, Heeren, de Wit, & Fried, 2019) for example], to our knowledge, only one study has used this approach to study associations between online social comparisons and mental health in *longitudinal* data. [See (Faelens et al., 2019) for a *cross-sectional* network analysis of EMA social comparison data, however]. In their longitudinal study, Faelens et al. (2021) explored moment-by-moment fluctuations in a range of variables including social comparisons, self-esteem, feelings of insecurity and repetitive negative thinking over the course of 14 consecutive days. Whilst links between higher online comparisons and indices of insecurity were evident in the *contemporaneous* network, counter to their predictions, insecurity emerged as a driver of social comparisons (rather than a consequence thereof) in the *temporal* network.

Despite its many strengths, Faelens et al., (2021) had a number of limitations, including the use of an unsigned social comparison item (i.e. they did not specifically look at *upward* social comparisons) and the inclusion of *negative* affect *only*, which may have primed participants to the negative effects of SM engagement, and did not allow for parallel positive effects to be explored, despite these (as noted above) existing with the literature. Further, the authors did not include any item/s relating to *offline* social comparisons. We think this is crucial, since online and offline social comparisons tend to be highly correlated, such that any documented associations may simply be due to online social comparisons acting as a proxy for offline comparisons.

Taken together, existing research suggests that (on balance) online social comparisons are associated with poorer mental health and wellbeing, as operationalized using a range of constructs including self-esteem, affect, anxiety and depression. However, there are a number of gaps in our understanding, including: (i) the relationship between (and relative impact of) online and offline social comparisons, (ii) potential differences in within- and between-subjects effects, and (iii) potential positive *and* negative effects on wellbeing, as well as a need for replication.

In an attempt to address these limitations, the overarching aim of this study was to explore the dynamic relationship between SM use, online social comparisons and wellbeing, with the latter conceptualized as self-esteem, mood/affect and loneliness. In addition, however, we explored the role of equivalent *offline* processes in parallel, namely, the dynamic interplay between these constructs and time spent in the physical (rather than virtual) presence of others, as well as *offline* social comparisons.

EMA and network analyses were employed for a number of reasons; first, because it enabled a more direct comparison with findings of Faelens et al., (2021), i.e. because it facilitated calculation and visualization of contemporaneous, temporal *and* between-subjects networks, as well as exploration of directionality and effects operating at multiple timescales.

Second, the use of EMA / network analyses allowed us to include an exploratory aspect to the study. Thus, whilst a number of specific hypotheses were identified (see below), in view of the relative lack of prospective studies in the field, inconsistencies in the literature, and our expectation of complex inter-relationships between multiple variables of interest, we were reluctant to specify too many overly focused hypotheses *a priori*, or overly constrain models. Thus, whilst there is a wealth of literature on associations between many of our variables of interest, e.g., the relationship between self-esteem and loneliness [see Vanhalst et al., (2013) for example] or the relationship between self-esteem and mood [see (Gomez-Baya et al., 2018) for example], little is known about how these particular variables interact dynamically with one another *en masse*, much less in relation to online and offline processes.

Finally, and relatedly, whilst alternative methods of analysing longitudinal, multivariate data exist, e.g., cross-lagged panel modelling and multi-levelling modelling, these require explicit specification of potential interactions of interest (*a priori*). In contrast, network analysis allows an exploratory analysis (and visualization) of complex dynamic interactions between multiple variables of interest, which some have argued more accurately reflect the nature of psychological and psychopathological processes (Cramer et al., 2010; Woerkom et al., 2022).

The following hypotheses were put forward:

(H1) Time spent on SM would be associated with poorer wellbeing (i.e. lower self-esteem, higher negative affect, lower positive affect and higher loneliness) across all three networks.

Whilst documented effect sizes are small, systematic reviews and meta-analyses of the literature tend to highlight a small but significant association between higher levels of SM use and poorer wellbeing / mental health (Valkenburg et al., 2022), including poorer self-esteem (Saiphoo et al., 2020), higher symptoms of depression (Cunningham et al., 2021), and higher levels of loneliness (O'Day & Heimberg, 2021). Further, at least one study has shown that this effect (with respect to self-esteem at least) persists even after controlling for online social comparisons, such that the association cannot be attributable solely to the latter (Tibber et al., 2020). Consequently, we predicted that time spent using SM would be associated with poorer wellbeing, including self-esteem, affect, *and* loneliness, aside from any association seen between online social comparisons and wellbeing. Given the relative dearth of research exploring causality, however, and inconsistencies in the findings where such studies have been undertaken (Valkenburg et al., 2022), we made no assumptions about underlying directions of causality or time-course of action (i.e. which network/s would show the effect).

(H2) Online upward social comparisons would be associated with poorer wellbeing (as defined above) across all three networks.

As described above, there is an extensive literature, which suggests that online upward social comparisons are linked to poorer wellbeing including greater negative affect [e.g., (Vogel et al., 2015)], loneliness [e.g., (Tibber et al., 2024)] and self-esteem [e.g., Vogel et al. (2014)]. Further, whilst most research has adopted cross-sectional, correlational methods, similar findings have been reported using a range of methodologies and designs, which have explored effects across a range of time-frames, including longitudinal (Schmuck et al., 2019), experimental (Appel et al., 2015; Vogel et al., 2014, 2015), and prospective (EMA) studies (Faelens et al., 2021). In addition, there is evidence to suggest that, with respect to self-esteem at least, associations with online upward social comparisons may be causal (Vogel et al., 2014), and possibly reciprocal (Schmuck et al., 2019b). Consequently, we predicted that the association between online upward social comparisons and poorer wellbeing would be evident in all three networks (contemporary, temporal and between-subjects).

(H3) Time spent in the physical presence of others would be associated with better wellbeing (as defined above) across all three networks.

There is a large body of evidence suggesting that social connections and social capital are central to wellbeing and mental health, and further, that loneliness and social disconnection are pathogenic (Harris & Orth, 2020). Whilst not all social interactions are positive, we proposed that on the weight of this evidence, higher levels of time spent in the presence of others would be associated with better wellbeing. Given that such findings have been documented using a range of methodologies and approaches, which have explored effects across a range of time-frames, we predicted that the effect would be seen across all three networks. Further, we predicted that the direction of causality would run from time spent with others to positive wellbeing.

(H4) Offline upward social comparisons will be associated with poorer wellbeing (as defined above) across all three networks.

There exists a long and rich history of research into the role of social comparisons in mental health and wellbeing, which far predates the development of the internet and SM

(Buunk & Gibbons, 2007), including with respect to self-esteem and mood (Collins, 1996), and to a lesser extent loneliness (Perlman & Peplau, 1982). Whilst this literature is complex and nuanced, with potential benefits as well as harms of social comparisons having been described (McCarthy & Morina, 2020; Sirgy, 2021), we predicted that upward (offline) social comparisons would be linked to poorer wellbeing. Thus, there are theoretical and empirical reasons to suspect that upward social comparisons may be particularly unhelpful when they are undertaken automatically (i.e. without specific intent), as one might expect to occur if such processes are sampled randomly and repeatedly throughout the day (Bocage-Barthélémy et al., 2018; Tibber & Silver, 2022). Further, findings from a recent meta-analysis suggest that in the offline context, upward social comparisons predominate, and drive negative self-evaluation, envy and a worsening of mood (Gerber et al., 2018). We predicted that such an effect would be evident across all three networks explored.

Finally, with respect to our different measures of wellbeing (loneliness, low self-esteem and affect), given the relative novelty of network analysis and its application to SM/wellbeing links, we made no prediction as to the sequence of expected effects, e.g., whether changes in levels of self-reported loneliness would have knock-on effects on affect and self-esteem, or vice versa. Further, whilst related predictions may be possible on the basis of the existing literature (e.g., loneliness will drive decreases in self-esteem), such effects do not constitute the primary focus of the study, i.e. exploring the links between online and offline comparative processes and wellbeing.

2. Materials and Methods

The study employed a prospective mobile-phone based EMA design.

2.1. Data Collection and participants. Ethical approval was given by the Ethics committee of College of Media and International Culture at Zhejiang University (Project ID: cmic20221102) and the work carried out in accordance with The Code of Ethics of the World Medical Association (Declaration of Helsinki) for experiments involving humans. There was minimal risk to participation and the survey was anonymous, with a low chance of participants being identified on the basis of responses given. Informed consent was obtained through an online consent form, which included information about study design, financial compensation for participation, data storage and sharing. Participants were also informed that their participation was completely voluntary, and that they could withdraw at any time during the study and request that their data be deleted. Data were collected between March and April of 2023. A recruitment advisement was posted on commonly used SM platforms used by the students of Zhejiang University (i.e., Duoduo Campus Circle and CC 98), with participants only recruited from within the University. There were no exclusion criteria for participation, e.g., with respect to age or student status; however, individuals who expressed their interest in participation were selected purposely in order to recruit a roughly equal number of male and female participants.

Participants were surveyed five times per day at the following times: 10am, 12:30pm, 4pm, 6pm and 10pm, with these times selected on the basis that they fall outside of university classes, and data collected for a total of 21 consecutive days. Participants were asked to download an application within WeChat, which gave access to the online survey and indicated participant progress through the study, including number of surveys completed and missed, as well as the cumulative money accrued. Thus, to encourage participation participants were paid ¥2 for each survey they completed (equivalent to approximately 24 pence at the time of data collection). A random half of the participants also received an additional ¥5 bonus if they completed all five surveys in a day. This manipulation was included as part of a separate study exploring the effects of incentivisation on survey response rates.

With respect to our sample size, we did not undertake a power calculation, but drew heavily on the methodology of Faelens et al. (2021), which reported highly significant and seemingly robust effects with a sample size of 98. We therefore aimed to recruit approximately 100 participants to the study.

2.2. Questionnaire items

The survey included 34 items in total, exploring associations between wellbeing and a range of daily activities including social media, gaming, studying, exercise and time spent outdoors. Our focus, however, was on SM and social comparisons (as well as parallel offline processes), so that we used a subset of these items (n=15) detailed in Table 1.

With respect to the source of included items, SM time and face-to-face time were measured using two, custom-written single-item questions, similar to those used previously in EMA studies including Beyens, Pouwels, van Driel, Keijsers, & Valkenburg (2020). Online and offline (upward) social comparisons were also measured using single-item questions, adapted from Faelens et al. (2021). Low self-esteem was measured using two items, the first taken from Faelens et al. (2021) (“felt insecure”), and a second added from the Rosenberg Self-esteem Scale (RSES) (Rosenberg, 1965) (“felt positive towards myself”), in order to ensure a balance of positively and negatively worded items. Loneliness was similarly measured using two items, with one item asking about whether the participant “felt lonely” directly, as has been used previously [e.g., Compernolle et al. (2021)] and one item taken from the social connectedness scale (SCS) (“felt close to people”) (Lee et al., 2001). Finally, affect was measured using seven items, three positive affect items translated from Faelens et al. (2021)

and four negative affect items translated from Hoorelbeke, Van den Bergh, Wichers, & Koster (2019).

Prior to launching the study a pilot study was run with six participants, using a translated version of the survey. Following feedback minor adjustments to item wording were made to increase intelligibility and relevance to the target population (see Supplementary Table 1).

Table 1. Items included in the analyses are included along with corresponding response options, and the source reference/s from which survey items were translated and adapted for use with our target sample. R=items that were reverse coded upon scoring.

Variable	Items	Source / adapted from	Response options
Social media time	(i) Over the past hour, how many minutes have you spent on social media platforms?	Beyens et al. (2020)	Numeric entry
Face-to-face time	(i) Over the past hour, how many minutes have you spent in the physical presence of others, i.e. at least one other person regardless of whether you interacted with them?	Beyens et al. (2020)	Numeric entry
Online upward SCs	(i) In the past hour, I have compared myself to others I encountered online who are better off than me.	Faelens et al. (2021)	0 (Not at all) - 10 (very much)
Offline upward SCs	(i) In the past hour, I have compared myself to others I encountered offline who are better off than me.	Faelens et al. (2021)	0 (Not at all) - 10 (very much)
Low self-esteem	(i) In the past hour, I have felt insecure.	Faelens et al. (2021)	0 (Not at all) - 10 (very much)
	(ii) In the past hour, I have felt positive toward myself (R).	Rosenberg (1965)	0 (strongly disagree) - 10 (strongly agree)
Loneliness	(i) In the past hour, I have felt close to people (R).	Lee et al. (2001)	0 (Not at all) - 10 (very much)
	(ii) In the past hour, I have felt lonely.	E.g., Compernolle et al. (2021)	0 (Not at all) - 10 (very much)
Affect	Please try and rate the separate emotions separately, so that for example a score of zero on happiness means that you are not feeling happy, but does not necessarily mean that you are feeling sad. In the past hour, I have felt…		
Positive affect	(i) Happy.	Hoorelbeke et al. (2019).	0 (Not at all) - 10 (very much)
	(ii) Satisfied.		0 (Not at all) - 10 (very much)
	(iii) Energetic.		0 (Not at all) - 10 (very much)
Negative affect	(i) Angry.	Faelens et al. (2021)	0 (Not at all) - 10 (very much)
	(ii) Tense.		0 (Not at all) - 10 (very much)
	(iii) Sad.		0 (Not at all) - 10 (very much)
	(iv) Anxious.		0 (Not at all) - 10 (very much)

2.3. Network analysi

All analyses were undertaken in R (Version 4.3.1). Participants with fewer than 50 completed responses were discarded from the analyses. Non-consecutive surveys / time-points (beeps as they are often called in EMA) were treated as missing; relatedly, the last beep of day X and first beep of day X+1 were not treated as consecutive. Missing data were dealt with using listwise deletion, i.e. all data for a given time-point / participant were excluded if any single variable within that time-point was missing. Since network analysis assumes stationarity all variables were de-trended in relation to day of study. Temporal and contemporaneous networks were generated using the *mlVAR package* (Version 0.5.1). The networks were generated by a two-stage multilevel vector autoregressive (VAR) approach (Epskamp, Waldorp, et al., 2018).

In the first stage, each variable at time-point t is regressed onto scores of all other variables at time t-1 (i.e. performance at the preceding time-point), including itself, such that an autocorrelation term is included. This generates a *temporal network model*, with directed edges (i.e. coefficients capturing directions of associations) between nodes (variables), describing the strength of associations between nodes across time (e.g., 'do higher social comparisons predict subsequent lower self-esteem?'). In the second stage, residuals from stage 1 are regressed onto residuals of all variables at the same time-point. This generates a *contemporaneous network model* with undirected edges, which captures patterns of co-occurring activity, whilst accounting for variance in scores at t-1 (Epskamp, Borsboom, et al., 2018), (e.g., 'is self-esteem higher when social comparisons are higher?').

Finally, for each person, the corresponding VAR model has an intercept associated with each variable, which represents the *mean* score of that variable across time. Thus, a final set of *between-subjects* partial correlations were undertaken to explore (undirected) associations between these mean variable values. This generates a *between-subjects network* *model*, whilst controlling for all other variables in the network (e.g., ‘do people who report higher social comparisons typically report lower self-esteem?’). The networks were then plotted using the *qgraph* package (Version 1.9.5).

Finally, for each network the centrality of each node was estimated using the *centrality* function. Although operationalized in different ways, within a network a more central node will have stronger and more numerous connections to other nodes, can receive and transfer information to others more quickly, and lays on major connection pathways (Opsahl et al., 2010). The centrality function, generates three indices of node centrality: degree, closeness, and betweenness, which (approximately) map onto the three descriptions described in the preceding sentence (respectively), and were included here.

3. Results

Data were collected on 100 participants. As noted, participants with fewer than 50 completed responses were discarded, resulting in a final sample, which formed the basis of the analyses, of 89 participants (analytic sample). Data were collected from a total of 7749 surveys across the 89 participants included in the analyses, with a possible maximum of 9,345 (89 participants receiving 5 beeps per day over the course of 21 days). The mean number of surveys collected per person was 87.07 (IQR=76-99), with a maximum of 105 (5 beeps per day over the course of 21 days). This means that, on average, participants completed just over four out of five surveys they were sent each day. See Table 2 for demographics and Table 3 for mean values for key variables.

To test for differences in key variables between participants who were excluded from the analysis (excluded sample; n=11) and those that were retained (retained sample; n=89), a series of independent samples t-tests and chi-squared tests were run on key demographic variables and variables included in the analyses. These indicated no significant differences with respect to the age ($t_{(13.14)}$=-0.04, p=0.97) or male-to-female ratio ($\chi2_{(1)}$=0, p=1) of participants, nor with respect to their mother's highest level of education ($\chi2_{(4)}$=7.49, p=0.11). There was, however, a difference in their father's highest level of education ($\chi2_{(4)}$=10.08, p=0.04). This reflected over-representation of those with father's who were relatively less educated in the excluded sample; note, however, that this effect would disappear with even the most lenient of *bon ferroni* correction methods, e.g., correction for two multiple comparisons, indicating a likely type 1 error.

With respect to variables included in the network analyses, for the samples that were available for each group, the mean self-reported time spent on SM (in the last hour) did not differ between the analytic and excluded samples ($t_{(12.47)}$=0.14, p=0.89), nor did the self-reported time spent face-to-face (in the last hour) ($t_{(13.56)}$=-0.9, p=0.39). Finally, the groups did not differ with respect to self-reported levels of upward comparisons undertaken online ($t_{(11.44)}$=0.35, p=0.73) or offline ($t_{(12.51)}$=-0.41, p=0.69) over the last hour, nor with respect to mean positive affect ($t_{(12.63)}$=0.58, p=0.57), negative affect ($t_{(13.63)}$=-0.42, p=0.68), low self-esteem ($t_{(14.67)}$=0.77, p=0.45) or loneliness ($t_{(17.3)}$=-0.2, p=0.85) scores, as self-reported over the last hour.

Taken together, these findings suggest that with respect to the variables included, there is no evidence for selective attrition.

Table 2. Participant details. Demographic and socioeconomic variables are presented for the total sample (n=100) and analytic sample (n=89).

Variable	Level	Frequency (%) or Mean (STD) N=89	Frequency (%) or Mean (STD) N=100
Age	-	22.39 (2.55)	22.39 (2.52)
Gender	Male	42 (47.19)	47 (47)
	Female	47 (52.81)	53 (53)
Mother's Education	Junior middle school or lower	30 (33.71)	38 (38)
	Vocational or ordinary high school / technical or technical secondary school	26 (29.21)	27 (27)
	College	14 (15.73)	14 (14)
	Undergraduate	16 (17.98)	18 (18)
	Graduate and above	3 (3.37)	3 (3)
Father's Education	Junior middle school or lower	26 (29.21)	32 (2)
	Vocational or ordinary high school / technical or technical secondary school	24 (26.97)	28 (28)
	College	15 (16.85)	15 (15)
	Undergraduate	23 (25.84)	23 (23)
	Graduate and above	1 (1.12)	2 (2)

Table 3. Mean values for key variables. Mean, standard deviation (SD), minima (min) and maxima (max) are shown for key variables included in the analyses. These represent summary statistics of values derived for each individual, averaged across time-points and days. For time spent on social media time (Online) and face-to-face (Offline), units are expressed in minutes; e.g., on average, individuals reported using social media 6.53 mins (SD=4.58) in the hour preceding each survey. Other items are expressed in arbitrary units reflecting Likert scale item ratings (see Table 1). *Values defined in minutes; elsewhere scores represent raw or summary Likert scale scores.

Domain	Variable	Mean (SD)	Min-Max
Online	Social media time	6.53 (4.58)*	0-20.56
	Online comparisons	1.24 (1.55)	0-7.22
Offline	Face-to-face time	32.93 (15.84)*	0.77-57.86
	Offline comparisons	1.61 (1.81)	0-7.01
Wellbeing	Positive affect	12.87 (5.92)	0.78-25.42
	Negative Affect	5.93 (5.26)	0.03-25.06
	Low Self Esteem	6.69 (2.17)	3.01-14.73
	Loneliness	7.6 (2.35)	2.58-14.9

3.1. Contemporaneous network

With respect to the contemporaneous network (Figure 1A and Supplementary Table 2), considering general time spent online/offline first, the only variable connected to time spent on SM was social comparisons, with a *positive* association linking higher levels of SM use to higher levels of *online* comparisons [Partial Correlation Coefficient (PCC)=0.07; SD=0.06; p<0.001]. Time spent face-to-face with others showed a (positive) connection to *offline* social comparisons (PCC=0.08; SD=0.02; p<0.001), but in addition, a negative connection to *online* social comparisons (PCC=-0.04; SD=0.03; p=0.01) and loneliness (PCC=-0.18; SD=0.06; p<0.001), with the association with *offline* social comparisons seemingly stronger than the association with *online* social comparisons.

Next, considering social comparisons as a particular online/offline behaviour more specifically, online and offline comparisons were positively correlated with one another (PCC=0.19; SD=0.19; p<0.001). In addition, *online* social comparisons was (positively) connected with low self-esteem (PCC=0.12; SD=0.1; p<0.001) and levels of SM use (PCC=0.07; SD=0.06; p<0.001). It was also associated with reduced face-to-face time, although the effect appeared to be relatively weak (PCC=-0.04; SD=0.03; p=0.01). With respect to *offline* social comparisons, this was connected (positively) to both positive (PCC=0.05; SD=0.04; p<0.01) *and* negative affect (PCC=0.13; SD=0.09; p<0.001), though the latter more strongly, as well as low self-esteem (PCC=0.09; SD=0.13; p<0.001). Also, whilst *online* social comparisons were (weakly) associated with less face-to-face time (PCC=-0.04; SD=0.03; p=0.01), *offline* social comparisons were associated with more face-to-face time (PCC=0.08; SD=0.02; p<0.001).

Other (psychological) variables showed patterns of connections that made intuitive sense: for example, low self-esteem was positively connected with loneliness (PCC=0.14; SD=0.1; p<0.001) and negative affect (PCC=0.08; SD=0.02; p<0.001), and negatively connected with positive affect (PCC=-0.31; SD=0.09; p<0.001), the latter most strongly. Low self-esteem was also (as noted) connected to both online (PCC=0.12; SD=0.1; p<0.001) and offline social comparisons (PCC=0.09; SD=0.13; p<0.001), the latter more strongly, and was the most central node in the temporal network, with the highest indices of node centrality of any variable included (see Supplementary Table A.5).

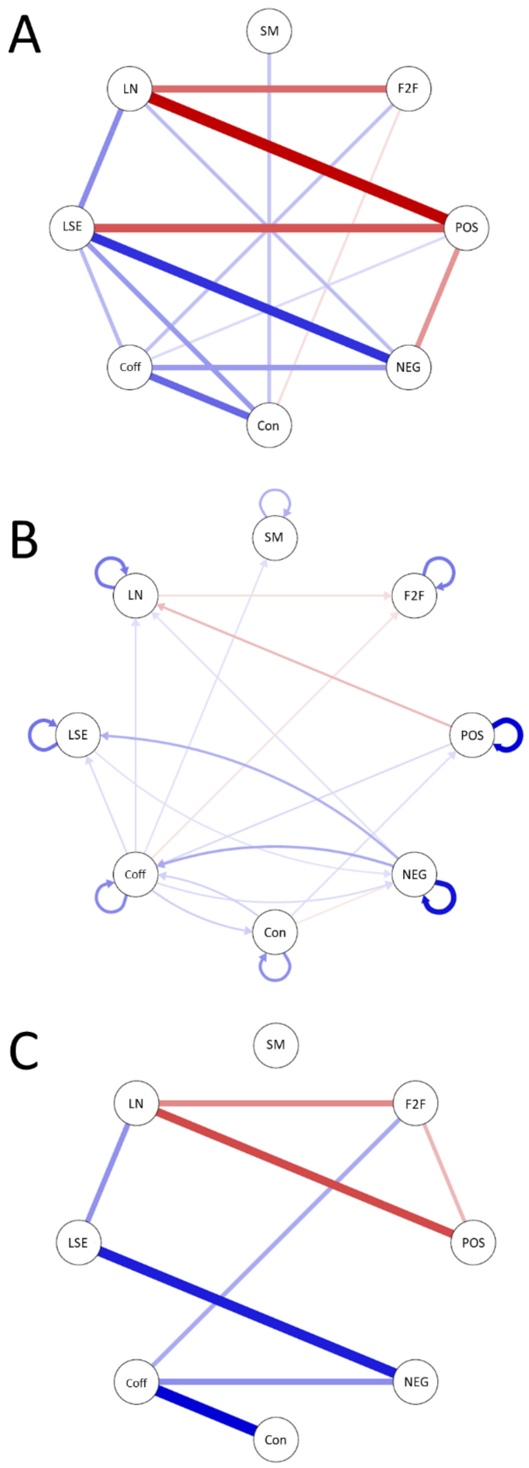

Figure 1. Plotted networks. (A) Contemporaneous, (B) temporal, and (C) between-subject networks are shown. Blue lines / edges represent positive associations between variables (nodes), and red edges represent negative associations, where the thickness of the line indicates strength of association. Only significant edges are shown. SM=time spent on social media; F2F=time spent face-to-face; POS=positive affect; NEG=negative affect; Con=(upward) comparisons in the online environment; Coff=(upward) comparisons undertaken in the offline environment; LSE=low self-esteem; LN=loneliness.

3.2. Temporal network

With respect to the temporal network (Figure 1B and Supplementary Table 3), all included variables were auto-correlated, e.g., social media use at time-point t, was predicted by use at t-1.

Considering general time spent online/offline first, level of SM use did not predict future affect (positive or negative), nor any of the other psychological measures. In fact, the only significant edge linked to SM use indicated that *offline* social comparisons predicted greater future SM use (Edge Weight (EW)=0.04; SE=0.02; p=0.02). Time spent face-to-face with others also did not predict any future variables (psychological or otherwise). However, both loneliness (EW=-0.04; SE=0.02; p=0.01) and offline social comparisons (EW=-0.04; SE=0.02; p<0.05) (negatively) predicted future face-to-face time, suggesting that individuals who were more lonely or compared themselves more to others offline at time t-1 were less likely to engage in face-to-face contact at time t.

With respect to social comparisons, there was a bidirectional link between online and offline comparisons (EW=0.05; SE=0.02; p=0.001; EW=0.06; SE=0.02; p=0.001). Focusing on the online context, however, counter to our expectations, online social comparisons were associated with less (future) *negative* affect (EW=-0.03; SE=0.01; p=0.04), and more future *positive* affect (EW=0.04; SE=0.02; p=0.02), with similar effect sizes / edge weights. Aside from the aforementioned association with *offline* comparisons, no other associations were seen with online social comparisons.

In the offline context, mirroring the findings from the contemporaneous network, social comparisons were predicted by both positive (EW=0.04; SE=0.02; p=0.01) *and* negative affect (EW=0.1; SE=0.02; p<0.001). Once again, however, the link with *negative* affect was the stronger of the two, and further, the connection reciprocal, such that there was a potential positive feedback loop, with offline social comparisons driving (EW=0.04;

SE=0.02; p=0.02) -and being driven by (EW=0.1; SE=0.02; p<0.001)- negative affect. [Note: on the basis of edge weights negative affect drove offline comparisons more strongly than offline comparisons drove negative affect]. Offline social comparisons also predicted future lower self-esteem (EW=0.04; SE=0.01; p<0.01), higher loneliness (EW=0.04; SE=0.02; p=0.02), more time spent using SM (EW=0.04; SE=0.02; p=0.02) and less time spent face-to-face with others (EW=-0.04; SE=0.02; p<0.05). Interestingly, offline social comparisons was by far the most connected of all included variables / nodes, as indicated by higher scores on all indices of node centrality (Supplementary Table 6).

Once again, links between psychological variables made intuitive sense, with (for example) negative affect predicting increased loneliness (EW=0.03; SE=0.02; p=0.04), and being predicted by lower self-esteem (EW=0.03; SE=0.02; p=0.04).

3.3. Between-subjects network

With respect to the between-subjects effects, this network was more sparse (Figure 1C and Supplementary Table 4). SM use was not significantly connected to any other variable, and face-to-face time was negatively associated with positive affect (PCC=-0.22; p<0.05) and loneliness (PCC=-0.36; p=0.001), and positively associated with offline social comparisons (PCC=0.26; p=0.02).

Mirroring the lack of association between SM use and other variables, online social comparisons were not associated with any other variable except offline social comparisons (PCC=0.78; p<0.001). With respect to offline social comparisons, as per contemporaneous and temporal networks, this was positively connected to negative affect (PCC=0.35; p=0.002). Offline social comparisons were also positively connected with face-to-face time (PCC=0.26; p=0.02). Once again, offline social comparisons was the most highly connected node, though loneliness scored equally highly on the 'betweenness' index (Supplementary Table 7).

Associations between psychological measures followed an intuitive pattern, with (for example) loneliness associated negatively with positive affect (PCC=-0.56; p<0.001), and low self-esteem associated positively with negative affect (PCC=0.69; p<0.001).

4. Discussion

With respect to our stated hypotheses, three out of four were either completely or partially supported. Thus contrary to (H1), time spent on SM was *not* associated with poorer wellbeing, across any of the networks, nor with respect to any of the mental health / wellbeing variables included. In partial support of (H2), an association *was* seen between online upward social comparisons and poorer wellbeing; however, this was only seen in the contemporaneous network for low self-esteem. Further, the temporal network indicated that online upward social comparisons in fact predicted subsequent *increases* in positive affect and decreases in negative affect, i.e. a sign of association that was opposite to that expected. In partial support of (H3), face-to-face time was associated with lower levels of loneliness in the contemporaneous and between-subjects networks; however, directions of effects in the temporal network suggest that (at this time-scale at least) higher levels of loneliness drove subsequent reductions in face-to-face time rather than the other way round. Finally, in support of (H4), offline upward social comparisons were associated with poorer wellbeing, including low self-esteem and negative affect in the contemporaneous and temporal networks, and negative affect in the between subjects-network. With respect to the temporal network, directions of associations suggest that offline social comparisons (at this time-scale at least) drive subsequent low self-esteem, loneliness and negative affect.

Digging into these findings a little deeper, if we consider associations between time spent online / offline first (i.e. on SM and face-to-face, respectively), SM use actually showed very few connections to other nodes (reflected in indices of node centrality also). In the between-subjects network, for example, SM use was not connected to any other variable, and in the contemporaneous and temporal networks it was connected with online and offline social comparisons only (respectively).

The finding that SM use was not connected to any of the wellbeing variables included (across any of the networks) is supportive of a growing understanding that SM use is not detrimental to one's wellbeing *per se*, and supports a move away from a *causasionist* assumption that underpins dose-response models of the SM-wellbeing link (Nesi et al., 2020). Instead, it is consistent with a more *contextual* approach (Nesi et al., 2018a, 2018b), which emphasises the complex interactions that occur between *person*-related and *technology*-related factors, including *what* content is being engaged with, *how* the individual is engaging with it, and *why*, i.e. for what purpose (Kaye, 2022; Tibber et al., 2022; Tibber & Silver, 2022).

Here we explored one particular type of online behavior: upward social comparisons, as well as its offline parallel. In the contemporaneous network online social comparisons related to other nodes (in large part) as we expected on the basis of previous research, including positive links to low self-esteem and offline social comparisons (Verduyn et al., 2020). Contemporaneous networks are seen as reflecting fast-paced interactions between variables of interest (Epskamp, Waldorp, et al., 2018). Consequently, this is consistent with previous research, which suggests that online upward social comparisons may be relatively automatic, and capable of driving thoughts and/or feelings associated with low self-esteem (Faelens et al., 2021; Tibber et al., 2020; Vogel et al., 2014). In the between-subjects network, however, online comparisons were not associated with wellbeing; in fact, online social comparisons showed only a single (positive) connection (with offline social comparisons) in the between-subjects network. This suggests that the association between online social comparisons and self-esteem may be stronger and/or more robust with respect to *within* rather than *between* subject effects. However, neither the contemporaneous nor the between-subjects networks speak to underlying directions of causality. For this we must turn to the temporal network.

The temporal network showed reciprocal connections between online and offline social comparisons, suggesting mutually reinforcing processes and an intimate association between these behaviours across contexts. This is consistent with one study that found high correlations between offline (face-to-face) and online (Facebook-mediated) social comparisons, with respect to both comparisons direction (upward vs. downward) and orientation (i.e. tendency to make comparisons) (Faranda & Roberts, 2019).

In the temporal network, however, online social comparisons were also found to drive future (increased) positive affect and (decreased) negative affect. This suggests that online social comparisons may have very different effects operating at different time-scales, e.g., a short/immediate (potentially automatic) effect that drives *decreases* in self-esteem (Faelens et al., 2021; Vogel et al., 2014), as well as a more positive impact on affect operating over a slightly longer timescale (e.g., of several hours). This is consistent with a two-step model of social comparisons that has been proposed (Buunk & Gibbons, 2007), with an unconscious / automatic step that is often unhelpful (Bocage-Barthélémy et al., 2018), followed by a slower more conscious step, in which the negative effects of comparisons may be undone through (for example) consideration of why the target is better or worse off.

Consistent with this two-step model, and our finding of differential effects operating at different timescales, one study, undertaken during the pandemic found that individuals who are more skilled in identifying their negative thoughts and feelings and replacing them with positive interpretations (high cognitive reappraisers), were less susceptible to upward *contrasts,* i.e. experiencing negative thoughts and/or feelings when making upward comparisons (Yue et al., 2022).

These findings are also (broadly) consistent with the only other study (to our knowledge) to have used EMA and network analysis to explore links between online social comparisons and wellbeing (Faelens et al., 2021). Exploring online comparisons on Facebook and Instagram use (separately), whilst the authors found an association between online social comparisons and insecurity in contemporaneous networks (as predicted), online social comparisons did not drive feelings of insecurity (or negative affect or repetitive negative thinking) in the temporal networks. For Facebook, online social comparisons were instead driven by feelings of insecurity, rather than the other way round.

Nonetheless, not only did we not find online social comparisons driving poorer wellbeing in the temporal network, we actually found that upward social comparisons predicted *higher* future positive affect and *lower* future negative affect. Whilst potential benefits of upward comparisons were counter to our predictions, they are not unprecedented in the literature. Thus, whilst online upward social comparisons have typically been linked to poorer wellbeing (Verduyn et al., 2020; Yang et al., 2019; Yoon et al., 2019), some studies have found links to better wellbeing (Verduyn et al., 2020). For example, one study, undertaken during the COVID-19 pandemic, found that online social comparisons predicted *improvements* in levels of anxiety, stress, loneliness and life satisfaction across a period of 18 days (Ruggieri et al., 2021b); see Tibber et al. (2024). The authors hypothesised that this might reflect the capacity for social comparisons to elicit a sense of a shared struggle, and/or an incentive for individuals to try to elevate their wellbeing to the level of their peers. However, the authors did not distinguish between upward and downward social comparisons, such that the possibility cannot be ruled out that participants were in fact benefiting from downward social comparisons, i.e. comparisons to those less well off than themselves (Wills, 1981).

Nonetheless, there is a growing body of literature into the impact of SM induced envy (Meier & Johnson, 2022), which indicates that for *some*, upward social comparisons may trigger a form of 'benign envy' (sometimes contrasted with 'malicious' envy), which is inspirational, and conducive to positive rather than negative wellbeing (Meier et al., 2020). Relatedly, individuals may look to others' success as a model of their own future, i.e. a form of upward *identification* (Yue et al., 2022). Further studies are needed to explore inter-individual differences that distinguish such responses from more harmful effects of upward social comparisons (de Vries et al., 2018; Park & Baek, 2018; Valkenburg et al., 2021), as well identify which features and affordances of the technology itself facilitate or minimize social comparison processes (Meier & Johnson, 2022).

One interesting possibility is that such 'benign envy' may be particularly common in collectivistic cultures, and more specifically *horizontal* (i.e. less hierarchical) collectivistic cultures, like China, in which the self is conceptualized as part of an in-group, and equality is emphasized (Baldwin & Mussweiler, 2018; Singelis et al., 1995). Speaking to this proposal, one study of European Canadians and Asian Canadians found that the latter made more upward social comparisons, but particularly so after experiencing failure and being primed to the possibility of self-improvement (White & Lehman, 2005). The authors concluded that *"Asian Canadians seek social comparisons in ways that facilitate self-improvement*" (p.239).

Turning next to the offline world, in the contemporaneous network face-to-face time was (negatively) connected to loneliness and online comparisons, and positively connected to offline upward social comparisons. Whilst (as noted) contemporaneous networks do not speak to underlying directions of causality, there is a temptation to interpret this in terms of the following: (i) offline social comparisons may be a relatively automatic consequence of offline socializing, much as online comparisons are (we would argue) a relatively automatic consequence of online socializing / SM use, and (ii) face-to-face time may reduce feelings of loneliness, and (iii) potentially relatedly, face-to-face time may reduce the need to compare oneself to others online, e.g., to seek reassurance from the online world.

The between-subjects network showed a similar pattern of findings, such that individuals who reported spending more time (on average) face-to-face with others were more likely to compare themselves offline, and further, felt less lonely. Interestingly, however, they also exhibited less positive affect, which might reflect a tendency for individuals lower in positive affect to turn to others to manage their mood. However, as noted, these directions of causality are merely speculative. Once again, to explore directionality we must turn to the temporal network.

With respect to the temporal network we found that loneliness was associated with less future face-to-face time, suggesting that at this timescale at least, individuals who feel lonely may be driven to withdraw from others, rather than the reverse direction of causality. One can see how this may set up (in some) a problematic cycle of loneliness and withdrawal that might become depressogenic. The only other association seen with face-to-face time was a connection to offline social comparisons; however, we shall discuss this finding below.

In terms of offline social comparisons, these showed a pattern of associations that was much more in line with what we expected of online social comparisons, and suggestive (we would argue) of potentially more negative / harmful effects. Thus, in the contemporaneous network offline social comparisons were positively associated with low self-esteem, negative affect and *online* comparisons. In addition, however, offline social comparisons were positively connected with positive affect (though weakly) and time spent socializing face-to-face. The between subjects network resembled a pruned version of this, such that individuals who (on average) reported more offline upward social comparisons reported more negative affect, more online comparisons, and spent more time face-to-face.

Turning to the temporal network, we see that aside from the reciprocal (positive) connection with online comparisons (already discussed), there was a similar reciprocal association between offline comparisons and negative affect, suggesting that individuals may get caught in a vicious cycle, whereby negative affect drives them to compare themselves to others offline, which in turn drives their affect lower. Offline social comparisons were also found to drive future low self-esteem, loneliness and greater SM use, the latter potentially reflecting a retreat to the online world to escape the pain of such offline comparative processes. Interestingly, the positive association seen in other networks between offline comparisons and face-to-face time is reversed (i.e. negative) in the temporal network, suggesting that at this timescale, offline social comparisons may drive social withdrawal. An indirect path between offline social comparisons and reduced face-to-face time through loneliness was also observed, reinforcing the notion of a potential for (offline) social comparisons to drive social withdrawal.

Taken together, these findings suggest a much more central, and potentially harmful, role for *offline* social comparisons than *online* social comparisons, particularly once one moves away from immediate, short-term effects. Thus, offline comparisons were found to be much more densely connected to other variables (reflected in measures of centrality), with paths to loneliness, low self-esteem, negative affect, and social withdrawal. In contrast, online social comparisons were far less densely connected, with a link seen to low self-esteem in the contemporaneous network only, but links to (more) positive affect and (less) negative affect in the temporal network. Consistent with these findings, in their review of social comparisons and envy on SM, Meier and Johnson write that *"initial studies show online social* *comparison produces more short-term negative affect, yet offline comparison may be more prevalent and consequential for well-being"* (p.3) (Meier & Johnson, 2022)

Why this should be the case is not clear. Indeed, a number of authors have hypothesised that online social comparisons may be *more* pervasive and problematic than offline because of the features and affordances of the online environment. For example, the *permanence, visualness* and *asynchronicity* of online communication, coupled with the potential to connect with large audiences and near ubiquitous inclusion of quantifiable social metrics (Nesi et al., 2018b, 2018a) may create a context in which users have near-constant and immediate access to a wide range of heavily curated and idealised comparison targets likely to trigger negative self-evaluations (Tibber & Silver, 2022).

Nonetheless, we may speculate why offline social comparisons may be more closely linked to poor wellbeing (than online social comparisons) in our data at least. First, it is possible that SM users are becoming increasingly digitally literate and hence immune (or less vulnerable) to the negative effects of online social comparisons. Thus, the potential harmful effects of SM use, particularly social comparisons have been well documented in the media, e.g., the notion of an online positivity bias and highlights reel, and there is evidence that encouraging social "savoring" over social comparisons on social media may have positive effects on self-esteem (Andrade et al., 2023). Further, there is evidence (as noted in the introduction) that Generation Z (which represent the bulk of our sample) is expressing concern about their SM use, and may be actively trying to limit or manage their engagement (GlobalWebIndex, 2023). In contrast, the harmful effects of *offline* social comparisons may be less obvious and less publicised. If this is the case we might expect to see a weakening of the online social comparisons / wellbeing link with time.

Second, it is possible that individuals have more control over online social comparisons than offline social comparisons. Thus, it may be far easier to 'log off' or re-direct engagement to less harmful online content (e.g., by joining a different interest group), than it is to avoid one’s family, peers and work mates. Indeed, the ‘easiest’ option in the offline world may be to completely socially withdraw (for which we see evidence in our data in the form of a temporal link, direct and indirect, between offline social comparisons and reduced face-to-face contact). Further, the *asynchronicity* of online communication may mean that cognitive reappraisal [the second step in the two-step model of social comparisons discussed (Buunk & Gibbons, 2007)] is facilitated, such that the initial automatic (and negative) effects of social comparisons are ameliorated (Buunk & Gibbons, 2007; Yue et al., 2022). This is consistent with the *trasndiagnostic cognitive behavioural conceptualisation* of SM use (Tibber & Silver, 2022), which proposes that the same features and affordances of SM may be conducive to benefits or harms depending on whether they are used automatically / habitually verses purposefully / intentionally.

Finally, it is possible that offline social comparisons are more harmful than online comparisons because offline peers represent a more powerful referent group. Thus, people with whom one has close contact in the offline/physical world (e.g., peers or close friends), may represent more realistic competition for tangible resources (e.g., prizes, jobs, friends, romantic/sexual partners, etc.) and be more salient by virtue of their similarity, conditions under which social comparisons are deemed to be more likely (Corcoran et al., 2011). Consistent with this notion, mean social comparison ratings (averaged across time-points) were higher in the offline compared to the online context.

With respect to the limitations of this study, there were several. First, our use of a single item measure of online and offline social comparisons, which may threaten measurement reliability, validity and sensitivity (Nunnally & Bernstein, 1994). Nonetheless, we note that this is common practice in the literature, particularly with respect to EMA, where the use of multiple time-point sampling places a heavy burden on the participants in terms of survey length (Faelens et al., 2021), and may be particularly appropriate where effects explored are robust and reliable, as is the case (we would argue) for documented associations between online social comparisons and mental health / wellbeing (Verduyn et al., 2020). More broadly, research has highlighted the acceptable reliability and validity of many single-item measures, including within mental health, e.g., (McKenzie & Marks, 1999).

Second, all items using in this study were based on self-report items / measures, including data with respect to SM use. Whilst EMA reduces the delay between behavior and reporting, there is still the potential for self-report to increase measurement noise and/or bias (Andrews et al., 2015; Ellis et al., 2019). However, more "objective" measures such as in-phone app trackers may also be inaccurate and/or biased; further, one study of EMA found little difference in subjective and objective measure of use, and no meaningful association between report accuracy and wellbeing, nor with inter-individual (personality) differences or emotional and motivational states (Johannes et al., 2021). Thus, whilst self-report methods may introduce error, this does not seem to be systematic.

Third, whilst well suited to the research questions we proposed, network analysis is not without its problems. For example, causal inferences in temporal networks assume that there are no time-varying confounders; in other words, it assumes that the influence of included variables do not vary as a function of time. However, we cannot exclude the possibility of time-varying confounders that might distort reported associations. In addition, network analysis - particularly where many variables of interest are modelled - may lead to spurious effects because of collider bias. Though a full explanation of collider bias lies beyond the remits of the paper, suffice to say that whilst intuition would suggest that inclusion of additional covariates to a model (e.g., regression or network analytic) would incrementally increase the accuracy of the estimates of a variable's effects, this is not *always* the case. In fact, under certain some circumstances, inclusion of covariates may actually *reduce* the accuracy of effect estimates (York, 2018), and we cannot rule out the possibility of such effects in our findings.

On the flipside, however, there were many potential mediators and moderators that were not included in this study, which may have identified distinct intervening pathways, or particularly at-risk groups. For example, it would have been interesting to explore the role of different patterns of SM engagement in examined processes, e.g., active versus passive engagement, as well as the potential for differential effects in males and females, or those with pre-existing mental health conditions.

Relatedly, a further limitation is that the measure of social comparisons used here did not capture the *contents* of participants' comparisons (e.g., comparisons of wealth, beauty or academic ability), nor their *motivations* for comparisons. Instead, upward social comparisons were measured *in general*, potentially masking sub-types of comparisons that may be particularly strongly linked to wellbeing. We note, however, that in a follow-up study that is currently underway, we are using network analysis of EMA data to explore the role of social comparisons across multiple dimensions of comparisons.

In conclusion, the study explored associations between SM use and online upward social comparisons with wellbeing, as well as parallel offline processes, addressing a number of major limitations in the literature, including a predominance of cross-sectional designs, lack of control for / examination of equivalent *offline* processes, exclusive focus on negative affect, and reliance on between-subjects effects that lack temporal precision. Using a sophisticated data sampling and statistical analysis methodology (EMA and network analysis), we explored dynamic effects between key variables of interest, operating at multiple time-scales. Our findings are not consistent with the idea that social comparisons are exacerbated by the online environment, but instead, suggest that the negative effects of offline social comparisons on wellbeing (as operationalized here) may in fact be more robust and consequential, with negative effects operating at multiple timescales, and evident within both *between* and *within* participant analyses. Whilst these findings do not rule out the potential for fast-acting negative effects of online social comparisons on wellbeing, or the possibility of other pathways driving purported SM-mental health risks, they do not support reductionistic, broad-sweeping, and catastrophizing narratives around the dangers of SM use, and more specifically, online social comparisons (Orben, 2020). Nonetheless, future research should explore the robustness of such findings across different cultural contexts, as well as the potential for particularly at risk groups.

References

Aalbers, G., McNally, R. J., Heeren, A., de Wit, S., & Fried, E. I. (2019). Social media and depression symptoms: A network perspective. *Journal of Experimental Psychology: General*, *148*(8), 1454–1462. https://doi.org/10.1037/xge0000528

Andrade, F. C., Erwin, S., Burnell, K., Jackson, J., Storch, M., Nicholas, J., & Zucker, N. (2023). Intervening on Social Comparisons on Social Media: Electronic Daily Diary Pilot Study. *JMIR Mental Health*, *10*. https://doi.org/10.2196/42024

Andrews, S., Ellis, D. A., Shaw, H., & Piwek, L. (2015). Beyond Self-Report: Tools to Compare Estimated and Real-World Smartphone Use. *PLOS ONE*, *10*(10), e0139004. https://doi.org/10.1371/journal.pone.0139004

Appel, H., Crusius, J., & Gerlach, A. L. (2015). Social comparison, envy, and depression on facebook: A study looking at the effects of high comparison standards on depressed individuals. *Journal of Social and Clinical Psychology*, *34*(4), 277–289. https://doi.org/10.1521/jscp.2015.34.4.277

Baldwin, M., & Mussweiler, T. (2018). The culture of social comparison. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(39), E9067–E9074. https://doi.org/10.1073/pnas.1721555115

Bewick, B. M., Gina, K., Miles, J., Slaa, E., & Barkham, M. (2010). Changes in undergraduate students' psychological well-being as they progress through university. *Studies in Higher Education*, *35*(6), 633–645.

Beyens, I., Pouwels, J. L., van Driel, I. I., Keijsers, L., & Valkenburg, P. M. (2020). The effect of social media on well-being differs from adolescent to adolescent. *Scientific Reports*, *10*(1), 10763. https://doi.org/10.1038/s41598-020-67727-7

Bocage-Barthélémy, Y., Chatard, A., Jaafari, N., Tello, N., Billieux, J., Daveau, E., & Selimbegović, L. (2018). Automatic social comparison: Cognitive load facilitates an increase in negative thought accessibility after thin ideal exposure among women. *PLOS ONE*, *13*(3), e0193200. https://doi.org/10.1371/journal.pone.0193200

Buunk, A. P., & Dijkstra, P. (2017). Social Comparisons and Well-Being. In M. D. Robinson & M. Eid (Eds.), *The Happy Mind: Cognitive Contributions to Well-Being* (pp. 311–330). Springer International Publishing/Springer Nature.

Buunk, A. P., & Gibbons, F. X. (2007). Social comparison: The end of a theory and the emergence of a field. *Organizational Behavior and Human Decision Processes*, *102*(1), 3–21. https://doi.org/10.1016/j.obhdp.2006.09.007

Clark, J. L., Algoe, S. B., & Green, M. C. (2018). Social Network Sites and Well-Being: The Role of Social Connection. *Current Directions in Psychological Science*, *27*(1), 32–37. https://doi.org/10.1177/0963721417730833

Collins, R. L. (1996). For better or worse: The impact of upward social comparison on self-evaluations. *Psychological Bulletin*, *119*(1), 51–69. https://doi.org/10.1037/0033-2909.119.1.51

Compernolle, E. L., Finch, L. E., Hawkley, L. C., & Cagney, K. A. (2021). Momentary loneliness among older adults: Contextual differences and their moderation by gender and race/ethnicity. *Social Science and Medicine, 285*, 114307. https://doi.org/10.1016/j.socscimed.2021.114307

Corcoran, K., Crusius, J., & Mussweiler, T. (2011). Social comparison: Motives, standards, and mechanisms. In D. Chadee (Ed.), *Theories in social psychology* (pp. 119–139). Wiley-Blackwell.

Cramer, A. O. J., Waldorp, L. J., Van Der Maas, H. L. J., & Borsboom, D. (2010). Comorbidity: A network perspective. *Behavioral and Brain Sciences*, *33*(2–3), 137–150. https://doi.org/10.1017/S0140525X09991567

Cunningham, S., Hudson, C. C., & Harkness, K. (2021). Social Media and Depression Symptoms: a Meta-Analysis. *Research on Child and Adolescent Psychopathology, 49*(2), 241–253. https://doi.org/10.1007/S10802-020-00715-7/FIGURES/4

de Ven, N. van, & Zeelenberg, M. (2020). Envy and Social Comparison. In *Social Comparison, Judgment, and Behavior* (pp. 226–250). Oxford University Press. https://doi.org/10.1093/oso/9780190629113.003.0009

de Vries, D. A., Möller, A. M., Wieringa, M. S., Eigenraam, A. W., & Hamelink, K. (2018). Social Comparison as the Thief of Joy: Emotional Consequences of Viewing Strangers' Instagram Posts. *Media Psychology, 21*(2), 222–245. https://doi.org/10.1080/15213269.2016.1267647

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

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods, 50*(1), 195–212. https://doi.org/10.3758/s13428-017-0862-1

Epskamp, S., Waldorp, L. J., Mõttus, R., & Borsboom, D. (2018). The Gaussian Graphical Model in Cross-Sectional and Time-Series Data. *Multivariate Behavioral Research, 53*(4), 453–480. https://doi.org/10.1080/00273171.2018.1454823

Faelens, L., Hoorelbeke, K., Fried, E., De Raedt, R., & Koster, E. H. W. (2019). Negative influences of Facebook use through the lens of network analysis. *Computers in Human Behavior, 96*, 13–22. https://doi.org/10.1016/j.chb.2019.02.002

Faelens, L., Hoorelbeke, K., Soenens, B., Van Gaeveren, K., De Marez, L., De Raedt, R., & Koster, E. H. W. (2021). Social media use and well-being: A prospective experience-sampling study. *Computers in Human Behavior*, *114*. https://doi.org/10.1016/j.chb.2020.106510

Faranda, M., & Roberts, L. D. (2019). Social comparisons on Facebook and offline: The relationship to depressive symptoms. *Personality and Individual Differences*, *141*, 13–17. https://doi.org/10.1016/j.paid.2018.12.012

Feltman, C. E., & Szymanski, D. M. (2018). Instagram Use and Self-Objectification: The Roles of Internalization, Comparison, Appearance Commentary, and Feminism. *Sex Roles*, *78*(5–6), 311–324. https://doi.org/10.1007/s11199-017-0796-1

Festinger, L. (1954). A Theory of Social Comparison Processes. *Human Relations*, *7*, 117–140.

Gerber, J. P., Wheeler, L., & Suls, J. (2018). A social comparison theory meta-analysis 60+ years on. *Psychological Bulletin*, *144*(2), 177–197. https://doi.org/10.1037/bul0000127

GlobalWebIndex. (2023). *Social - Behind the Seens*.

Gomez-Baya, D., Mendoza, R., Gaspar, T., & Gomes, P. (2018). Responses to positive affect, life satisfaction and self-esteem: A cross-lagged panel analysis during middle adolescence. *Scandinavian Journal of Psychology*, *59*(4), 462–472. https://doi.org/10.1111/SJOP.12450

Harris, M. A., & Orth, U. (2020). The link between self-esteem and social relationships: A meta-analysis of longitudinal studies. *Journal of Personality and Social Psychology*, *119*(6), 1459–1477. https://doi.org/10.1037/pspp0000265

Hoorelbeke, K., Van den Bergh, N., Wichers, M., & Koster, E. H. W. (2019). Between vulnerability and resilience: A network analysis of fluctuations in cognitive risk and protective factors following remission from depression. *Behaviour Research and Therapy*, *116*, 1–9. https://doi.org/10.1016/j.brat.2019.01.007

Johannes, N., Nguyen, T., Weinstein, N., & Przybylski, A. K. (2021). Objective, subjective, and accurate reporting of social media use: No evidence that daily social media use correlates with personality traits, motivational states, or well-being. *Technology, Mind, and Behavior*, *2*(2). https://doi.org/10.1037/tmb0000035

Kaye, L. K. (2022). Social Media and Wellbeing. In *Issues and Debates in Cyberpsychology* (First, pp. 66–77). Open University Press.

Kim, H. H. (2017). The impact of online social networking on adolescent psychological well-being (WB): a population-level analysis of Korean school-aged children. *International Journal of Adolescence and Youth*, *22*(3), 364–376. https://doi.org/10.1080/02673843.2016.1197135

Lee, R. M., Draper, M., & Lee, S. (2001). Social connectedness, dysfunctional interpersonal behaviors, and psychological distress: Testing a mediator model. *Journal of Counseling Psychology*, *48*(3), 310–318. https://doi.org/10.1037/0022-0167.48.3.310

Lei, X. Y., Xiao, L. M., Liu, Y. N., & Li, Y. M. (2016). Prevalence of Depression among Chinese University Students: A Meta-Analysis. *PLoS ONE*, *11*(4). https://doi.org/10.1371/journal.pone.0153454

McCarthy, P. A., & Morina, N. (2020). Exploring the association of social comparison with depression and anxiety: A systematic review and meta-analysis. In *Clinical Psychology and Psychotherapy* (Vol. 27, Issue 5, pp. 640–671). John Wiley and Sons Ltd. https://doi.org/10.1002/cpp.2452

McElroy, E., Tibber, M., Fearon, P., Patalay, P., & Ploubidis, G. B. (2022). Socioeconomic and sex inequalities in parent-reported adolescent mental ill-health: time trends in four British birth cohorts. *Journal of Child Psychology and Psychiatry and Allied Disciplines*, *64*(5). https://doi.org/10.1111/jcpp.13730

McKenzie, N., & Marks, I. (1999). Quick rating of depressed mood in patients with anxiety disorders. *British Journal of Psychiatry*, *174*(MAR.), 266–269. https://doi.org/10.1192/bjp.174.3.266

Meier, A., Gilbert, A., Börner, S., & Possler, D. (2020). Instagram Inspiration: How Upward Comparison on Social Network Sites Can Contribute to Well-Being. *Journal of Communication*, *70*(5), 721–743. https://doi.org/10.1093/joc/jqaa025

Meier, A., & Johnson, B. K. (2022). Social comparison and envy on social media: A critical review. In *Current Opinion in Psychology* (Vol. 45, p. 101302). Elsevier B.V. https://doi.org/10.1016/j.copsyc.2022.101302

Nesi, J., Choukas-Bradley, S., & Prinstein, M. J. (2018a). Transformation of Adolescent Peer Relations in the Social Media Context: Part 1—A Theoretical Framework and Application to Dyadic Peer Relationships. In *Clinical Child and Family Psychology Review* (Vol. 21, Issue 3, pp. 267–294). Springer New York LLC. https://doi.org/10.1007/s10567-018-0261-x

Nesi, J., Choukas-Bradley, S., & Prinstein, M. J. (2018b). Transformation of Adolescent Peer Relations in the Social Media Context: Part 2—Application to Peer Group Processes and Future Directions for Research. In *Clinical Child and Family Psychology Review* (Vol. 21, Issue 3, pp. 295–319). Springer New York LLC. https://doi.org/10.1007/s10567-018-0262-9

Nesi, J., Telzer, E. H., & Prinstein, M. J. (2020). Adolescent Development in the Digital Media Context. In *Psychological Inquiry* (Vol. 31, Issue 3, pp. 229–234). Routledge. https://doi.org/10.1080/1047840X.2020.1820219

Ngai, E. W. T., Tao, S. S. C., & Moon, K. K. L. (2015). Social media research: Theories, constructs, and conceptual frameworks. *International Journal of Information Management*, *35*(1), 33–44. https://doi.org/10.1016/j.ijinfomgt.2014.09.004

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric Theory* (Third). McGraw-Hill.

O'Day, E. B., & Heimberg, R. G. (2021). Social media use, social anxiety, and loneliness: A systematic review. *Computers in Human Behavior Reports*, *3*, 100070. https://doi.org/10.1016/J.CHBR.2021.100070

Opsahl, T., Agneessens, F., & Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks*, *32*(3), 245–251. https://doi.org/10.1016/j.socnet.2010.03.006

Orben, A. (2020). The Sisyphean Cycle of Technology Panics. *Perspectives on Psychological Science*, 174569162091937. https://doi.org/10.1177/1745691620919372

Park, S. Y., & Baek, Y. M. (2018). Two faces of social comparison on Facebook: The interplay between social comparison orientation, emotions, and psychological well-being. *Computers in Human Behavior*, *79*, 83–93. https://doi.org/10.1016/j.chb.2017.10.028

Perlman, D., & Peplau, L. A. (1982). Loneliness research: a survey of empirical findings. In L. A. Peplau & S. E. Goldston (Eds.), *Preventing the Harmful Consequences of Severe and Persistent Loneliness* (First, pp. 13–46). Department of Health and Human Services.

Pomery, E. A., Gibbons, F. X., & Stock, M. L. (2012). Social comparison. In V. S. Ramachandran (Ed.), *Encyclopedia of human behavior* (pp. 463–469). Academic Press.

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

Ruggieri, S., Ingoglia, S., Bonfanti, R. C., & Lo Coco, G. (2021a). The role of online social comparison as a protective factor for psychological wellbeing: A longitudinal study during the COVID-19 quarantine. *Personality and Individual Differences*, *171*, 110486. https://doi.org/10.1016/j.paid.2020.110486

Ruggieri, S., Ingoglia, S., Bonfanti, R. C., & Lo Coco, G. (2021b). The role of online social comparison as a protective factor for psychological wellbeing: A longitudinal study during the COVID-19 quarantine. *Personality and Individual Differences*, *171*, 110486. https://doi.org/10.1016/j.paid.2020.110486

Saiphoo, A. N., Dahoah Halevi, L., & Vahedi, Z. (2020). Social networking site use and self-esteem: A meta-analytic review. *Personality and Individual Differences*, *153*, 109639. https://doi.org/10.1016/J.PAID.2019.109639

Schmuck, D., Karsay, K., Matthes, J., & Stevic, A. (2019a). "Looking Up and Feeling Down". The influence of mobile social networking site use on upward social comparison, self-esteem, and well-being of adult smartphone users. *Telematics and Informatics*, *42*, 101240. https://doi.org/10.1016/J.TELE.2019.101240

Schmuck, D., Karsay, K., Matthes, J., & Stevic, A. (2019b). "Looking Up and Feeling Down". The influence of mobile social networking site use on upward social comparison, self-esteem, and well-being of adult smartphone users. *Telematics and Informatics*, *42*, 101240. https://doi.org/10.1016/J.TELE.2019.101240

Servidio, R., Sinatra, M., Griffiths, M. D., & Monacis, L. (2021). Social comparison orientation and fear of missing out as mediators between self-concept clarity and problematic smartphone use. *Addictive Behaviors*, *122*. https://doi.org/10.1016/j.addbeh.2021.107014

Singelis, T. M., Triandis, H. C., Bhawuk, D. P. S., & Gelfand, M. J. (1995). Horizontal and Vertical Dimensions of Individualism and Collectivism: A Theoretical and Measurement Refinement. *Cross-Cultural Research*, *29*(3), 240–275. https://doi.org/10.1177/106939719502900302

Sirgy, M. J. (2021). Effects of Social Comparisons on Wellbeing. In *The Psychology of Quality of Life. Social Indicators Research Series.* (pp. 321–338). Springer, Cham. https://doi.org/10.1007/978-3-030-71888-6_15

Sivertsen, B., Hysing, M., Knapstad, M., Harvey, A. G., Reneflot, A., Lønning, K. J., & O'Connor, R. C. (2019). Suicide attempts and non-suicidal self-harm among university students: prevalence study. *BJPsych Open*, *5*(2). https://doi.org/10.1192/bjo.2019.4

Storrie, K., Ahern, K., & Tuckett, A. (2010). A systematic review: Students with mental health problems-A growing problem. *International Journal of Nursing Practice*, *16*(1), 1–6. https://doi.org/10.1111/j.1440-172X.2009.01813.x

Tibber, M. S., Milne, G., Fonagy, P., & Dekker, T. M. (2024). The online world as a means of connection and disconnection during the COVID-19 pandemic: A test of the interpersonal-connections-behaviour framework. *Journal of Affective Disorders*, *347*, 533–540. https://doi.org/10.1016/J.JAD.2023.12.006

Tibber, M. S., & Silver, E. (2022). A Trans-Diagnostic Cognitive-Behavioural Conceptualisation of the Positive and Negative Roles of Social Media Use in Adolescents' Mental Health and Wellbeing. *The Cognitive Behaviour Therapist*, *15*(e7).

Tibber, M. S., Wang, M., & Zhang, C. (2022). The Role of Platform Brand in the Association Between Social Media Use, Stress and Educational Attainment. *International Journal of Human–Computer Interaction*, 1–12. https://doi.org/10.1080/10447318.2022.2064035

Tibber, M. S., Zhao, J., & Butler, S. (2020). The association between self-esteem and dimensions and classes of cross-platform social media use in a sample of emerging adults – Evidence from regression and latent class analyses. *Computers in Human Behavior*, *109*, 106371. https://doi.org/10.1016/j.chb.2020.106371

Turel, O., & Qahri-Saremi, H. (2016). Problematic Use of Social Networking Sites: Antecedents and Consequence from a Dual-System Theory Perspective. *Journal of Management Information Systems*, *33*(4), 1087–1116. https://doi.org/10.1080/07421222.2016.1267529

Valkenburg, P. M., Beyens, I., Pouwels, J. L., van Driel, I. I., & Keijsers, L. (2021). Social Media Browsing and Adolescent Well-Being: Challenging the "Passive Social Media Use Hypothesis." *Journal of Computer-Mediated Communication*, *27*(1). https://doi.org/10.1093/jcmc/zmab015

Valkenburg, P. M., Meier, A., & Beyens, I. (2022). Social media use and its impact on adolescent mental health: An umbrella review of the evidence. In *Current Opinion in Psychology* (Vol. 44, pp. 58–68). Elsevier B.V. https://doi.org/10.1016/j.copsyc.2021.08.017

Vanhalst, J., Luyckx, K., Scholte, R. H. J., Engels, R. C. M. E., & Goossens, L. (2013). Low self-esteem as a risk factor for loneliness in adolescence: Perceived - But not actual - Social acceptance as an underlying mechanism. *Journal of Abnormal Child Psychology*, *41*(7), 1067–1081. https://doi.org/10.1007/S10802-013-9751-Y/FIGURES/3

Verduyn, P., Gugushvili, N., Massar, K., Täht, K., & Kross, E. (2020). Social comparison on social networking sites. In *Current Opinion in Psychology* (Vol. 36, pp. 32–37). Elsevier B.V. https://doi.org/10.1016/j.copsyc.2020.04.002

Vogel, E. A., Rose, J. P., Okdie, B. M., Eckles, K., & Franz, B. (2015). Who compares and despairs? The effect of social comparison orientation on social media use and its outcomes. *Personality and Individual Differences*, *86*, 249–256. https://doi.org/10.1016/J.PAID.2015.06.026

Vogel, E. A., Rose, J. P., Roberts, L. R., & Eckles, K. (2014). Social comparison, social media, and self-esteem. *Psychology of Popular Media Culture*, *3*(4), 206–222. https://doi.org/10.1037/ppm0000047

White, K., & Lehman, D. R. (2005). Culture and social comparison seeking: The role of self-motives. *Personality and Social Psychology Bulletin*, *31*(2), 232–242. https://doi.org/10.1177/0146167204271326

Wills, T. A. (1981). Downward comparison principles in social psychology. *Psychological Bulletin*, *90*(2), 245–271. https://doi.org/10.1037/0033-2909.90.2.245

Woerkom, M. van, Constantin, M., Janssens, M., Reijnders, J., Jacobs, N., & Lataster, J. (2022). Networks of happiness: applying a Network Approach to Well-Being in the General Population. *Journal of Happiness Studies*, *23*(7), 3215–3231. https://doi.org/10.1007/S10902-022-00546-X/FIGURES/2

Yang, F.-R., Wei, C.-F., & Tang, J.-H. (2019). Effect of Facebook Social Comparison on Well-being: A Meta-Analysis. *Journal of Internet Technology*, *20*, 1829–1836.

Yoon, S., Kleinman, M., Mertz, J., & Brannick, M. (2019). Is social network site usage related to depression? A meta-analysis of Facebook–depression relations. In *Journal of Affective Disorders* (Vol. 248, pp. 65–72). Elsevier B.V. https://doi.org/10.1016/j.jad.2019.01.026

York, R. (2018). Control variables and causal inference: a question of balance. *International Journal of Social Research Methodology*, *21*(6), 675–684. https://doi.org/10.1080/13645579.2018.1468730

Yue, Z., Zhang, R., & Xiao, J. (2022). Passive social media use and psychological well-being during the COVID-19 pandemic: The role of social comparison and emotion regulation. *Computers in Human Behavior*, *127*, 107050. https://doi.org/10.1016/j.chb.2021.107050

Supplementary Table 1. Chinese translation of items included.

Variable	Items (English)	Items (Chinese)
Social media time	(i) Over the past hour, how many minutes have you spent on social media platforms?	(i)在过去的一小时内，你花了多少分钟在社交媒体平台上？
Face-to-face time	(i) Over the past hour, how many minutes have you spent in the physical presence of others, i.e. at least one other person regardless of whether you interacted with them?	(i)在过去的一小时内，你花了多少分钟在现实生活中与他人在一起（无论你是否与他人有交流）？
Online upward SCs	(i) In the past hour, I have compared myself to others I encountered online who are better off than me.	(i)在过去的一小时内，我将自己和在网络上遇到的比自己更好的人相互比较。
Offline upward SCs	(i) In the past hour, I have compared myself to others I encountered offline who are better off than me.	(i)在过去的一小时内，我将自己和在现实生活中遇到的比自己更好的人相互比较。
Low self-esteem	(i) In the past hour, I have felt insecure.	(i)在过去的一小时内，我缺乏安全感。
	(ii) In the past hour, I have felt positive toward myself (R).	(ii)在过去的一小时内，我对于自己是抱着肯定的态度（R）。
Loneliness	(i) In the past hour, I have felt close to people (R).	(i)在过去的一小时内，我感到与他人亲近（R）。
	(ii) In the past hour, I have felt lonely.	(ii)在过去的一小时内，我感到孤独。
Affect	Please try and rate the separate emotions separately, so that for example a score of zero on happiness means that you are not feeling happy, but does not necessarily mean that you are feeling sad. In the past hour, I have felt…	请对下列情绪进行独立地评分，比如，给"高兴的"选择 0 分意味着你没有感受到高兴，但并不一定意味着你感受到悲伤。在过去的一小时内，我感到:
Positive affect	(i) Happy.	(i) 高兴的。
	(ii) Satisfied.	(ii) 满意的。
	(iii) Energetic.	(iii) 精神充沛的。
Negative affect	(i) Angry.	(i) 生气的。
	(ii) Tense.	(ii) 紧张的。
	(iii) Sad.	(iii)悲伤的。
	(iv) Anxious.	(iv) 焦虑的。

Supplementary Table 2. Effects are shown for the contemporaneous network. Partial and first-order correlation coefficients and associated standard deviations (SD) are shown for all significant effects. Non-significant effects are not shown.

Variable 1	Variable 2	P value	Partial correlation (SD)	Correlation (SD)
Negative affect	Positive affect	<0.001	-0.13 (0.15)	-0.26 (0.22)
Online comparisons	Social media	<0.001	0.07 (0.06)	0.07 (0.07)
Online comparisons	Face-to-face	0.01	-0.04 (0.03)	-0.03 (0.05)
Offline comparisons	Face-to-face	<0.001	0.08 (0.02)	0.07 (0.04)
Offline comparisons	Positive affect	<0.01	0.05 (0.04)	-0.001 (0.12)
Offline comparisons	Negative affect	<0.001	0.13 (0.09)	0.17 (0.15)
Offline comparisons	Online comparisons	<0.001	0.19 (0.19)	0.21 (0.22)
Low self-esteem	Positive affect	<0.001	-0.21 (0.1)	-0.22 (0.18)
Low self-esteem	Negative affect	<0.001	0.25 (0.15)	0.35 (0.2)
Low self-esteem	Online comparisons	<0.001	0.12 (0.1)	0.17 (0.16)
Low self-esteem	Offline comparisons	<0.001	0.09 (0.13)	0.14 (0.2)
Loneliness	Face-to-face	<0.001	-0.18 (0.06)	-0.21 (0.09)
Loneliness	Positive affect	<0.001	-0.31 (0.09)	-0.4 (0.12)
Loneliness	Negative affect	<0.001	0.08 (0.02)	0.21 (0.13)
Loneliness	Low self-esteem	<0.001	0.14 (0.1)	0.28 (0.17)

Supplementary Table 3. Significant edges are shown for the temporal network (with a lag of one). Edge weight=fixed effects coefficients; SE=standard error of fixed effects.

From	To	Edge Weight (SE)	P value
Social media	Social media	0.09 (0.02)	<0.001
Face-to-face	Face-to-face	0.15 (0.02)	<0.001
Positive affect	Positive affect	0.29 (0.02)	<0.001
Positive affect	Offline comparisons	0.04 (0.02)	0.01
Positive affect	Loneliness	-0.08 (0.02)	<0.001
Negative affect	Negative affect	0.27 (0.02)	<0.001
Negative affect	Offline comparisons	0.1 (0.02)	<0.001
Negative affect	Low self-esteem	0.09 (0.02)	<0.001
Negative affect	Loneliness	0.03 (0.02)	0.04
Online comparisons	Online comparisons	0.13 (0.02)	<0.001
Online comparisons	Positive affect	0.04 (0.02)	0.02
Online comparisons	Negative affect	-0.03 (0.01)	0.04
Online comparisons	Offline comparisons	0.05 (0.02)	0.001
Offline comparisons	Offline comparisons	0.14 (0.02)	<0.001
Offline comparisons	Social media	0.04 (0.02)	0.02
Offline comparisons	Face-to-face	-0.04 (0.02)	<0.05
Offline comparisons	Negative affect	0.04 (0.02)	0.02
Offline comparisons	Online comparisons	0.06 (0.02)	0.001
Offline comparisons	Low self-esteem	0.04 (0.01)	<0.01
Offline comparisons	Loneliness	0.04 (0.02)	0.02
Low self-esteem	Low self-esteem	0.16 (0.02)	<0.001
Low self-esteem	Negative affect	0.03 (0.02)	0.04
Loneliness	Loneliness	0.16 (0.02)	<0.001
Loneliness	Face-to-face	-0.04 (0.02)	0.01

Supplementary Table 4. Effects are shown for the between-subjects network. Partial correlation coefficients and associated standard deviations (SD) are shown for all significant effects. Non-significant effects are not shown.

Variable 1	Variable 2	P value	Partial correlation	Correlation
Offline comparisons	Negative affect	0.002	0.35	0.93
Offline comparisons	Face-to-face	0.02	0.26	-0.39
Offline comparisons	Online comparisons	<0.001	0.78	0.97
Low self-esteem	Negative affect	<0.001	0.69	0.97
Loneliness	Face-to-face	0.001	-0.36	-0.56
Loneliness	Positive affect	<0.001	-0.56	-0.75
Loneliness	Low self-esteem	0.002	0.33	0.88
Positive affect	Face-to-face	<0.05	-0.22	0.29

Supplementary Table 5. Indices of node centrality for the contemporaneous network. Bold indicates strongest node/s in the network.

	Degree	Closeness	Betweenness
Social media	0.07	0.006	0
Face-to-face	0.3	0.009	0
Positive affect	0.7	0.013	4
Negative affect	0.59	0.012	2
Online comparisons	0.42	0.012	12
Offline comparisons	0.52	0.011	4
Low self-esteem	**0.81**	**0.014**	**14**
Loneliness	0.71	0.011	6

Supplementary Table 6. Indices of node centrality for the temporal network. Bold indicates strongest node/s in the network.

	In degree	Out degree	Closeness	Betweenness
Social media	0.03	0	0	0
Face-to-face	0.07	0	0	0
Positive affect	0.04	0.12	0.004	1
Negative affect	0.11	0.22	0.005	6
Online comparisons	0.06	0.12	0.004	3
Offline comparisons	**0.19**	**0.25**	**0.005**	**15**
Low self-esteem	0.13	0.03	0.002	0
Loneliness	0.15	0.04	0	1

Supplementary Table 7. Indices of node centrality for the between-subjects network. Bold indicates strongest node/s in the network.

	Degree	Closeness	Betweenness
Social media	0	0	0
Face-to-face	0.83	0	8
Positive affect	0.77	0	0
Negative affect	1.03	0	4
Online comparisons	0.78	0	0
Offline comparisons	**1.38**	0	**12**
Low self-esteem	1.03	0	4
Loneliness	1.25	0	**12**