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No Relationships Between Self-Reported Instagram Use or Type of Use and Mental Well-Being: A Study Using a Nationally Representative Online Sample of UK Adults

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Abstract

Use of Instagram has grown rapidly in the last decade, but the effects of Instagram use on well-being are still unclear, with many studies based on younger samples with a female bias. The aim of this study was to examine the associations between Instagram use and levels of anxiety, depression, and loneliness in a nationally representative sample of UK adults by age and gender. An online sample of 498 UK adults were recruited using Prolific (Age: M = 49, SD = 15, range 19–82 years old; 52% female, 47% male). Participants stated whether or not they used Instagram, reported their frequency of Broadcast, Interaction and Browsing Instagram use and completed the Revised UCLA Loneliness Scale, and the Hospital Anxiety and Depression Scale. A genetic matching algorithm was used to match Instagram users (n = 372) and non-Instagram users (n = 100) on age, gender, education and nationality. There were no significant differences between users versus non-users of Instagram in levels of anxiety, depression or loneliness. There were also no significant associations between type of Instagram use (Broadcast, Interaction or Browsing) and levels of anxiety, depression or loneliness. The Bayes Factors for these models moderately to strongly supported the null model of no effect for Depression and Loneliness. This research adds to recent findings that suggests that the overall effect of SNSs on well-being may be small to non-existent. Future research should examine how exposure to different types of content on social media are related to well-being.

Keywords: loneliness; depression; anxiety; social media; Instagram; passive social media use; active social media use

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Introduction

The rise in popularity of social network sites (SNSs) over the last two decades has led to active debates about whether using SNSs has a positive or negative effect on well-being in both academic research (e.g., Appel et al., 2020; Faelens et al., 2021; Orben, 2020b; Twenge et al., 2022) and wider society (e.g., Haidt, 2021; Lanier, 2018; Orben, 2020a; Twenge, 2017a, 2017b). SNSs such as Facebook, Instagram, Twitter and TikTok are defined as web-based services that allow people to construct a profile, build a list of users with whom they have a connection and view their list of connections and those made by others (boyd & Ellison, 2007), as well as post and consume usergenerated content and exchange messages with others. Some research has found SNSs to have a positive impact on well-being. For example, Facebook can facilitate social connections and communication with others, leading to lower feelings of loneliness (Burke & Kraut, 2016; Burke et al., 2010; Lin et al., 2020; Liu et al., 2016). Further, posting and commenting on Instagram during the COVID-19 pandemic was positively associated with satisfaction with life (Masciantonio et al., 2021). However, other researchers argue that overall, using SNSs has a negative impact on the well-being of users (e.g., Twenge et al., 2022), in relation to aspects such as depression (Huang, 2017), anxiety (O'Day & Heimberg, 2021), loneliness (Huang, 2017; Liu & Baumeister, 2016; O'Day & Heimberg, 2021) or body image (Fardouly & Vartanian, 2016; Saiphoo & Vahedi, 2019). These negative effects may arise due to a number of different processes, including replacement of face-to-face communication with SNSs use which may lead to feelings of loneliness (Liu et al., 2019; Twenge et al., 2019). Further, upwards social comparison with other users' idealised posts may lead to feelings of anxiety or depression (Reer et al., 2019), or decreased body dissatisfaction due to viewing idealised body images (Brown & Tiggemann, 2016; Vandenbosch et al., 2022). Finally, other researchers argue that the overall effect of SNSs on well-being is negative but relatively small (Appel et al., 2020; Orben, 2020b), or non-existent (Coyne et al., 2020). As different SNSs have different user bases and characteristics, the effect of SNSs on well-being is likely to vary across both social media platforms (Masciantonio et al., 2021) and type of use (Burke & Kraut, 2016). Given the mixed research picture, there is therefore a need for research focused on how specific SNSs platforms and different types of use influence different aspects of well-being.

Instagram Use and Mental Well-Being

Instagram is a SNS that has grown rapidly over the last decade, launching in 2010 and reaching 2 billion active monthly users in 2021 (Dixon, 2022c). Instagram enables users to share image-based content (e.g., photos and videos) accompanied by text, and is especially popular among adolescents and young adults, with 70.8% of users under 35 (Dixon, 2022b). Thus, whilst much of the earlier research on well-being and SNSs focused on Facebook (Song et al., 2014; Yoon et al., 2019), more recently there has been an increased focus on the links between Instagram use and well-being (Faelens et al., 2021). Both correlational (e.g., Hendrickse et al., 2017) and experimental (e.g., Brown & Tiggemann, 2016) research suggests Instagram can have a negative impact on users' body image, through the mechanism of upwards social comparison to other users (Faelens et al., 2021). However, the research evidence for other aspects of well-being such as loneliness, depression and anxiety is inconclusive, with negative (e.g., Sherlock & Wagstaff, 2019), positive (e.g., Mackson et al., 2019) and no effects (e.g., Fardouly et al., 2020) of using Instagram reported in different studies (see Faelens et al., 2021 for a review). This may partly be due to the different research designs used, with some research comparing users versus non-users of Instagram, with other studies focusing on different types of Instagram use.

To examine whether overall use of Instagram is associated with well-being, some research has compared levels of anxiety, depression and/or loneliness in people who use Instagram to people who do not use Instagram, with inconsistent results (Table 1). Some studies have found no significant effect on Instagram use on well-being (Brailovskaia & Margraf, 2018; Fardouly et al., 2020), whilst others have found a positive effect of Instagram use on well-being (Mackson et al., 2019; Pittman & Reich, 2016; Umegaki & Higuchi, 2022). However, none of these studies used a representative sample of the population and some did not account for demographic differences between Instagram users compared to non-users. Therefore, the effects of using versus not using Instagram on loneliness, anxiety and depression are still unclear.

In addition to research focusing on users versus non-users of Instagram, another body of research has examined how different types of Instagram use affects well-being, including duration of time spent on Instagram, number and type of followers, and exposure to different types of Instagram images (Faelens et al., 2021). A key distinction in this research has been between "active" and "passive" Instagram use. Active Instagram use involves users posting content, and interacting publicly or privately with other users, whilst passive use involves simply browsing through the newsfeed (Yang, 2016). Early research on Facebook suggests that whilst active use helped build social connections and was therefore associated with higher levels of well-being (e.g., lower levels of loneliness), passive use was associated with lower levels of well-being as it induced social comparison (Burke & Kraut, 2016), although later research has found more inconsistent results (Valkenburg, van Driel, et al., 2022). Similarly, research focusing on active versus passive use of Instagram has found inconsistent results, with a longitudinal study suggesting that browsing at Time 1 was related to increases in depression at Time 2, with depression at Time 1 related to increases in posting at Time 2 (Frison & Eggermont, 2017). There is no strong evidence for a consistent association between

Instagram use and anxiety, with little research specifically focused on whether type of use is associated with anxiety (Faelens et al., 2021). Finally, Yang (2016) found that Instagram Interaction and Browsing were related to lower levels of loneliness, with Broadcasting associated with higher levels of loneliness. Therefore, there is little consensus on how different types of use of Instagram use are associated with anxiety, depression and loneliness (Valkenburg, van Driel, et al., 2022), with a recent systematic review calling for more research in this area (Faelens et al., 2021).

Table 1. *Summary Table of Selected Studies Comparing Levels of Anxiety, Depression and Loneliness in Instagram Users vs. Non-Instagram Users. The Results for the Current Study Are Also Summarised in This Table*.

Study	*n* users	*n* non-users	Mean age	Matched sample	Representative sample by country	Country	Measures of well-being	Statistically significant difference ($p < .05$) between users and non-users of Instagram
(Fardouly et al., 2020)	190	332	11	No	No	Australia	Social Anxiety (SCAS) Depression (SMFQ)	No No
(Mackson et al., 2019)	157	47	25	No	No	Not reported	Anxiety (STAI) Depression (CES-D) Loneliness (UCLA-V3)	Yes—positive Yes—positive Yes—positive
(Brailovskaia & Margraf, 2018)	251	382	22	No	No	Germany	Depression (DASS) Anxiety (DASS)	No No
(Pittman & Reich, 2016)[a]	101	152	23	No	No	United States	Loneliness (UCLA-3)	Yes—positive
(Umegaki & Higuchi, 2022)	715	315	21	No	No	Japan	Anxiety (GAD-7) Depression (PHQ-9)	Yes—positive No
(Sarman & Tuncay, 2023)	865	311	13–18	No	No	Turkey	Loneliness (R-UCLA, Turkish translation)	No
Current study	372	100	49	Yes	Yes	United Kingdom	Anxiety (HADS) Depression (HADS) Loneliness (R-UCLA)	No No No

Note. Positive refers to Instagram use having a positive effect on levels of anxiety, depression or loneliness, in that Instagram users have significantly lower levels of these traits as compared to non-Instagram users. Mean age is provided in years. SMFQ: Short Mood and Feelings Questionnaire. SCAS: Spence Children's Anxiety Scale. STAI: State Trait Anxiety Inventory. CES-D: Centre for Epidemiologic Studies Depression Scale. DASS: Depression, Anxiety and Stress Scale. HADS: Hospital Anxiety and Depression Scale. R-UCLA: Revised UCLA Loneliness Scale. UCLA-3: Three Item Loneliness Scale. GAD-7: General Anxiety Disorder-7. PHQ-9: Patient Health Questionnaire 9. [a] This paper combined users of Snapchat and Instagram and compared them to non-users of these two platforms.

Rationale for Current Study

Given these inconsistent findings in previous research, the aims of this study were: i) To compare a matched sample of users versus non-users of Instagram on levels of anxiety, depression and loneliness; ii) To examine how Instagram Interaction, Browsing and Broadcast are associated with levels of anxiety, depression and loneliness among Instagram users. This extends previous research in this area in three key ways. First, many previous studies examining Instagram use have used student or convenience samples, focusing on young adults aged 18–30 with a female bias (Faelens et al., 2021). However, Instagram is used by all ages and genders, and has approximately 580 million users over the age of 35 (Dixon, 2022b). It is therefore important to examine the effects of Instagram on well-being in a broader sample. In this study, we use a large online sample of UK adults that is nationally representative by age and gender to enable broader generalisations to be made about the effect of Instagram on well-being. Based on Instagram advertising data, in January 2023 the UK had 29 million Instagram users (Dixon, 2023). Therefore examining how Instagram use is associated with well-being in UK adults is an important issue.

Second, previous research comparing users versus non-users of Instagram (Table 1) has tended to rely on small samples of non-users and has not used matched samples, meaning differences in well-being may be due to differences in the demographics of the two samples (e.g., age differences), rather than Instagram use itself. In this study, we compare a sample of participants who stated that they used Instagram to a sample of non-users matched by age, gender and educational status. Finally, given the small or non-existent effects of Instagram use on well-being found in some previous studies (Appel et al., 2020; Coyne et al., 2020; Orben, 2020b), it is important to examine the strength of evidence for the null hypothesis, in addition to examining if there are statistically significant associations between Instagram use and well-being. In this study, we use Bayes Factors to compare the evidence for the null hypothesis (no effect of Instagram use on well-being) as compared to the alternative hypotheses (an effect of Instagram use on well-being; Dienes, 2016). This enables a more robust test of the effect of Instagram on well-being, compared to previous studies which have focused on statistical significance (*p* values) and thus cannot provide evidence for the null hypothesis (Dienes, 2016). Given the inconsistent research in this area, with positive, negative, and non-significant associations between SNSs use and indicators of well-being, we did not make directional hypotheses. Instead, in a design pre-registered on the Open Science Framework, OSF (https://osf.io/m7w5d), we examined the associations between use vs. non-use of Instagram, and type of use of Instagram, on loneliness, anxiety and depression. Specifically, we examined the following research questions:

RQ1: Are there significant differences on levels of anxiety, depression and loneliness Instagram users, as compared to a matched sample of non-Instagram users?

RQ2: Are levels of anxiety associated with frequency of Instagram Interaction, Browsing or Broadcast behaviour?

RQ3: Are levels of depression associated with frequency of Instagram Interaction, Browsing or Broadcast behaviour?

RQ4: Are levels of loneliness associated with frequency of Instagram Interaction, Browsing or Broadcast behaviour?

Methods

Participants

We used a crowd-sourcing website, http://www.prolific.co to request a sample of 500 UK-based adults whose age and gender were nationally representative of the UK. Prolific is a platform that enables participants to complete surveys for monetary reward, and researchers to recruit participants for a fee based on the number of participants and type of sample. There were 498 complete responses (self-reported gender: 257 women, 236 men, 2 neither male nor female, 3 non-disclosures). Of the 498 participants. 438 reported that they had British nationality. Three participants chose not to provide their age. These are excluded for analyses with age. For the remaining participants, the ages ranged from 19 to 82 years (M = 49.15, SD = 15.53). 289 out of 498 participants indicated that they had completed at least a Bachelor level degree and 375 out of 498 participants indicated that they used Instagram. Participants were paid £3.35 for completing the survey.

Measures

Loneliness

To measure loneliness, we used the Revised UCLA Loneliness scale (UCLA-R; Russell et al., 1980), which is one of the most widely used loneliness scales in this research area (Huang, 2017; O'Day & Heimberg, 2021). The R-UCLA is a 20-item scale with positively (e.g., *There are people I feel close to*) and negatively (e.g., *I feel left out*) worded items. Participants indicated how often they felt the way described in each of the items on a 4-point Likert scale (*Never, Rarely, Sometimes, Often*). Positively worded items were reverse scored, and items were averaged to produce a total score of 1–4, with higher scores indicating higher levels of loneliness. The R-UCLA showed excellent reliability (Cronbach's α = .94). As some research has suggested that the R-UCLA scale has a multidimensional structure (e.g., Hawkley et al., 2005), we also examined the reliability of the three subscales identified in this research. These showed adequate to good reliability: Collective Connectedness (α = .77), Isolation (α = .92), Relational Connectedness: (α = .89).

Anxiety and Depression

We used the Hospital Anxiety and Depression (HADS) scale to measure levels of anxiety and depression (Zigmond & Snaith, 1983). As with the R-UCLA, the HADS is one of the most widely used scales in this research area (Appel et al., 2020; Faelens et al., 2021), enabling our results to be compared to previous research. The HADS is a 14-item scale, with 7 items relating to anxiety (e.g., *Worrying thoughts go through my mind*) and 7 items related to depression (e.g., *I still enjoy the things I used to enjoy*). Participants indicated how often they have been feeling the way described in the items in the last week on a 4-point Likert scale that varies between the items (e.g., *Most of the time, A lot of the time, From time to time, Not at all*). Positively worded items were reverse scored, and items were averaged separately for anxiety and depression, with scores ranging from 0–3 and higher scores indicating higher feelings of depression or anxiety. Anxiety (α = .87) and depression (α = .83) both showed good levels of reliability.

Instagram Use Scale

We defined being an Instagram user based on a Yes/No question (*Do you use Instagram?*). For Instagram users, we used the Yang (2016) scale to measure three key types of Instagram use—Interaction, Broadcast and Browsing. Interaction and Broadcast are "active" use of Instagram as they involve either communication with others, or posting content. Browsing is "passive" use as it relates to just browsing through the newsfeed without interacting with anyone or leaving any comments. The scale consists of two items measuring Interaction (*Comment on or reply to other's posts; Tag others in your posts or comments*), two items measuring Broadcast (*Post/upload on your profile without tagging anyone; Post something that is not directed to specific people*), and two items measuring Browsing (*Browse the homepage/newsfeed without leaving comments; Check out others profiles without leaving comments*). The original version of the scale (Yang, 2016) measured frequency of different types of Instagram activity using a 5-point Likert scale (1 = *Never*, 5 = *A lot*), but this relies on the participants subjective judgment about, for example, what is "a lot" of a specific Instagram activity. We therefore asked participants how frequently they engaged in each activity on a 1–10 scale based on specific frequencies (1 = *Never*; 2 = *Once a month*; 3 = *Several times a month*; 4 = *Once a week*; 5 = *Several times a week*; 6 = *Once a day*, 7 = *Several times a day*; 8 = *Once an hour*; 9 = *Several times an hour*; 10 = *All the time*). Items were averaged for Interaction, Broadcast and Browsing separately, producing a total of 1–10 for each subscale, with higher scores indicating more frequent Instagram activity. The reliability was acceptable for Interaction (Cronbach's α = 0.75), and good for Browsing (α = .81) and Broadcasting (α = .83), with lower alphas expected given there were only two items in each subscale (Cortina, 1993).

As we modified the anchors and given that the Yang (2016) scale has not been widely validated, we also examined the factor structure via exploratory factor analysis, with "varimax" rotation and the minimum residuals method (Revelle, 2015). Parallel analysis suggested three factors (Horn, 1965) as did the Very Simple Structure procedure (Revelle & Rocklin, 1979). These three factors explain 72% of total variance. These three factors correspond to the items relating to Interaction, Browsing and Broadcast, supporting the use of these separate type of Instagram activities in our analysis. It should be noted though that the Velicer MAP tests suggested 2 factors (Velicer, 1976).

Procedure

We recruited participants using Prolific, a survey platform which advertises studies to potential eligible participants. This study was part of a larger online egocentric social network study. The full study protocol was preregistered on the OSF (https://osf.io/twjup). Participants followed an online link to the survey which was completed in Graphical Ego-centered Network Survey Interface (GENSI) software (Stark & Krosnick, 2017; Stulp, 2021) to allow the collection of social network data. Participants were presented with an information sheet, provided demographic information (age, gender, level of educational attainment), and then provided information about their social network using the graphical interface. We did not include any analysis of this social network information in the current paper. Participants then completed the UCLA-R (Russell et al., 1980), the HADS (Zigmond & Snaith, 1983), and the Instagram scale (Yang, 2016). At the end of the study, participants were provided with a debrief sheet. The data was collected between 13th and 15th March 2020. The first restrictions on work, travel and socialising due to the COVID-19 pandemic were introduced in the UK on 23rd March 2020 (Walker, 2020). Participants therefore completed the study before any COVID restrictions were in place in the UK.

Ethics

We received ethical approval for the study from the local ethics committee (Faculty of Health and Life Sciences, Northumbria University). We ensured anonymity of participants by not collecting any information that could identify individual participants such as email or IP addresses. Participants indicated their informed consent to take part in the study by a tick box on the questionnaire. We provided participants with a debrief sheet with support information after they had completed the survey.

Statistical Analysis

The analyses were conducted in R 4.0.2 (R Development Core Team, 2008). One participant had a response missing for a single item on the UCLA-R loneliness scale (Russell et al., 1980). For this one participant, we produced the total score for the scale by averaging across 19 rather than 20 items. We used a genetic matching algorithm to match Instagram users and non-Instagram users on age, gender, education and nationality via a Nearest Neighbour Method (Tables 1 and 2; Ho et al., 2007, 2011). Genetic matching uses multivariable matching to determine the weight each covariate is given in creating matched samples (Diamond & Sekhon, 2013). We used this approach to matching to reduce the effects of confounding in our observational data (Austin, 2011). This creates a powerful test for the research questions: if any potential confound was strongly related to any of the covariates, then its impact would be greatly reduced. It also implies that we no longer need to examine these covariates. This procedure allowed us to match 372 Instagram users to 100 non-users on age, education, gender and nationality, and provided weights to be used for an Ordinary Least Squares (OLS) model (see Supplementary Information in the Open Science Framework, OSF, https://osf.io/9xvfw/). We used raincloud plots (Allen et al., 2019) implemented in R 4.0.2 (R Development Core Team, 2008) for Figures 1, 2 and 3.

For Instagram users, we build further hierarchical OLS regressions. For this analysis, we used all participants who reported that they used Instagram, giving a sample size of 375 participants, rather than the 372 Instagram users who formed the matched sample. In the first step, we examine the bivariate relationships between types of Instagram use and anxiety, depression and loneliness. Next, we considered gender, age, nationality and education, as control variables, as these variables could relate to anxiety, depression and loneliness (Barreto et al., 2021; Bucher et al., 2018; Rajapaksa & Dundes, 2002; Sawir et al., 2008; Wu et al., 2015). To maximise the sample size and ensure we did not exclude participants based on their demographic characteristics, we included all participants even when the number of participants in specific groups (e.g., non-binary or "prefer not to answer" for gender) was small. For education and gender, we used dummy coding to allow these categorical variables to be entered into the regression.

We also calculate Bayes Factors (BF) which allow weighing evidence for the null model vs. hypothesised model (Dienes, 2016; Morey et al., 2015). Many rules of thumb for the interpretation of BFs exist (Jarosz & Wiley, 2014). Here, we rely on qualifications for evidence by Jeffreys (1961): BF = 1 – No evidence, 1 < BF <= 3 – Anecdotal, 3 < BF <= 10 – Moderate, 10 < BF <= 30 – Strong, 30 < BF <= 100 – Very strong, BF > 100 – Extreme.

In the main analysis presented in the paper, we treated the UCLA-R loneliness scale (Russell et al., 1980) as having a unidimensional structure. Given that some research suggests a multidimensional structure for this scale (Hawkley et al., 2005; Pollet et al., 2022), we also repeated all the analyses using three loneliness subscales identified in previous research: Collective Connectedness, Isolation and Relational Connectedness (Hawkley et al., 2005). The analyses using these three subscales showed the same pattern of statistical significance as when the UCLA-R was analysed as a unidimensional scale. We therefore report the analyses based on three subscales, along with additional analyses (e.g., assumptions checks) and the data in the Supplementary Information in the OSF (https://osf.io/9xvfw/).

Results

Instagram Users Versus Non-Users Do Not Vary in Levels of Anxiety, Depression or Loneliness

There were no statistically significant bivariate correlations between being a user versus non-user of Instagram and levels of anxiety, depression or loneliness (Table 2, Figures 1, 2 and 3). Instagram users were significantly younger than non-users. Younger participants had significantly higher levels of anxiety and loneliness.

Table 2. *Descriptive Statistics and Bivariate Pearson's Correlations for Instagram Use, Anxiety, Depression, Loneliness and Participant Age.*

Variable	*M*	*SD*	1	2	3	4
1. Instagram user						
2. Anxiety	1.09	0.66	.04 [−.05, .12]			
3. Depression	0.79	0.58	−.04 [−.12, .05]	.66** [.60, .70]		
4. Loneliness	2.26	0.56	−.00 [−.09, .08]	.52** [.45, .58]	.66** [.60, .70]	
5. Age	44.92	15.53	−.24** [−.32, −.15]	−.21** [−.29, −.13]	−.08 [−.16, .01]	−.14** [−.22, −.05]

Note. Instagram use was coded as 0 = *Nonuser*, 1 = *User*. M and SD refer to mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates $p < .05$, ** indicates $p < .01$.

Figure 1. *Raincloud Plots Showing Boxplot and Distribution of Scores for Levels of Anxiety in Instagram Users (n = 372) and Instagram Non-Users (n = 100).*

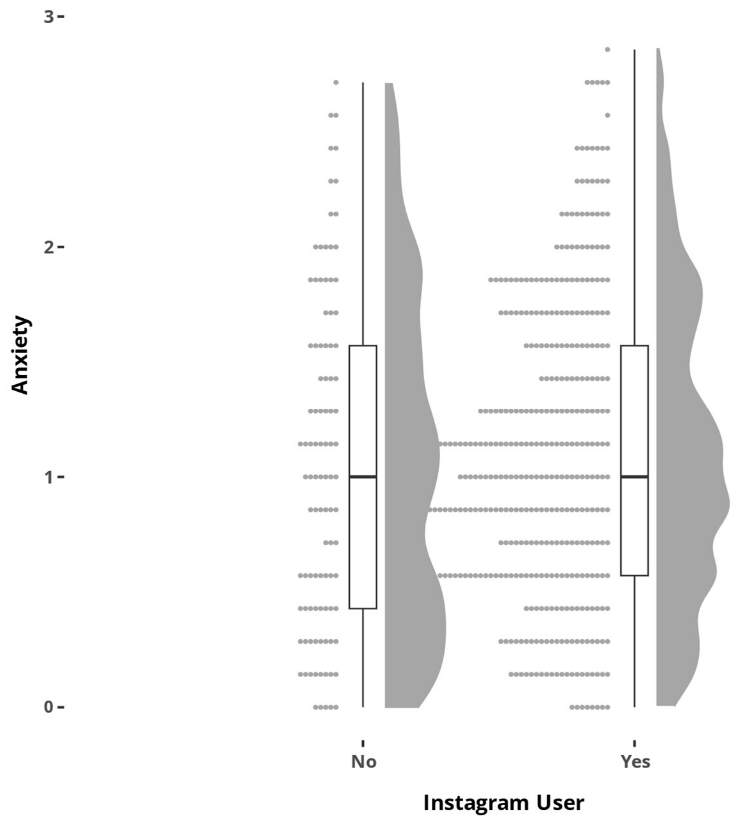

Figure 2. *Raincloud Plots Showing Boxplots and Distribution of Scores for Levels of Depression in Instagram Users (n = 372) and Instagram Non-Users (n = 100).*

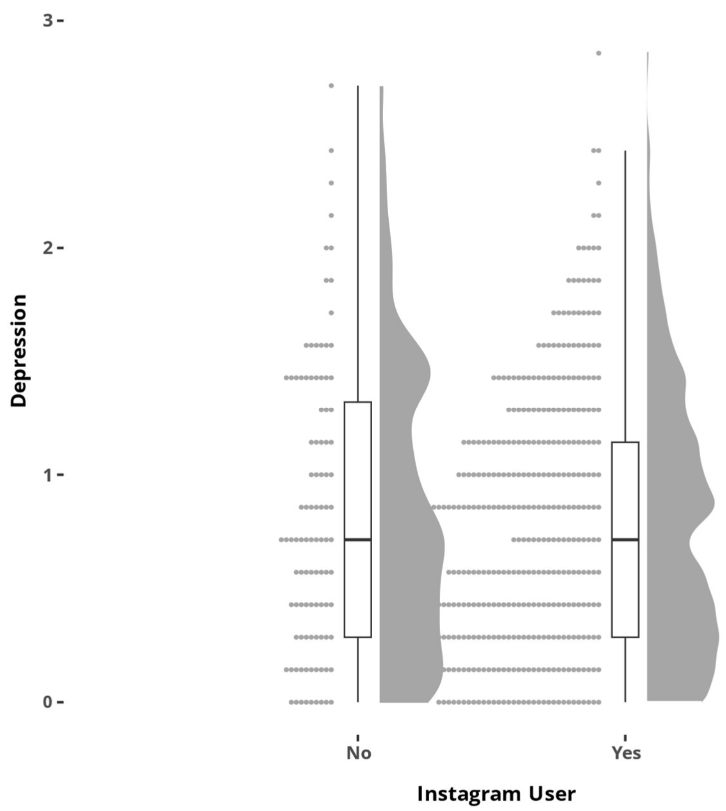

Figure 3. *Raincloud Plots Showing Boxplots and Distribution of Scores for Levels of Loneliness in Instagram Users (n = 372) and Instagram Non-Users (n = 100).*

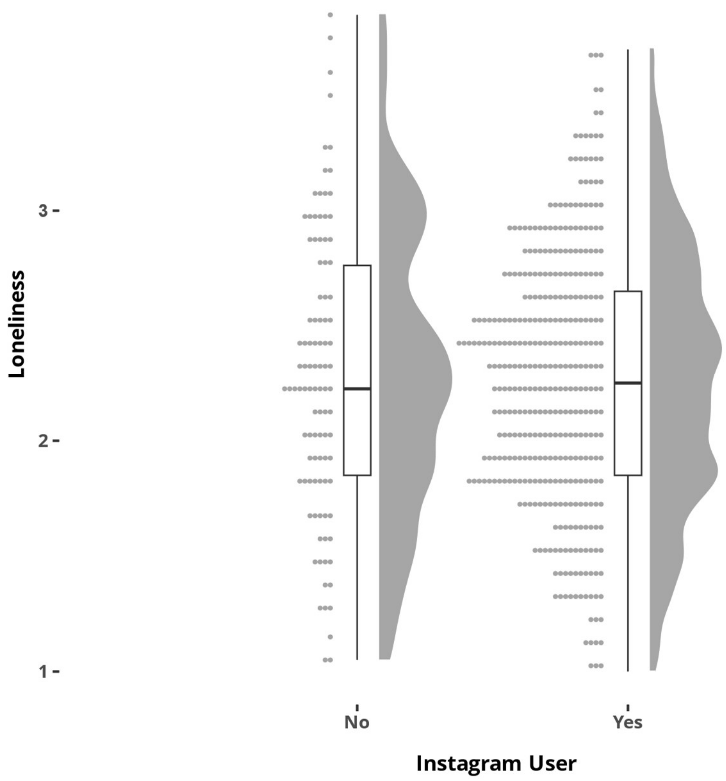

Table 3 shows the results for weighted OLS regressions. Instagram usage did not significantly predict anxiety (Model 1), depression (Model 2) or loneliness (Model 3). The signs of the coefficient suggest that, if anything, Instagram users are less anxious, depressed and lonely than non-users. Bayes Factors suggested support for the null model versus a model containing Instagram use with factors of 9.41 for anxiety, 4.01 for depression and 3.08 for loneliness. This suggests moderate support against the hypothesis that being an Instagram user compared to a non-user is related to mental well-being.

Table 3. *Weighted OLS Regression Models for Matched Instagram Users and Non-Users*.

	Anxiety	Depression	Loneliness
	Model 1	Model 2	Model 3
Instagram User	−0.020 (0.074)	−0.087 (0.064)	−0.095 (0.062)
Constant	1.129*** (0.066)	0.862*** (0.057)	2.357*** (0.055)
N	472	472	472
R^2	.0002	.004	.005
Adjusted R^2	−.002	.002	.003
Residual Std. Error (df = 470)	0.655	0.567	0.548
F Statistic (df = 1; 470)	0.073	1.848	2.393

Note. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Type of Instagram Use Is Not Associated With Levels of Anxiety, Depression or Loneliness

In the next set of analyses, we focused on Instagram users (n = 375) and examined the associations between type of Instagram use and levels of anxiety, depression and loneliness. We first used bivariate Pearson's correlations to examine the associations between variables. There was a significant, positive correlation between levels of anxiety and the frequency of both Instagram Browsing and Instagram Broadcast behaviour (Table 4). The frequency of Instagram Interaction, Browsing and Broadcast were not significantly correlated with levels of depression or loneliness.

Table 4. *Bivariate Pearson's Correlations and Descriptive Statistics for Instagram Interaction, Instagram Browsing, Instagram Broadcast, Anxiety, Depression, Loneliness and Participant Age*.

Variable	*M*	*SD*	1	2	3	4	5	6
1. Interaction	3.32	2.07						
2. Browsing	5.65	2.59	.28** [.18, .37]					
3. Broadcast	3.03	2.23	.38** [.29, .46]	.30** [.20, .39]				
4. Anxiety	1.11	0.65	.09 [−.01, .19]	.17** [.07, .26]	.14** [.03, .23]			
5. Depression	0.78	0.56	.02 [−.08, .12]	.05 [−.06, .15]	.05 [−.06, .15]	.64** [.57, .70]		
6. Loneliness	2.26	0.55	−.01 [−.11, .10]	.05 [−.05, .15]	.06 [−.05, .16]	.52** [.44, .59]	.66** [.60, .71]	
7. Age	42.77	15.35	−.12* [−.22, −.01]	−.42** [−.50, −.33]	−.14** [−.23, −.03]	−.21** [−.31, −.12]	−.08 [−.18, .02]	−.12* [−.22, −.02]

Note. *M* and *SD* refer to mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates $p < .05$. ** indicates $p < .01$.

In the OLS regressions, only Browsing was significantly related to Anxiety (Table 5, Model 1). This effect was still present after adjusting for gender (Model 2). However, after adjusting for age (Model 3), there was no longer any support for a significant association between Browsing and Anxiety (p = .364). Therefore, overall, the results do not demonstrate a significant association between Browsing and Anxiety after controlling for demographic variables. In the final Model 5, younger participants, and women (compared to men) had significantly higher levels of anxiety.

Table 5. *OLS Regressions for Anxiety. Coefficients and Standard Errors.*

	Anxiety				
	Model 1	Model 2	Model 3	Model 4	Model 5
Interaction	0.008 (0.018)	0.005 (0.017)	0.004 (0.017)	0.004 (0.017)	0.003 (0.017)
Browsing	0.033* (0.014)	0.032* (0.013)	0.013 (0.015)	0.013 (0.015)	0.013 (0.015)
Broadcasting	0.025 (0.016)	0.026 (0.016)	0.026 (0.016)	0.025 (0.016)	0.026 (0.016)
Gender: Male		−0.180** (0.066)	−0.186** (0.066)	−0.191** (0.066)	−0.194** (0.066)
Gender: Other		0.252 (0.451)	0.242 (0.444)	0.288 (0.446)	0.262 (0.449)
Gender: Prefer not to say		−0.535 (0.449)	−0.559 (0.443)	−0.516 (0.444)	−0.502 (0.445)
Age			−0.008*** (0.002)	−0.009*** (0.002)	−0.008*** (0.002)
Nationality: British				0.127 (0.101)	0.105 (0.103)
Education: Bachelor					−0.011 (0.085)
Education: High School					−0.064 (0.108)
Education: Postgraduate					−0.104 (0.096)
Education: Primary/none					0.336 (0.263)
Constant	0.815*** (0.087)	0.909*** (0.093)	1.365*** (0.163)	1.162*** (0.230)	1.229*** (0.241)
N	374	374	371	371	371
R^2	.036	.059	.086	.090	.099
Adjusted R^2	.029	.044	.068	.070	.069
Residual Std. Error	0.636 (*df* = 370)	0.631 (*df* = 367)	0.623 (*df* = 363)	0.622 (*df* = 362)	0.622 (*df* = 358)
F Statistic	4.648** (*df* = 3; 370)	3.861*** (*df* = 6; 367)	4.872*** (*df* = 7; 363)	4.466*** (*df* = 8; 362)	3.276*** (*df* = 12; 358)

Note. Reference categories are female (gender), other (nationality) and a-level (education). *$p < .05$; **$p < .01$; ***$p < .001$. Exact p-values are available in the supplementary material on the OSF page: https://osf.io/9xvfw/

There were no significant associations between types of Instagram use and Depression (Table 6). Models 2 to 5 suggested that none of the sociodemographic variables were significantly associated with Depression.

Table 6. *OLS Regressions for Depression. Coefficients and Standard Errors.*

	Depression				
	Model 1	Model 2	Model 3	Model 4	Model 5
Interaction	−0.001 (0.016)	−0.002 (0.016)	−0.002 (0.016)	−0.002 (0.016)	−0.003 (0.016)
Browsing	0.008 (0.012)	0.008 (0.012)	−0.002 (0.013)	−0.002 (0.013)	−0.002 (0.013)
Broadcasting	0.009 (0.015)	0.010 (0.015)	0.011 (0.015)	0.011 (0.015)	0.012 (0.015)
Gender: Male		−0.003 (0.059)	−0.008 (0.060)	−0.009 (0.060)	−0.008 (0.060)
Gender: Self-defined		0.218 (0.405)	0.213 (0.404)	0.219 (0.406)	0.229 (0.410)
Gender: Other		0.446 (0.403)	0.439 (0.402)	0.445 (0.404)	0.446 (0.407)
Age			−0.003 (0.002)	−0.003 (0.002)	−0.003 (0.002)
Nationality: British				0.017 (0.092)	0.008 (0.094)
Education: Bachelor					−0.040 (0.078)
Education: High School					0.002 (0.099)
Education: Postgraduate					−0.061 (0.088)
Education: Primary/none					0.004 (0.240)
Constant	0.706*** (0.078)	0.706*** (0.083)	0.876*** (0.149)	0.849*** (0.209)	0.902*** (0.221)
N	374	374	371	371	371
R^2	.003	.007	.012	.012	.014
Adjusted R^2	−.005	−.009	−.007	−.010	−.019
Residual Std. Error	0.566 (df = 370)	0.567 (df = 367)	0.566 (df = 363)	0.566 (df = 362)	0.569 (df = 358)
F Statistic	0.406 (df = 3; 370)	0.457 (df = 6; 367)	0.620 (df = 7; 363)	0.545 (df = 8; 362)	0.418 (df = 12; 358)

Note. Reference categories are female (Gender), Other (Nationality) and A-Level (Education). $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$. Exact p-values are available in the supplementary material on the OSF page: https://osf.io/9xvfw/

Finally, there were no significant associations between types of Instagram usage and Loneliness (Table 7). Models 3 and 4 are suggestive of a negative association between age and loneliness, but this association is no longer statistically significant when adjusting for educational attainment (p = .055; Model 5).

Table 7. *OLS Regressions for Loneliness. Coefficients and Standard Errors.*

	Loneliness				
	Model 1	Model 2	Model 3	Model 4	Model 5
Interaction	−0.011 (0.015)	−0.011 (0.015)	−0.012 (0.015)	−0.012 (0.015)	−0.014 (0.015)
Browsing	0.010 (0.012)	0.011 (0.012)	−0.001 (0.013)	−0.001 (0.013)	−0.0004 (0.013)
Broadcasting	0.014 (0.014)	0.014 (0.014)	0.014 (0.014)	0.014 (0.014)	0.016 (0.014)
Gender: Male		0.052 (0.058)	0.047 (0.058)	0.047 (0.058)	0.043 (0.058)
Gender: Self-defined		0.250 (0.395)	0.244 (0.393)	0.249 (0.395)	0.241 (0.397)
Gender: Prefer not to say		0.018 (0.393)	0.006 (0.392)	0.011 (0.393)	0.003 (0.394)
Age			-0.004^{*} (0.002)	-0.004^{*} (0.002)	−0.004 (0.002)
Nationality: British				0.014 (0.090)	0.006 (0.091)
Education: Bachelor					−0.038 (0.075)
Education: High School					−0.136 (0.096)
Education: Postgraduate					−0.082 (0.085)
Education: Primary/none					0.330 (0.233)
Constant	2.195^{***} (0.076)	2.170^{***} (0.081)	2.429^{***} (0.145)	2.406^{***} (0.204)	2.455^{***} (0.214)
N	374	374	371	371	371
R^2	0.006	0.009	0.021	0.021	0.035
Adjusted R^2	−0.002	−0.007	0.003	−0.0002	0.003
Residual Std. Error	0.552 (df = 370)	0.553 (df = 367)	0.551 (df = 363)	0.552 (df = 362)	0.551 (df = 358)
F Statistic	0.743 (df = 3; 370)	0.558 (df = 6; 367)	1.134 (df = 7; 363)	0.993 (df = 8; 362)	1.095 (df = 12; 358)

Note. Reference categories are female (Gender), Other (Nationality) and A-Level (Education). $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$. Exact p-values are available in the supplementary material on the OSF page: https://osf.io/9xvfw/

We examined the Bayes factors for Models 1 from the OLS regressions for Anxiety (Table 5), Depression (Table 6) and Loneliness (Table 7). For Anxiety, the Bayes Factor suggested anecdotal evidence for an effect (2.78) but note that the effect was no longer supported once age was adjusted for. For Depression and Loneliness, the Bayes Factors overwhelmingly supported the null model over the presence of an effect of Instagram usage (Depression: 127.52; Anxiety: 79.68). Table 8 provides a summary of all the analyses. After the inclusion of the control variables in the regression models, there were no statistically significant associations between Instagram use and anxiety, depression or loneliness.

Table 8. *Summary of Results.*

Analysis	Instagram activity	Outcome variable	Association at baseline	Association after inclusion of control variables
Users vs. non-users		Anxiety	No	NA
		Depression	No	NA
		Loneliness	No	NA
Instagram users	Interaction	Anxiety	No	No
	Browsing	Anxiety	Positive	No
	Broadcasting	Anxiety	No	No
	Interaction	Depression	No	No
	Browsing	Depression	No	No
	Broadcasting	Depression	No	No
	Interaction	Loneliness	No	No
	Browsing	Loneliness	No	No
	Broadcasting	Loneliness	No	No

Note. Positive refers to a statistically significant ($p < .05$) association between the variables in the OLS regression analyses and gives the direction of the effect. No refers to a non-statistically significant ($p > .05$) association between the variables in the OLS regression analyses. See Tables 4, 6, 7 and 8 for full regression results. NA is Not Applicable. Users vs. non-users compared participants who had an Instagram account to those who did not have an Instagram account. As users and non-users were matched on age, gender, ethnicity, and nationality and these were accounted for via weights in the regression analysis, there was no need to control for these variables in the regression analysis.

Discussion

Summary of Findings

In this study, we examined associations between Instagram use and anxiety, depression and loneliness in an online UK adult sample that was nationally representative by age and gender. We compared participants who used Instagram to a sample of non-users, matched by age, gender, educational status and nationality. There were no significant differences between users versus non-users of Instagram in levels of anxiety, depression or loneliness. Further, there were no significant associations between active use of Instagram (Broadcast, Interaction) or passive use (Browsing) and levels of anxiety, depression or loneliness once sociodemographic variables were included in the models. The Bayes factors for these analyses moderately to strongly supported the null model of no effect – with the exception of anxiety. Here, the Bayes Factor showed anecdotal evidence for an effect and the regression model contained a statistically significant effect of Browsing. However, when participant age was included in the regression model, there was no longer any support for a statistically significant effect.

Comparison to Previous Work and Theoretical Implications

This study adds to recent research suggesting that the overall effect of Instagram, and SNSs more broadly, on well-being may be small to non-existent (Appel et al., 2020; Coyne et al., 2020; Orben, 2020b; Orben et al., 2019). The three key novel contributions this study makes to the previous research are its use of a country representative sample by age and gender, the use of matched control groups for Instagram users versus non-users, and the use of Bayes factors to examine the strength of evidence for the null hypothesis. The effects of Instagram use on well-being may vary with gender, with some studies finding a larger negative effect of social media use on well-being for females rather than males (Jarman et al., 2023; Twenge & Martin, 2020). Therefore, the existing studies with a female bias (Faelens et al., 2021) may not reflect the overall effect of social media use on well-being. Further, the effect of SNS on well-being may be affected by age, with different effects found for different developmental stages through adolescence (Orben et al., 2022) and therefore studies based mainly on 18–30 year olds (Faelens et al., 2021) may not be reflective of the effect of Instagram on an older sample. In this study we used a representative UK sample and accounted for key demographic factors such as age and gender that vary between users and non-users of Instagram (Dixon, 2022a) and which may influence well-being (Faravelli et al., 2013). This study therefore provides a robust examination of the effect of being a user of Instagram on well-being in an older (mean age: 49 years old) UK sample, with the null model of no effect supported by Bayes factors.

There are many factors that influence an individual's level of loneliness, anxiety and depression, including the extent to which they have meaningful social connections to others (Hawkley & Cacioppo, 2010), unemployment (Paul & Moser, 2009), socio-economic status (Lorant et al., 2003), attachment style (Riggs & Han, 2009) and gender (Faravelli et al., 2013). One potential explanation for the lack of an significant differences between users versus non-users of Instagram and levels of anxiety, depression and loneliness is that, as compared to other factors that influence well-being, being a user or not of Instagram has a much smaller effect on well-being (Appel et al., 2020; Orben & Przybylski, 2019; Orben et al., 2019). Overall our results on Instagram membership is consistent with a recent review of the evidence in this area which concluded that simply being a user of Instagram is not robustly associated with well-being in terms of depression, anxiety or loneliness (Faelens et al., 2021).

Whilst using versus not using SNSs may not have a large effect on well-being, early research on Facebook suggested that the way in which people use SNSs may have more of an effect, with passive use associated with more negative outcomes than active use (Burke & Kraut, 2016). However, this study did not find any robust support for associations between well-being and active use of Instagram (Interaction and Broadcast) as compared to more passive use (Browsing). Many previous studies in this area have focused on adolescents (Frison & Eggermont, 2017; Orben, 2020b) or young adults (Coyne et al., 2020). In contrast, we used an older adult sample. Given that adolescents and young adults spend more time on Instagram than older adults (Auxier & Anderson, 2021), this could account for the differences in findings, although the overall associations between type of SNSs use and well-being are inconsistent for all ages (Valkenburg, van Driel, et al., 2022). Therefore, whilst these results may generalise to the UK adult population as a whole given the representative sample, they may not generalise to specific groups or populations who may be differentially affected by social media use according to gender (Jarman et al., 2023; Twenge & Martin, 2020), developmental stage (Orben et al., 2022), or country (Ghai et al., 2023).

More broadly, the results of this study and recent reviews (e.g., Orben, 2020b; Valkenburg, 2022; Valkenburg, van Driel, et al., 2022) suggest that to understand the more nuanced effects of SNS use on well-being may require a move away from overall measures of SNS use (user vs. non-users, amount of use), or categorising use into active and passive, in two key directions. First, unlike exposure to magazines, TV shows or movies, each SNSs user has a different experience when they use SNSs depending on who they follow, the type of feedback they receive when they post and the content of private and public comments (Harriger et al., 2023). Thus, the effects of SNS on well-being are likely to be affected by this variation in the experience of each users, based on factors such as the type of content they follow (e.g., idealised body images, Brown & Tiggemann, 2016), their emotional reactions to the feedback they receive on SNS (e.g., Jackson & Luchner, 2018) and their motivations for using SNS (e.g., Phua et al., 2017). Capturing this variation in content is challenging using either survey or phone log methods, and therefore may require a greater use of experimental (e.g., Meier et al., 2020) or data donation approaches (van Driel et al., 2022). A second, related point is that if the overall effects of SNS on well-being are likely to vary according to the user, this may require a different statistical approach where person-specific effects of SNS on well-being are explicitly modelled (Valkenburg, 2022). Some studies using this approach have found that whilst some users of SNS experience negative effects, others experience positive effects and a third group no effect (Beyens et al., 2021)

Limitations and Future Research

Whilst we used a large, nationally representative sample to examine associations between Instagram use and well-being, this study did have two key limitations. First, we relied on self-report to measure the frequency of different types of Instagram use. Assuming participants answered honestly about whether they used Instagram, this limitation does not apply to the comparison of users versus non-users of Instagram. However, the duration of self-reported social media use is only moderately correlated with objective logs of use (Parry, Davidson, et al., 2021), meaning that the participants' estimates of their frequency of Browsing, Broadcast and Interaction on Instagram may be inaccurate. Future research should therefore use objective logs of social media use (Parry, Davidson, et al., 2021). However, most currently available systems for passively logging smartphone usage can measure time spent on specific SNSs apps, but not the specific type of use (e.g., active or passive) when using the SNSs (Christner et al., 2022; Deng et al., 2019; Ferreira et al., 2015; Parry, Fisher, et al., 2021). Second, this was a cross-sectional study and therefore cannot establish causal relationships, or the lack of such relationships, between Instagram use and anxiety, loneliness and depression. In longitudinal studies, there are often important differences in between-person and within-person analyses, with within-person effects typically smaller than between-person effects (Coyne et al., 2020; Orben et al., 2019). This suggests that variations in well-being may predict social media use, rather than vice versa (Coyne et al., 2020).

Conclusion

In conclusion, in a representative sample of UK adults, users versus non-users of Instagram did not significantly differ in their levels of anxiety, depression or loneliness. Further, there were no robust associations between the type of Instagram use (Browsing, Broadcast, Interaction) and anxiety, depression or loneliness. The Bayes factors for these analyses moderately to strongly supported the null model of no effect—with the exception of anxiety. For anxiety, there was no support for a statistically significant effect of type of Instagram use after including socio-demographic variables in the model. Overall, therefore this study adds to recent evidence that the overall effect of SNSs use on well-being may be small or non-existent (Appel et al., 2020; Coyne et al., 2020; Orben et al., 2019). Future work should use objective and longitudinal data to examine how individual differences and the specific nature of different types of social media content may influence the effect of using social media on well-being (Beyens et al., 2020; Orben, 2020b; Parry, Fisher, et al., 2021; Valkenburg, Beyens, et al., 2022; Valkenburg, van Driel, et al., 2022).

Conflict of Interest

Thomas Pollet and Sam Roberts received funding from Facebook Research for this research project. Facebook Research had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Authors' Contribution

Sam Roberts: conceptualization, funding acquisition, methodology, writing—original draft preparation, writing—reviewing and editing. **Connor Malcom:** data curation, investigation, methodology, software. **Kristofor McCarty:** methodology, project administration, software, supervision. **Thomas Pollet:** conceptualization, data curation, formal analysis, funding acquisition, methodology, project administration, software, supervision, visualization, writing—original draft preparation, writing—reviewing and editing.

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The data, analysis code and additional analysis relating to this study can be accessed at the OSF page (https://osf.io/9xvfw/).

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