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Social Media Use Does Not Increase Individual-Based Relative Deprivation: Evidence From a Five-Year RI-CLPM

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Abstract

Although a growing literature demonstrates that social media usage fosters upward social comparisons, the potential for social media use to elicit perceptions of unjust disadvantage relative to others remains unexplored. We address this oversight by leveraging six annual waves of a nationwide random probability sample of adults (ages 18–99; N = 62,017) to examine the average between- and within-person associations between social media use and feelings of individual-based relative deprivation (IRD) over time. Results from our preregistered analyses revealed that those who are high social media users across time tend to also experience higher levels of IRD. After adjusting for these stable between-person differences, within-person changes in social media use failed to predict changes in IRD over time (or vice versa). Subsequent exploratory analyses replicated these results across different age- and gender-based subgroups. Our results relieve concerns that social media use fosters long-term perceptions of disadvantage over time within individuals and suggest that concerns over the long-term detrimental effects of social media use on social comparison processes may be unfounded. These results also highlight the need to separate between-person stability from within-person change when investigating temporal precedence in longitudinal research.

Keywords: social media use; relative deprivation; cross-lagged panel model; longitudinal analysis

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Introduction

Over the last two decades, social media has skyrocketed to an estimated 4.6 billion active users—equivalent to more than half of the world's total population (Kemp, 2022). Indeed, the proliferation of social networking sites like Facebook, TikTok, and Instagram has led to a substantial amount of time spent online, particularly among young people (Pew Research Center, 2021). Thus, it is unsurprising that social media's effects on interpersonal processes are of interest to social scientists. Certainly, as social media use has increased, so, too, has research on its effects, including its positive impact on health promotion (Gabarron & Wynn, 2016) and inspiration (Meier & Schäfer, 2018), as well as its adverse effects on well-being (Jarman et al., 2022; Stronge et al., 2019; for a recent review, see Valkenburg, 2022), social connectedness (Ryan et al., 2017), and body image (Saiphoo & Vahedi, 2019).

Central to the impacts of social media are its associations with social comparisons (Verduyn et al., 2020). Social comparison theory argues that people use others as "yardsticks" to evaluate their social standing, opinions, abilities, and behaviours (Festinger, 1954). Whereas "offline" comparisons are limited to targets known to an individual, social media provides unprecedented access to a broader network of people whose lives and circumstances are prominently on display. It is perhaps unsurprising, then, that social media use correlates positively with social comparison processes (Chou & Edge, 2012; Latif et al., 2021; Verduyn et al., 2020; Wirtz et al., 2021). However, because social media typically exposes users to *idealized* versions of others (e.g., see Chou & Edge, 2012; Kross et al., 2013), social media use mostly fosters *upward* (i.e., where the comparison target is "better off" than the comparer) rather than downward (i.e., where the comparison target is worse off than the comparer) comparisons. In other words, social media users are particularly likely to compare themselves to "superior" comparison targets.

The effects of upward comparisons differ depending on whether individuals engage in assimilation or contrast (Gerber et al., 2018). Assimilation refers to the comparer's self-evaluations changing *towards* the comparison target (i.e., becoming more positive after an upwards comparison and more negative after a downward comparison). Accordingly, assimilation promotes more positive self-evaluations after upward comparisons on social media, particularly when the comparison target is perceived as similar to the comparer (e.g., see Kang & Liu, 2019). Conversely, contrast refers to the comparer's self-evaluation changing *away* from the comparison target (i.e., becoming more *negative* after an upwards comparison and more positive after a downward comparison). A recent meta-analysis suggests that people generally compare themselves to superior others in a *contrasting* manner (Gerber et al., 2018) and, thus, people on social media may be most likely to make contrasting upward social comparisons.

A wealth of research supports this thesis and suggests that the positivity bias on social media can fuel skewed perceptions of others' lives (e.g., Chou & Edge, 2012) and discontentment with one's position relative to others (Midgley et al., 2021; Vogel et al., 2014; Wirtz et al., 2021; Yang, 2016). For example, Wirtz and colleagues (2021) found that day-to-day social media use *adversely* affects well-being over time by increasing social comparisons. Likewise, Schmuck and colleagues (2019) found that Facebook usage predicts upward social comparisons, which, in turn, predicts lower self-esteem and well-being four months later. Thus, while social media has the potential to improve one's well-being (e.g., Allen et al., 2014; Kang & Liu, 2019), upward comparisons on social media are strongly associated with negative affect and reduced life satisfaction (e.g., Muller & Fayant, 2010), particularly for those with low levels of perceived social support and life satisfaction offline (see Gomez et al., 2022).

Despite the well-documented associations between social media use and upward social comparisons, these associations are primarily explored using cross-sectional and experimental designs. Indeed, longitudinal methods have only recently been used in this literature. Critically, most longitudinal research examines adolescent social media use and reveals weak, inconsistent associations between social media use and both social comparison processes (Meier & Johnson, 2022) and well-being (e.g., Valkenburg et al., 2022). As such, more longitudinal research is necessary to examine the temporal ordering of these variables, particularly among adult samples who are often peripheral to the focus of this emerging literature.

Perhaps more importantly, longitudinal research that separates between-person (i.e., stable differences between people) from within-person (i.e., temporary departures from an individual's "typical" levels of a construct) processes is needed to fully elucidate the effects of social media use on upward comparisons. Indeed, failing to separate these sources of variance confounds the ability to model temporal precedence in longitudinal research (see Hamaker et al., 2015; Osborne & Little, in press)—it is untenable to assume that stable, between-person associations reflect within-person changes over time. Given that people are spending increasingly more time on social media (Kemp, 2022), it is critical to examine how *changes* in social media use *within* individuals affect social comparison processes (see also Stavrova & Denissen, 2020).

Concerningly, the tendency for social media to foster upward—and potentially contrasting—social comparisons suggests that social media could also promote greater perceptions of *inequality* by highlighting differences between the "haves" (those materially well-off) and the "have-nots" (those who are deprived). Indeed, relative deprivation theory argues that people's *subjective* experiences of inequality are the result of individuals' upward social comparisons to (similar) individuals (individual-based relative deprivation; IRD) or groups (group-based relative deprivation; GRD). These social comparisons elicit feelings of anger and frustration when one—or one's group—is disadvantaged relative to the comparison target (Smith & Huo, 2014; Smith et al., 2012). Given social media's propensity to encourage greater social comparisons between *individuals*, social media use could increase feelings of IRD. However, no research to date has investigated this hypothesis.

The current study addresses this oversight by examining the longitudinal associations between social media use and IRD across six annual assessments of a nationwide longitudinal probability sample. Given that social media can highlight differences between those who are materially well-off (versus deprived), fiscal social comparison processes appear particularly relevant in the current context. Indeed, previous research has identified links between social media and fiscal social comparisons among adolescents (e.g., Pahlevan Sharif et al., 2022) and working-age adults (She et al., 2023). As such, we focus on a fiscal measure of IRD (i.e., feelings of financial deprivation relative to others). Thus, our study examines the effects of social media use on perceived *income* inequality in a sample that has traditionally been excluded from research on social media use (namely, adults).

We also address the limitations of previous longitudinal research by using a random intercept cross-lagged panel model (RI-CLPM; Hamaker et al., 2015) to investigate the associations between social media use and IRD. By using this approach, we can directly assess the a) between- and within-person associations between our variables of interest and b) temporal ordering of these variables (Hamaker et al., 2015; Osborne & Little, in press). Given previous longitudinal research suggests social media usage promotes greater upward social comparisons (e.g., Schmuck et al., 2019; Wirtz et al., 2021) and that social comparisons are more likely to be *contrasting* (and, thus, elicit a negative self-evaluation; see Gerber et al., 2018), we expected social media use to correlate positively with IRD at both the between- and within-person levels of analysis. Specifically, we test the following pre-registered hypotheses:

H1: People relatively high on social media use should be relatively high on IRD (**H1a**). Likewise, at the within-person level of analysis, temporary increases from one's typical social media use should correlate positively with temporary increases from one's typical levels of IRD (**H1b**).

H2: Although the tendency to engage in social comparisons (and, thus, experience feelings of IRD) could predict increased social media use (e.g., see Vogel et al., 2015), social media typically *elicits* social comparisons (Verduyn et al., 2020). As such, the within-person effects of social media use on IRD should be *stronger* than the within-person effects of IRD on social media use. Our novel use of an RI-CLPM allows us to arbitrate between these two possibilities in the current study.

In a set of unregistered exploratory analyses, we also examine the possibility that social media's association with IRD differs by gender and age. Specifically, social media may have a greater impact on women than men (Booker et al., 2018; Twenge & Martin, 2020). Likewise, younger adults use a greater variety of social media sites—and spend more time online—than their older counterparts (e.g., Hruska & Maresova, 2020; Pew Research Center, 2021). As such, the effects of social media use on IRD may differ between age groups—a possibility we examine by pursuing multi-group RI-CLPMs. In sum, we provide a novel investigation of the impact social media usage has on perceptions of inequality by examining whether the social comparisons elicited by social media extend to comparisons about one's relative fiscal position and seeing if these hypothesized effects vary by gender or age.

Methods

Preregistration and Data Availability

Our primary analyses were preregistered on the Open Science Framework (https://osf.io/ceby5). While the data analysed in this study were collected and available prior to the present study, no preliminary or formal analyses were conducted before preregistration. Due to restrictions imposed by our University's Ethics Committee, the data presented here are not publicly available. However, a deidentified dataset containing the variables analysed in this article is available upon request for replication purposes.

We deviated from our preregistration in two ways (see the Transparent Changes Document: https://osf.io/ah3fc/. First, we applied a constant and a log transformation to participants' reported social media use at each wave to adjust for skewness in the data (our pre-registered plan proposed using raw scores). Moreover, due to poor model fit and the nested structure of our preregistered measure of objective deprivation, we removed a neighbourhood-level measure of deprivation from our primary analyses and focused solely on the associations between social media use and IRD[1]. We followed all other preregistered procedures. Subsequent analyses assessing group differences based on gender and age were exploratory and, thus, were not preregistered. The syntax for all models tested in the present study is available on the Open Science Framework (https://osf.io/ah3fc/).

Participants and Procedure

We utilise data from the New Zealand Attitudes and Values Study (NZAVS), a longitudinal nationwide panel study of New Zealand adults that began in 2009. Participants were initially randomly sampled from the electoral roll at Time 1 (2009; N = 6,518). To address sample attrition and diversify the sample, five subsequent booster samples were collected at Time 3 (2011; booster n = 2,966), Time 4 (2012; booster n = 5,107), Time 5 (2013; booster n = 7,579), Time 8 (2016; booster n = 7,667), and Time 10 (2018; booster n = 29,293). Registration for the electoral roll is compulsory in New Zealand from age 18, which allows for random sampling of the voting-age population. Accordingly, NZAVS participants closely reflect the New Zealand population in age, socioeconomic status, and region of residence. That said, the NZAVS overrepresents women by around 10%, as they are more likely to respond to the survey than men. Sibley (2023) provides full details of the sampling procedure, sample demographics, retention rates, and ethics approvals for the NZAVS.

Although the NZAVS began in 2009, our measure of social media usage was first assessed at Time 7 (2015). As such, we use all available data from participants who completed at least one wave of the NZAVS from Time 7 (2015) to Time 12 (2020) and who provided partial or complete responses to our variables of interest (N_{total} = 62,017; $M_{\text{waves completed}}$ = 2.94, range: 1–6). The covariance coverage—the proportion of complete cases on a single or pair of variables—ranged from 0.14 to 0.77 (M = 0.31, SD = 0.18). Low covariance coverage among some variables is due to the combination of sample attrition and booster sampling *between* waves rather than missing responses *within* waves (see Table 1 for the percentage of complete responses at each assessment occasion).

Of the total sample, 63.1% were female and 77.8% were born in New Zealand. With respect to ethnicity, most participants identified as either New Zealand European (80.4%) or Māori (12.0%), with a smaller percentage identifying as Asian (5.2%) or Pasifika (2.5%). The average age of participants at Time 7 (2015) was 50.80 years (SD = 13.90, range: 19–96). Table 1 summarises key participant demographics at each assessment occasion.

Table 1. *Sample Demographic Characteristics Across Six Annual Waves.*

	T7 (2015)	T8 (2016)	T9 (2017)	T10 (2018)	T11 (2019)	T12 (2020)
Sample Size	13,94	21,935	17,07	47,94	42,676	38,547
Age	50.80 (13.90)	49.62 (13.93)	51.33 (13.77)	48.59 (13.86)	51.56 (13.88)	52.96 (13.70)
Range	19–96	18–97	18–98	18–99	18–96	18–96
Gender (Women)	62.7%	62.7%	63.4%	62.8%	64.1%	64.0%
Ethnicity						
NZ Euro/Pakeha	81.5%	81.7%	82.3%	82.8%	83.7%	85.4%
Māori	12.3%	11.6%	11.9%	10.1%	10.3%	8.9%
Pasifika	2.6%	2.3%	1.9%	1.9%	2.0%	1.9%
Asian	3.6%	4.3%	3.9%	5.2%	4.1%	3.8%
Born in NZ	80.0%	79.3%	79.6%	78.2%	78.2%	78.6%
Household Income[1]	1.07 (0.87)	1.09 (0.97)	1.14 (0.94)	1.15 (0.96)	1.19 (1.21)	1.22 (1.16)
Range	0–20.0	0–45.0	0–30.4	0–40.0	0–72.0	0–60.0
Employed	76.4%	77.8%	77.0%	79.5%	75.6%	76.6%
Social Media Use[2]	3.37 (6.42)	4.19 (7.69)	3.96 (7.02)	4.29 (7.74)	4.87 (7.65)	4.64 (7.42)
Range	0–100	0–168	0–100	0–150	0–168	0–168
n responses (% of wave *n*)	13,576 (97.4%)	21,188 (96.7%)	16,663 (97.6%)	46,41 (96.8%)	41,85 (98.1%)	37,437 (97.1%)
Individual-Based Relative Deprivation	3.40 (1.52)	3.46 (1.54)	3.38 (1.54)	3.47 (1.57)	3.36 (1.54)	3.28 (1.53)
Range	1–7	1–7	1–7	1–7	1–7	1–7
n responses (% of wave *n*)	13,894 (99.7%)	21,882 (99.8%)	17,018 (99.7%)	47,817 (99.7%)	42,019 (98.4%)	37,812 (98.1%)

Note. [1]Annual Household Income (before tax), divided by NZD$100,000. [2]Raw score for weekly social media use.

Measures

Social Media Use

Participants were asked to *…estimate how many hours you spent doing each of the following things last week*, followed by a series of weekly activities. Social media use was assessed using participants' responses to the option *Using social media (e.g., Facebook)*. Because a sizable proportion of participants reported that they spent no time on social media at each wave ($M_{(\text{no SMU})}$ = 27.5%, *SD* = 3.67, range: 23.1–33.6%), we deviated from our preregistration plan to correct for skewness in these data by adding a small constant (i.e., .001) to participants' scores and applying a log transformation at each assessment occasion. Table 1 displays the raw scores for social media use.

Individual-Based Relative Deprivation

We averaged two items adapted from Abrams and Grant (2012) to assess IRD at each assessment occasion: a) *I'm frustrated by what I earn relative to other people in New Zealand*, and b) *I generally earn less than other people in New Zealand*. Both items were measured on a 1 (*strongly disagree*) to 7 (*strongly agree*) scale (*r*s = .40–43, $p < .001$).

Results

Preregistered Analyses

Analytic Approach

To examine the between-person and within-person associations between social media use and IRD, we estimated an RI-CLPM in *Mplus* v8.8 using maximum likelihood with robust estimation of the standard errors. While an RI-CLPM is conceptually similar to a traditional cross-lagged panel model, the RI-CLPM separates trait-like, between-person stability from within-person change via the inclusion of correlated random intercepts (see Hamaker et al., 2015). In doing so, the autoregressive and cross-lagged parameters reflect within-person associations. Specifically, the autoregressive parameters capture the extent to which within-person deviations from an individual's mean score on a given variable carry over and impact departures in the same variable at the subsequent assessment occasion. In contrast, the cross-lagged associations reflect the extent to which departures from an individual's mean score on a given variable at one time point predict departures from their expected score on another variable at a later time point (Osborne & Little, in press).

We depart from Hamaker and colleagues' approach by standardizing the scales of our between- and within-person constructs at each assessment occasion (for a recent example, see Lilly et al., 2023; Osborne & Little, in press). Specifically, we freely estimate, but constrain to equality, the factor loadings for each random intercept before constraining their means and variances to 0 and 1, respectively (Hamaker and colleagues constrain the factor loadings to 1 and freely estimate the means and variances of the random intercepts). Additionally, while Hamaker and colleagues model the within-person components of the RI-CLPM by constraining to 1 the regression of each first-order construct (i.e., the observed scores), we freely estimate these parameters and constrain the residual variances to 1. This approach does not alter model fit but places our constructs on a common metric by standardizing the latent variances. This is particularly important in the current model, as our variables of interest are measured on different scales. By taking this approach, we facilitate the interpretation and comparison of the unstandardized effect sizes[2] and place our measures on a common metric.

Finally, we estimate the autoregressive and cross-lagged effects of social media use and IRD across the six annual assessments. We then specified our model as a stationary process, as there was no theoretical reason to expect different effects at different assessment occasions (Orth et al., 2021). For example, the cross-lagged effect of social media use on IRD from Time 7 to Time 8 was constrained to be equal to the cross-lagged effect of social media use on IRD from Time 8 to Time 9, and so on. Importantly, the stationary model fit these data well ($\chi^2_{(53)}$ = 639.05, $p < .001$; CFI = .995, RMSEA = .013 [.012, .014], $p > .999$, SRMR = .018).

Between-Person Effects

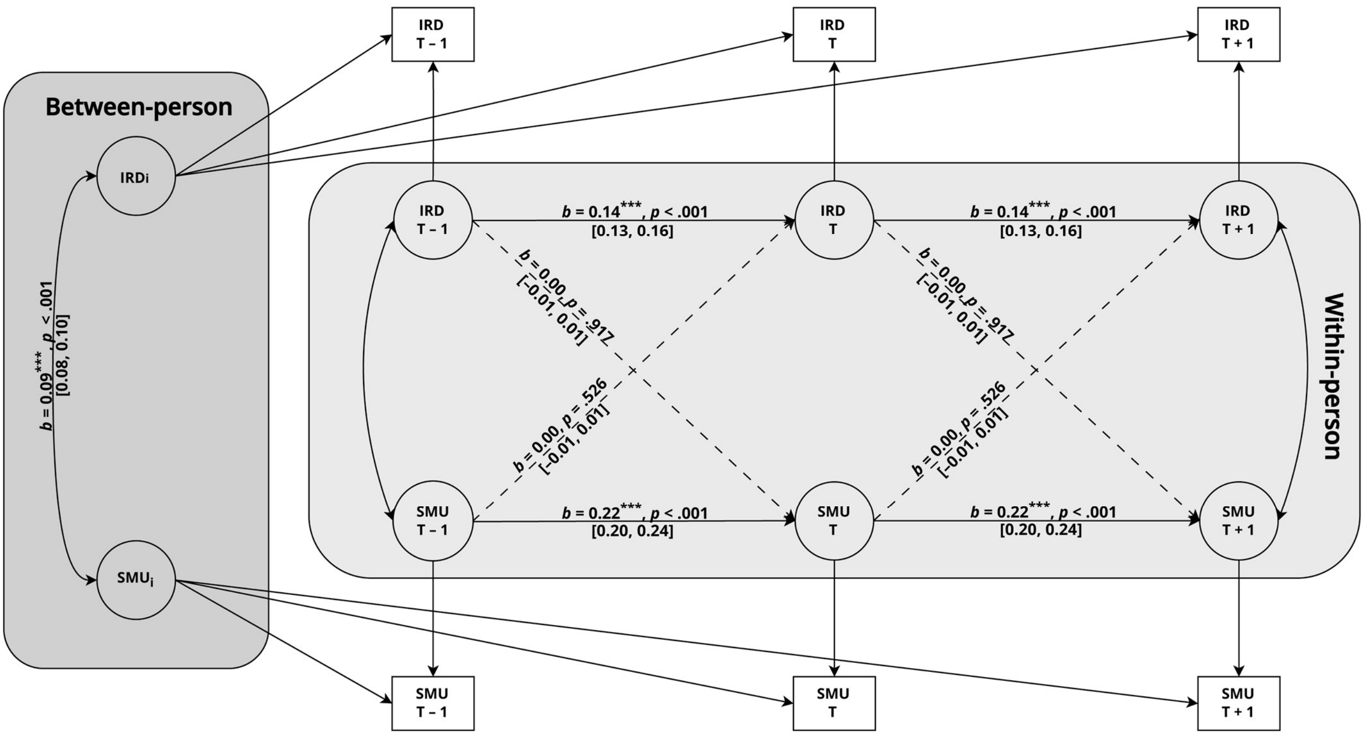
Table 3 displays the between-person associations between our variables of interest (see also Figure 1). Consistent with Hypothesis 1a, the random intercept for social media use correlated positively with the random intercept for IRD (b = 0.09, 95% CI [0.08, 0.10], p < .001). Thus, those who were relatively high in social media use across all six annual assessments also tended to be relatively high on IRD cross time.

Within-Person Effects

Turning attention to the within-person associations, we first examine the contemporaneous correlations between our variables of interest at each wave. While still cross-sectional, within-person correlations differ from between-person correlations in that they reflect associations between individuals' temporary deviations from their "trait"-levels of two constructs (Hamaker, 2023). Contemporaneous within-person correlations thus capture the relationship between residuals at the same time point after accounting for both the (a) stable between-person components of the construct and (b) prior cross-lagged and auto-regressive within-person associations. In other words, within-person correlations in an RI-CLPM reflect the associations between temporary departures from trait-level means in our variables of interest at each assessment occasion, i.e., correlated *change*, though note the correlations between constructs at the first assessment occasion (i.e., Time 7) are simple correlations. Table 2 displays the results of these analyses and reveals no significant within-person associations between our variables of interest (ps ≥ .165). Thus, contrary to Hypothesis 1b, within-person deviations from one's trait-level social media use were not reliably associated with contemporaneous within-person deviations from one's trait-level IRD at any of the six assessment occasions.

Regarding the longitudinal associations, inspection of the autoregressive effects reveals that within-person deviations in social media use (b = 0.22, 95% CI [0.20, 0.24], p < .001) and IRD (b = 0.14, 95% CI [0.13, 0.16], p < .001) predicted within-person deviations in those same variables over time. However, there were no significant cross-lagged associations between social media use and IRD (ps ≥ .526). Thus, contrary to Hypothesis 2, within-person deviations in social media use did not reliably predict within-person deviations in IRD at subsequent assessment occasions (b = 0.00, 95% CI [−0.01, 0.01], p = .526)

Figure 1. *RI-CLPM of the Associations Between Social Media Use (SMU) and Individual-Based Relative Deprivation (IRD).*



Note. The model was estimated as a stationary process across six annual waves (N = 62,017). For clarity, (residual) covariances between variables were estimated at each wave but excluded from the Figure. Estimates are unstandardized (but variables were placed on a common metric using Osborne and Little's, in press, approach) with 95% confidence intervals. Dashed lines reflect nonsignificant paths. $^{***}p$ < .001.

Table 2. *Contemporaneous Correlations Between Social Media Use and IRD at Each Wave*.

Wave	*b* (95% CI)	*SE*	*p*-value
Time 7[1]	−0.01 (−0.03, 0.02)	0.01	.552
Time 8	0.01 (−0.01, 0.03)	0.01	.195
Time 9	−0.01 (−0.03, 0.01)	0.01	.257
Time 10	0.00 (−0.02, 0.01)	0.01	.881
Time 11	0.01 (−0.01, 0.03)	0.01	.246
Time 12	0.01 (0.00, 0.02)	0.01	.165

Note. [1]T7 coefficients are simple correlations between constructs, while the remaining waves depict correlated innovations (i.e., correlated *change*).

Table 3. *RI-CLPM Estimates for the Relationships Between Social Media Use and Individual-Based Relative Deprivation (IRD).*

Between-person effects						
		b	*SE*	95% CI	β	*p*-value
Social Media Use ⟷ IRD		0.09^{***}	0.01	(0.08, 0.10)	.09	< .001
Within-person effects						
Outcome_{T}	Predictor_{T-1}	*b*	*SE*	95% CI	β	*p*-value
Social Media Use	Social Media Use	0.22^{***}	0.01	(0.20, 0.24)	.22	< .001
	IRD	0.00	0.01	(−0.01, 0.01)	.00	.917
IRD	Social Media Use	0.00	0.01	(−0.01, 0.01)	.00	.526
	IRD	0.14^{***}	0.01	(0.13, 0.16)	.14	< .001

Note. Model fit indices: $\chi2_{(53)}$ = 639.05, p < .001; CFI = .995, RMSEA = .013 [.012, .014], p > .999, SRMR = .018. $^{***}p$ < .001.

Exploratory Analyses

Although our analyses demonstrate that within-person deviations in social media use are unassociated with within-person deviations in IRD, our results may vary by gender or age. Indeed, research suggests that women may be more likely than men to be negatively affected by social media use (e.g., Jarman et al., 2022) and that younger people spend more time online (Pew Research Center, 2021) and, thus, may be more (or less) impacted by social media relative to their older counterparts. Therefore, the within-person effects of social media use on IRD may vary by gender or age.

To examine this possibility, we conducted additional exploratory analyses[3] using multigroup RI-CLPMs (see Mulder & Hamaker, 2021) to determine whether the (non-significant) within-person associations between our variables of interest differed by (a) gender or (b) age. To do so, we compared multiple group versions of the RI-CLPM in which there were no constraints across groups with models where the lagged associations were constrained to equality. As in our primary analyses, all models were estimated in *Mplus* v8.8 using maximum likelihood with robust estimation of the standard errors. To determine whether these constraints were reasonable, we utilised the Satorra-Bentler scaled chi-square difference (scaled $\Delta\chi^2$) test, which is mean adjusted to approximate a chi-square distribution under conditions of non-normality (Muthén & Muthén, 2005). If constraining these paths significantly reduced the model fit, then (some of) the lagged coefficients differed across groups.

Gender

To examine gender differences, we first estimated a stationary multigroup RI-CLPM without constraints across men and women ($\chi^2_{(106)}$ = 708.73, p < .001; CFI = .995, RMSEA = .014 [.013, .015], p > .999, SRMR = .020; see Table A3). We then tested whether parameters differed across groups by constraining the autoregressive and cross-lagged coefficients for women and men to equality. This test subsequently revealed that the significant autoregressive and non-significant cross-lagged estimates were equivalent across men and women (scaled

$\Delta\chi^2_{(4)} = 1.21$, $p = .877$). A visual inspection of the cross-lagged parameters in the unconstrained model confirmed this assumption; for both women and men, the cross-lagged associations between social media use and IRD were non-significant (*p*s ≥ 269; see Table A4 in the Appendix).

Age

We grouped participants into three age groups to examine age differences based on their age at Time 7. These groups were specified based on broader life stages to maximise sample size and, thus, the power to detect small effects: younger (18–34; *N* = 14,219), middle (35–49; *N* = 18,532) and older (≥ 50 years; *N* = 29,095) adulthood (for a recent example, see Jarman et al., 2022). First, we estimated a stationary multigroup RI-CLPM without constraints across age groups ($\chi^2_{(159)} = 718.39$, $p < .001$; CFI = .995, RMSEA = .013 [.012, .014], $p > .999$, SRMR = .020; see Table A3). We then tested for differences between the cross-lagged and autoregressive estimates among the different age groups. Constraining the parameter estimates across groups revealed significant differences between younger adults (18–34 years) and middle-aged individuals (35–49 years; scaled $\Delta\chi^2_{(4)} = 26.91$, $p < .001$), as well as between younger and older adults (≥ 50 years; scaled $\Delta\chi^2_{(4)} = 70.42$, $p < .001$). There were also significant differences between middle-aged and older adults (scaled $\Delta\chi^2_{(4)} = 20.52$, $p < .001$). Thus, (some of) the lagged coefficients differed between age groups.

Although these tests demonstrate that *some* of the lagged paths varied across age groupings, inspection of the unconstrained model revealed no significant cross-lagged associations between social media use and IRD across all three age groups (*p*s ≥ .133; see Table A5). Instead, age-based differences emerged for the autoregressive effects of IRD. Specifically, the autoregressive effects of IRD were largest among younger adults ($b = 0.27$, 95% CI [0.24, 0.31], $p < .001$), then middle-aged ($b = 0.16$, 95% CI [0.14, 0.19], $p < .001$) and finally weakest among older adults ($b = 0.10$, 95% CI [0.09, 0.12], $p < .001$). Constraining the remaining lagged paths to equality did not significantly alter model fit (scaled $\Delta\chi^2_{(6)} = 6.34$, $p = .386$), revealing that the different age groups differed only in the extent to which deviations in an individual's IRD predicted deviations in their IRD at subsequent assessments.

Discussion

Social media presents a largely idyllic view of people's conditions and fosters *contrasting* upward social comparisons that correlate negatively with well-being and self-esteem (e.g., Schmuck et al., 2019; Wirtz et al., 2021). However, it is unknown whether the effects of social media on social comparisons extend to perceptions of unjust *deprivation* compared to others. The present study is the first to examine this possibility by investigating the longitudinal associations between social media use and fiscal IRD among a large, nationwide random sample of adults over five years. Critically, we utilised an RI-CLPM—a modelling approach that distinguishes trait-like, between-person stability from within-person change (Hamaker et al., 2015). In doing so, we directly examined whether within-person *changes* in social media use predict within-person changes in IRD over time.

Our results demonstrate that—at the between-person level—people who were relatively high in social media use across all six assessment occasions were also relatively high in IRD. That this association emerged in an adult sample—where a sizeable minority of participants reported no social media use at each wave—is noteworthy. Indeed, most studies of social media use and social comparisons focus on adolescents or young adults, particularly given that young people spend significantly more time on social media (relative to their older counterparts; see Hruska & Maresova, 2020; Pew Research Center, 2021). Our results, however, suggest that the between-person association between social media use and IRD emerges for the general adult population—including older adults. These results highlight the need for research that examines social media use across age groups.

Although our results reveal potentially critical between-person associations, these correlations were small. Moreover, we failed to identify within-person associations between social media use and IRD. Subsequent exploratory analyses replicated these (non-significant) results across distinct age- and gender-based groups. Specifically, within-person deviations from an individual's trait-level social media use did not predict subsequent within-person deviations from one's trait-level IRD (and vice versa) across the whole sample, nor within specific subgroups defined by gender and age, respectively. Thus, although social media plays an increasingly important role in society and fosters discontent when one's circumstances do not "measure up" to others (Chou & Edge, 2012), our results allay widespread concerns that social media use has long-term consequences for perceptions of disadvantage among the general population. Given the well-known associations IRD has with poor physical and mental health outcomes (for a meta-analytic review, see Smith et al., 2012), these results are encouraging (but contrary to our hypotheses).

Though somewhat surprising, our results corroborate recent research suggesting that social media use does not lead to within-person changes in well-being over time (e.g., Beeres et al., 2021; Cotten et al., 2023; Di Blasi et al., 2022; Geusens & Beullens, 2021). Although previous longitudinal research predominantly focuses on the associations between social media use and well-being among adolescents, the similar null effects for IRD found here among adults raises questions about the impact of social media in the general population. Indeed, research often posits that social media undermines one's quality of life, with enduring moral panics of how social media fosters discontent and social disconnect (see Walsh, 2020). Our results contrast with this prevailing theory and suggest that social media use, while likely a *factor* in one's well-being and feelings of IRD, does not *drive* changes in individuals across time. As such, our results highlight the need for research to reframe the impacts of social media use, particularly when claiming causal processes.

Relatedly, our study demonstrates the growing methodological concerns over using between-person analyses to support claims about within-person processes (Berry & Willoughby, 2017; Curran & Bauer, 2011; Lucas, 2023). Traditional models of longitudinal change (e.g., the cross-lagged panel model) assume that individuals vary over time around the same mean and, thus, fail to separate stable, trait-like differences between people from focal *changes within* individuals (Hamaker et al., 2015). However, between-person differences do not necessarily generalize to intraindividual differences over time (Curran & Bauer, 2011). That our study identified stable between-person associations between social media use and IRD, but no evidence of a within-person association, supports this assertion and speaks to the need to examine social media use as a predictor of interindividual (rather than intraindividual) differences.

On a related note, the positive relationship between social media use and IRD at the between-person level of analysis suggests that those who tend to be heavy consumers of social media across time also tend to experience higher levels of IRD. There are several potential explanations for this association worthy of consideration. Namely, our measure of *fiscal* IRD may indicate that lower-income earners spend *more* time on social media than do higher-income earners. Although this association is relatively unexplored, some research suggests lower socioeconomic status predicts higher *problematic* social media use (He et al., 2021), though others find no association (Geurts et al., 2022). Thus, the association between social media use and IRD may reflect a general tendency for those of a lower *objective* income to use social media. Future research is needed to elucidate whether differences in social media use are associated with differences in *objective* or *relative* financial status between individuals.

Additionally, the between-person association social media use has with IRD may reflect interindividual differences in a general social comparison *orientation*. In other words, particular subgroups of the population may be more prone to social comparisons and, thus, spend more time on social media *and* experience higher levels of IRD. Indeed, feelings of IRD stem from upward social comparisons, and accordingly, those with a higher tendency to make social comparisons report higher levels of IRD (e.g., Callan et al., 2015). Likewise, those higher in social comparison orientation report higher social media usage and, perhaps more importantly, more negative impacts from social media use (e.g., Vogel et al., 2015). Although our exploratory analyses ruled out age and gender-related differences, a significant *within*-person association between social media use and IRD may emerge within other subgroups. For example, people higher in neuroticism and fear of missing out tend to make more upward comparisons on social media (see Gomez et al., 2022), and the association between social media use and IRD may be stronger (or counterintuitively, weaker) among these subgroups. Thus, differences in social comparison orientation and personality may impact the association between social media use and IRD at the between- and—potentially—within-person levels of analysis.

Finally, whether someone is an active or passive social media user may shape how social media use affects social comparison processes and well-being (see Verduyn et al., 2017). Indeed, active social media use may positively affect well-being (relative to passive use) if the active use is reciprocated and targeted at establishing positive connections (for a conceptual model, see Verduyn et al., 2022). Likewise, passive social media use may be most detrimental when social media consumption is relevant to the self (see Festinger, 1954) and centres on others' achievements. As such, how one uses social media—in tandem with general dispositional factors—may explain differences between individuals in their social media use and IRD levels. While examining these different features is beyond the scope of the present study, future research should investigate these factors when examining the long-term effects of social media use, particularly at the between-person level of analysis.

Strengths, Caveats, and Future Directions

In addition to important theoretical and practical implications, the present study utilises a large-scale, national probability sample of adults across six annual assessments, providing sufficient statistical power to detect even small effects. As such, there is notable confidence in the generalizability of our (non-significant) results—if we could not detect an association with over 62,000 participants, studies with smaller sample sizes are unlikely to as well. Critically, that we found no within-person associations between our variables of interest speaks to the need to separate these two distinct processes, as failing to do so may result in an error of inference (see Hamaker et al., 2015; Molenaar, 2004). As such, our results contribute to the ongoing call to distinguish between within- and between-person effects (e.g., Curran & Bauer, 2011).

Despite these contributions, it is important to note that we examined the *annual* associations between our variables of interest. As such, social media use may have short-term effects on IRD that we were unable to capture in our analyses. Future research should utilise shorter assessment intervals (i.e., days or weeks) to investigate these potential associations (see Orth et al., 2021). Moreover, our measure of social media use only assessed self-reports of social media use in the last week, and the associations between social media use and IRD may differ depending on the platform (e.g., Facebook versus Instagram; see Limniou et al., 2022), the motives for social media use (Schivinski et al., 2020; Van Zoonen et al., 2022), or whether usage is active or passive (Verduyn et al., 2022). Examining these potential factors in future research will provide a more nuanced understanding of the relationship between social media use and feelings of IRD.

Finally, our measure of IRD focused solely on one's *fiscal* status relative to other people in New Zealand (i.e., the country of the present study)—social media may promote more general feelings of deprivation, particularly as it allows individuals to compare themselves to others cross-nationally across several life domains. That said, examining social media use and fiscal IRD is appropriate given the association between social media use, financial comparisons, and materialism (e.g., Pahlevan Sharif et al., 2022). Additionally, our measure of IRD includes both a cognitive-based measure of relative status and an affective-based measure of *frustration*. Indeed, including both cognitive and affective items is pivotal to appropriately identifying feelings of relative deprivation (see Smith et al., 2012). Thus, we have confidence that our measure accurately reflects its respective construct. In doing so, our study provides the foundations for future research examining social media use's associations with different forms of relative deprivation.

Conclusion

Although social media has increased the frequency of people's upward social comparisons, research has yet to examine whether these comparisons extend to perceptions of unjust *deprivation* relative to others. The present study addressed this oversight by examining the between- and within-person associations between social media use and IRD across six annual assessments. Despite significant associations at the between-person level of analysis demonstrating that those who are high social media users across time tend to experience higher levels of IRD in general, our results failed to detect reliable within-person associations between social media use and IRD. Notably, these (non-significant) effects replicated across multiple gender- and age-based subgroups. These results alleviate widespread concern that social media usage fosters long-term perceptions of disadvantage and provide the foundations for future research examining social media's between-person and short-term within-person effects on feelings of deprivation over time.

Footnotes

[1] For transparency purposes, the Appendix presents the results of our analyses including our measure of objective deprivation.

[2] For completeness, we display the standardized estimates provided by Mplus alongside our rescaled estimates.

[3] These analyses were not preregistered and are merely robustness checks of our findings.

Conflict of Interest

The authors have no conflicts of interest to declare.

Authors' Contributions

Kieren J. Lilly: conceptualization, formal analysis, writing—original draft, writing—review & editing. **Chris G. Sibley:** conceptualization, data curation, funding acquisition, writing—review & editing, supervision. **Danny Osborne:** conceptualization, writing—review & editing, supervision.

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Data Availability Statement

The current study was preregistered on the Open Science Framework (https://osf.io/ceby5). The data described in this research are part of the New Zealand Attitudes and Values Study (NZAVS). Full copies of the NZAVS data files are held by all members of the NZAVS management team and advisory board. A de-identified dataset containing the variables analysed in this manuscript is available upon request from the corresponding author or any NZAVS advisory board member for replication or checking of any published study using NZAVS data. The Mplus syntax used to test all models reported in this manuscript is available via the Open Science Framework: https://osf.io/ah3fc/

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Appendix

Analyses of Social Media Use, IRD, and Deprivation

Our preregistered analyses included an examination of the associations between social media use and objective deprivation. We measured objective deprivation via the New Zealand Deprivation Index, which uses census information to assign decile-rank scores from 1 (*least deprived*) to 10 (*most deprived*) to small neighbourhood-type units (i.e., meshblocks; see Atkinson et al., 2014). Specifically, the index uses a series of nine variables (in weighted order) to create an average level of deprivation based on neighbourhood: proportion of adults who received a means-tested benefit, mean household income, proportion not owning their own home, proportion of single-parent families, proportion unemployed, proportion lacking qualifications, proportion living in crowded households, proportion with no telephone access, and proportion with no car access. The nested structure of our measure of objective deprivation was unsuitable for our analytic approach and was thus removed from our primary analyses. For transparency purposes, we report the results of our original preregistered analyses below.

Although we initially specified our model as a stationary process, constraining the autoregressive effect of area deprivation to equality across assessment occasions resulted in a significant decline in model fit (compared to the unconstrained model; scaled $\Delta\chi^2_{(4)} = 381.93$, $p < .001$). Thus, we allowed these estimates to vary across assessment occasions. The final RI-CLPM with partial stationarity fit these data well ($\chi^2_{(116)} = 2{,}765.74$, $p < .001$; CFI = .987, RMSEA = .019 [.019, .020], $p > .999$, SRMR = .017). As shown in Table A1, the inclusion of area deprivation in our analyses revealed similar associations between social media and IRD at the between-person level, as well as similar (nonsignificant) associations between these two variables at the within-person level of analysis. We present these results in detail below.

Between-Person Effects

Table A1 displays the between-person associations between our variables of interest and reveals that those relatively high in social media use across all six annual assessments also tended to be relatively high on IRD ($b = 0.09$, 95% CI [0.08, 0.10], $p < .001$). Those living in areas of high deprivation also tended to be relatively high on IRD ($b = 0.25$, 95% CI [0.23, 0.26], $p < .001$) and social media use ($b = 0.02$, 95% CI [0.01, 0.03], $p < .001$). A Wald test of equality constraints revealed that the between-person association social media use had with IRD was stronger than the corresponding association with area deprivation ($Wald_{(1)} = 87.71$, $p < .001$). These results indicate that social media use is associated with *perceived* deprivation more so than objective conditions.

Within-Person Effects

Turning first to the contemporaneous within-person correlations, Table A2 reveals no significant contemporaneous within-person associations between our variables of interest (ps ≥ .155), except for a weak association between IRD and area deprivation at Time 12 ($b = 0.02$, 05% CI [0.00, 0.03], $p = .020$).

Regarding the longitudinal associations, inspection of the autoregressive effects reveals that within-person deviations in social media use ($b = 0.22$, 95% CI [0.20, 0.24], $p < .001$) and IRD ($b = 0.14$, 95% CI [0.13, 0.16], $p < .001$) predicted within-person deviations in those same variables over time. Similarly, within-person deviations in area deprivation predicted subsequent within-person deviations in area deprivation (see Table A1). However, this latter autoregressive effect was not stationary. For example, the carry-over effect of area deprivation from Time 7 to Time 8 was greater than the corresponding carry-over effect from Time 8 to Time 9. Nonetheless, these results demonstrate that temporary departures from an individual's "typical" levels of deprivation predict temporary departures from their level of deprivation at subsequent assessment periods.

Finally, we examine the cross-lagged associations between our variables of interest. As shown in Table A1, our results revealed no significant cross-lagged associations between social media use, IRD, and area deprivation (ps ≥ .343).

Table A1. *RI-CLPM Estimates for the Relationships Between Social Media Use, Individual-Based Relative Deprivation (IRD), and Area Deprivation.*

Between-person effects						
		b	*SE*	95% CI	β	*p*-value
Social Media Use ↔ IRD		0.09	0.01	(0.08, 0.10)	.09	< .001
Deprivation ↔ IRD		0.25	0.01	(0.23, 0.26)	.25	< .001
Social Media Use ↔ ADep		0.02	0.01	(0.01, 0.03)	.02	< .001
Within-person effects						
Outcome$_T$	Predictor$_{T-1}$	*b*	*SE*	95% CI	β	*p*-value
Social Media Use	Social Media Use	0.22^{***}	0.01	(0.20, 0.24)	.22	< .001
	IRD	0.00	0.01	(−0.01, 0.01)	.00	.981
	Deprivation	0.00	0.01	(−0.01, 0.01)	.00	.681
IRD	Social Media Use	0.00	0.01	(−0.01, 0.01)	.00	.566
	IRD	0.14^{***}	0.01	(0.13, 0.16)	.14	< .001
	Deprivation	0.00	0.01	(−0.01, 0.01)	.00	.940
Deprivation[1]	Social Media Use	0.00	0.00	(−0.01, 0.01)	.00	.596
	IRD	0.01	0.00	(−0.01, 0.02)	.01	.343
	Deprivation$_{T7}$	1.19^{***}	0.16	(0.87, 1.51)	.77	< .001
	Deprivation$_{T8}$	0.33^{***}	0.09	(0.16, 0.50)	.45	< .001
	Deprivation$_{T9}$	0.96^{***}	0.14	(0.68, 1.23)	.73	< .001
	Deprivation$_{T10}$	0.27^{***}	0.05	(0.17, 0.38)	.37	< .001
	Deprivation$_{T11}$	0.72^{***}	0.02	(0.67, 0.77)	.61	< .001

Note. Model fit indices: $\chi2_{(116)} = 2{,}765.74$, $p < .001$; CFI = .987, RMSEA = .019 [.019, .020], $p > .999$, SRMR = .017. [1]Autoregressive effects of deprivation were free to vary across assessment occasions.

Table A2. *Contemporaneous Correlations Between Social Media Use (SMU), Individual-Based Relative Deprivation (IRD), and Area Deprivation (ADep).*

	ADep ↔ IRD		SMU ↔ IRD		SMU ↔ ADep	
Wave	*b* (95% CI)	*p-value*	*b* (95% CI)	*p*-value	*b* (95% CI)	*p*-value
Time 7[1]	0.03 (0.00, 0.06)	.050	0.00 (−0.03, 0.02)	.712	0.01 (−0.02, 0.04)	.642
Time 8	0.00 (−0.02, 0.02)	.806	0.01 (−0.01, 0.03)	.220	0.00 (−0.02, 0.02)	.886
Time 9	0.00 (−0.02, 0.02)	.946	−0.01 (−0.03, 0.01)	.243	0.00 (−0.03, 0.02)	.767
Time 10	0.00 (−0.02, 0.02)	.730	0.00 (−0.02, 0.01)	.909	0.01 (−0.01, 0.02)	.582
Time 11	0.01 (−0.02, 0.02)	.739	0.01 (−0.01, 0.02)	.331	0.00 (−0.02, 0.02)	.933
Time 12	0.02^{*} (0.00, 0.03)	.020	0.01 (0.00, 0.02)	.155	0.00 (−0.01, 0.01)	.730

Note. [1]T7 coefficients are simple correlations between constructs, while the remaining waves depict correlated change. $^{*}p < .05$.

Table A3. *Model Fit Statistics and Comparisons for Gender and Age-Based Multigroup RI-CLPMs.*

	Model	χ^2	*df*	MLR	*p*-value	CFI	RMSEA	SRMR	$\Delta\chi^2$ (*df*)	*p*-value	ΔCFI
Gender	Free across groups	708.73	106	1.273	< .001	.995	.014	.020	—	—	—
	Constrained[a]	704.14	110	1.284	< .001	.995	.013	.020	1.21 (4)	.877	.000
Age	Free across groups	718.39	159	1.335	< .001	.995	.013	.020	—	—	—
	Constrained[a]	809.19	167	1.349	< .001	.994	.014	.022	81.45 (8)	< .001	.001
	Young–Middle	747.65	163	1.344	< .001	.994	.013	.021	26.91 (4)	< .001	.001
	Young–Older	802.74	163	1.344	< .001	.994	.014	.022	70.42 (4)	< .001	.001
	Middle–Older	739.27	163	1.340	< .001	.995	.013	.020	20.52 (4)	< .001	.000
	Partially constrained[b]	719.42	165	1.348	< .001	.995	.013	.020	6.34 (6)	.386	.000

Note. All models were estimated as a stationary process. MLR = Scaling Correction Factor for MLR. $\Delta\chi^2$ = Satorra-Bentler Scaled Chi-Square Difference. [a]All paths were constrained to equality across groups. [b]Autoregressive associations for IRD were free to vary across groups.

Table A4. *Unconstrained Multigroup RI-CLPM Estimates for the Relationship Between Social Media Use and IRD by Gender.*

		Between-person Effects				
		b	*SE*	95% CI	*β*	*p*-value
Women (*N* = 38,954)						
Social Media Use ↔ IRD		0.06***	0.01	(0.05, 0.08)	.06	< .001
Men (*N* = 22,755)						
Social Media Use ↔ IRD		0.06***	0.01	(0.04, 0.08)	.06	< .001
		Within-person Effects				
Outcome$_T$	Predictor$_{T-1}$	*b*	*SE*	95% CI	*β*	p-value
Women (*N* = 38,954)						
Social Media Use	Social Media Use	0.22***	0.01	(0.19, 0.24)	.22	< .001
	IRD	0.00	0.01	(−0.01, 0.01)	.00	.749
IRD	Social Media Use	0.01	0.01	(−0.01, 0.02)	.01	.269
	IRD	0.15***	0.01	(0.13, 0.16)	.15	< .001
Men (*N* = 22,755)						
Social Media Use	Social Media Use	0.22***	0.01	(0.20, 0.25)	.22	< .001
	IRD	0.00	0.01	(−0.02, 0.01)	−.01	.437
IRD	Social Media Use	0.00	0.01	(−0.02, 0.01)	.00	.768
	IRD	0.14***	0.01	(0.12, 0.16)	.14	< .001

Note. N = 61,709. Model fit indices: $\chi2_{(106)}$ = 708.73, *p* < .001; CFI = .995, RMSEA = .014 [.013, .015], *p* > .999, SRMR = .020. ****p* < .001.

Table A5. *Unconstrained Multigroup RI-CLPM Estimates for the Relationship Between Social Media Use and IRD by Age Group.*

		Between-person Effects				
		b	*SE*	95% CI	β	*p*-value
Younger 18–34 (*N* = 14,219)						
Social Media Use ⟷ IRD		0.08***	0.02	(0.04, 0.11)	.08	< .001
Middle 35–49 (*N* = 18,532)						
Social Media Use ⟷ IRD		0.06***	0.01	(0.03, 0.08)	.06	< .001
Older ≥ 50 (*N* = 29,095)						
Social Media Use ⟷ IRD		0.07***	0.01	(0.05, 0.09)	.07	< .001

		Within-person Effects				
Outcome$_T$	Predictor$_{T-1}$	*b*	*SE*	95% CI	β	*p*-value
Younger 18–34 (*N* = 14,219)						
Social Media Use	Social Media Use	0.21***	0.03	(0.16, 0.26)	.20	< .001
	IRD	0.02	0.01	(−0.01, 0.04)	.02	.133
IRD	Social Media Use	0.01	0.01	(−0.02, 0.03)	.01	.708
	IRD	0.27***	0.02	(0.24, 0.31)	.27	< .001
Middle 35–49 (*N* = 18,532)						
Social Media Use	Social Media Use	0.25***	0.02	(0.22, 0.29)	.25	< .001
	IRD	0.00	0.01	(−0.02, 0.02)	.00	.889
IRD	Social Media Use	0.00	0.01	(−0.01, 0.02)	.00	.638
	IRD	0.16***	0.01	(0.14, 0.19)	.16	< .001
Older ≥ 50 (*N* = 29,095)						
Social Media Use	Social Media Use	0.22***	0.01	(0.20, 0.24)	.22	< .001
	IRD	0.00	0.01	(−0.01, 0.01)	.00	.976
IRD	Social Media Use	0.00	0.01	(−0.01, 0.01)	.00	.875
	IRD	0.10***	0.01	(0.09, 0.12)	.10	< .001

Note. *N* = 61,846. Model fit indices: $\chi 2_{(159)} = 718.39$, $p < .001$; CFI = .995, RMSEA = .013 [.012, .014], $p > .999$, SRMR = .020. ***$p < .001$.

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