Media Psychology

ISSN: 1521-3269 (Print) 1532-785X (Online) Journal homepage: www.tandfonline.com/journals/hmep20

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To cite this article: Eetu Marttila , Aki Koivula , Iina Savolainen , Anu Sirola & Atte Oksanen (03 Mar 2026): The Dynamic and Reciprocal Relationship Between Problematic Internet Use and Loneliness: A Longitudinal Study, Media Psychology, DOI: 10.1080/15213269.2026.2633579

To link to this article: https://doi.org/10.1080/15213269.2026.2633579

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MEDIA PSYCHOLOGY
https://doi.org/10.1080/15213269.2026.2633579

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The Dynamic and Reciprocal Relationship Between Problematic Internet Use and Loneliness: A Longitudinal Study

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ABSTRACT

Problematic internet use (PIU) and loneliness are consistently linked, but whether one drives the other over time is unclear. Using six-wave panel data from 753 Finnish adults recruited through an online panel (4,518 observations), we examined how PIU and loneliness relate to each other within individuals. We used dynamic panel models that account for stable between-person differences and examine within-person changes, testing both contemporaneous (within-wave) and lagged (across-wave) associations over 6- and 12-month intervals. Results revealed strong reciprocal contemporaneous effects: when individuals experienced elevated PIU, they also reported greater loneliness, and vice versa. However, we found no evidence of lagged effects at either 6- or 12-month intervals. This suggests the relationship between PIU and loneliness unfolds within rather than across the specific measurement periods examined, though the contemporaneous effects may reflect unmeasured shorter-term dynamic processes occurring between waves.

Introduction

Over recent decades, concerns have been growing about the negative effects of digital communication technologies (e.g., Valkenburg, 2022), with problematic internet use (PIU) and loneliness emerging as two significant psychosocial challenges. PIU involves poorly controlled internet use that causes distress and functional impairment (Moretta et al., 2022), while loneliness reflects the subjective experience of inadequate or unsatisfying social relationships (Buecker, Mund, et al., 2021). Prior research has found a consistent positive relationship between PIU and loneliness (e.g., Fam & Männikkö, 2025; Tokunaga, 2017), but it remains unclear which precedes the other, or

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/15213269.2026.2633579.

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whether they mutually reinforce over time (e.g., Wang & Zeng, 2024; Zhang et al., 2024).

PIU and loneliness can be related to each other through several mechanisms. PIU is characterized by uncontrollable preoccupation with internet use, which can damage close social relationships and, in turn, increase loneliness (e.g., Meshi & Ellithorpe, 2021; Tokunaga & Rains, 2016). Conversely, because loneliness is an emotionally unpleasant state tied to the basic need for social connections (Hawkley & Cacioppo, 2010), it may drive individuals to use the internet excessively to soothe negative feelings and fulfill their need to belong (e.g., Cauberghe et al., 2021). While such interactions can be rewarding, heavy reliance on online support may increase the risk of PIU. Together, these perspectives have led to a third line of work proposing a reciprocal relationship in which PIU and loneliness reinforce each other over time (e.g., Brand et al., 2019).

Earlier longitudinal studies have supported both directional hypotheses (e.g., Tóth-Király et al., 2021). However, many of these studies overlook the possibility of reverse causality, which can bias results (see Leszczensky & Wolbring, 2022). Studies that address reverse causality often use cross-lagged panel models (CLPMs), which have notable limitations under several circumstances (Hamaker et al., 2015; Lucas, 2023), and recent studies with more robust methods have produced results that contradict earlier findings (Zhao et al., 2024). These discrepancies call for further research on within-person associations between PIU and loneliness over time.

This study examines the dynamic, reciprocal within-person relationship between PIU and loneliness. To address the reciprocal causality while controlling for unobserved heterogeneity, we used six-wave panel data of 753 Finnish adults (N = 4,518) and dynamic linear panel models (DPMs) with fixed effects (Allison et al., 2017). We hypothesized that, within individuals, increased PIU increases loneliness, increased loneliness increases PIU, and that past levels of both variables have persistent effects on their future values through autoregressive processes.

Effects of PIU on Loneliness

Despite decades of research, there is no consensus on how PIU should be defined and measured (e.g., Moretta et al., 2022; Tokunaga & Rains, 2016). In this study, we use the term PIU to refer to poorly controlled internet-related thoughts and behaviors that cause psychological distress and interfere with daily functioning (Moretta & Buodo, 2020; Moretta et al., 2022). This aligns with earlier literature that frames cognitive and behavioral symptoms, such as loss of control, preoccupation, mood modification, and interpersonal conflict, over mere frequency or duration of internet use (Meerkerk et al., 2009; Tokunaga & Rains, 2016).

Although PIU shares features with clinical conditions such as substance addictions and gambling disorders (e.g., Potenza, 2014), it lacks recognition as a clinical diagnosis in the *Diagnostic and Statistical Manual of Mental Disorders* (American Psychiatric Association, 2013), and its equivalence to addictive disorders remains debated. We consider that Orford's (2001) view of addictive behaviors as strong attachments to rewarding activities that overpower self-control provides a useful non-clinical framework. This continuum-based perspective captures patterns of internet overuse that may not have diagnostic thresholds yet cause functional impairment.

Several mechanisms have been proposed to explain why PIU may increase loneliness. A core feature of PIU is poor regulation of online behaviors and spending more time online than intended (Meerkerk et al., 2009). According to a popular *displacement hypothesis*, time spent online may replace daily face-to-face social activities and reduce the quality of social relationships, but empirical findings are mixed (Hall & Liu, 2022). Part of the ambiguity stems from the fact that displacement can refer to distinct processes. S*ocial displacement* occurs when offline relationships are replaced by digital ones (e.g., Valkenburg & Peter, 2007), while *time displacement* refers to reduced time spent on face-to-face interactions because of online use (e.g., Hall et al., 2019).

However, displacement may also happen in subtler form at the level of attention. Digital technologies can draw the attention from immediate social environment toward online content and reduce the cognitive and emotional resources used to sustain important close relationships (Sbarra et al., 2019). Being distracted by and preoccupied with internet use can create strain, cause conflicts and decrease the quality of close relationships (e.g., Roberts & David, 2016). Device use can undermine relationship quality by diverting attention, especially when it represents solitary engagement rather than a jointly shared activity with family members (Tammisalo & Rotkirch, 2022). Given that is PIU marked by persistent cognitive and emotional preoccupation with internet use (Meerkerk et al., 2009; Moretta et al., 2022), it is likely to reduce the perceived quality of relationships, and in turn, increase loneliness (Kerkhof et al., 2011).

A further mechanism involves the role of PIU in mood regulation. PIU is often characterized by using the internet to avoid or alleviate negative emotions (Meerkerk et al., 2009). Digital platforms often present idealized and excessively positive depictions of life (Reinecke & Trepte, 2014), and sustained exposure has been shown to promote upward social comparison and fear of missing out (de Vries et al., 2018; Park & Park, 2024). Because loneliness reflects the perceived quality of close relationships rather than the number of actual social relationships (Hawkley & Cacioppo, 2010), these dynamics of contemporary digital platforms may intensify the negative affect and thereby increase loneliness.

Effects of Loneliness on PIU

Loneliness is an adverse subjective experience of social disconnection and perceived discrepancy between one's desired and actual social relationships (Perlman & Peplau, 1981). In Weiss's (1973) typology, loneliness comprises two distinct yet often interrelated dimensions. Social loneliness refers to the absence of social connections and lack of adequate social network, while emotional loneliness refers to a lack of intimate and meaningful relationships (DiTommaso & Spinner, 1997; Russell et al., 1984; Weiss, 1973). Loneliness is essentially a subjective and emotionally painful experience, and given that humans have a fundamental need for relatedness and meaningful relationships (Baumeister & Leary, 1995; Deci & Ryan, 2000), loneliness poses various threats via unmet psychological needs. It is a risk factor for individuals' health and well-being, even premature death, making it a significant public health concern (e.g., Holt-Lunstad et al., 2015; Leigh-Hunt et al., 2017), and a significant portion of the global population experiences loneliness on some level (Lim et al., 2023; Surkalim et al., 2022).

Loneliness may increase the risk of PIU through both social and emotional mechanisms. Loneliness is an unpleasant feeling and people aim to maintain and form new social connections in various ways (Hawkley & Cacioppo, 2010). As lonely individuals consistently score lower on self-reported social skills (Spithoven et al., 2017) and are more likely to suffer from social anxiety (Reinwarth et al., 2024), they often prefer online to face-to-face interactions to satisfy their social needs (O'Day & Heimberg, 2021). Online communities can foster a sense of belonging and provide social support for users (e.g., Oldemburgo de Mello et al., 2024), and sometimes enhance the quality of offline social relationships (e.g., Vriens & van Ingen, 2018; Winstone et al., 2021). However, if the internet becomes the primary means to meet social and emotional needs, it can increase the risk of PIU, especially if offline support is limited. For instance, pressures to maintain constant engagement within online communities (Turel & Osatuyi, 2017), as well as the strong reinforcement of belonging they afford (Miranda et al., 2023), have each been linked to increased risk of PIU over time.

Beyond providing rewarding social connections, the internet also provides many ways to cope with the negative affective states associated with loneliness (Brand et al., 2019; Cauberghe et al., 2021). Digital platforms afford maladaptive usage styles, such as passive scrolling of social media (de Segovia Vicente et al., 2024), which afford distraction from difficult feelings and mood modification. Moreover, loneliness increases sensitivity to social threats and exclusion (Hawkley & Cacioppo, 2010), and lonely individuals are overly sensitive to feelings of being left out, or fear of missing out (Servidio et al., 2025). This vulnerability may amplify the motivation to stay connected through compulsively monitoring social relationships in digital environments (e.g., Wang et al., 2025). In sum, loneliness may increase the risk of PIU by making online connections more rewarding and by reinforcing maladaptive coping behaviors.

The Dynamic and Reciprocal Relationship Between PIU and Loneliness

Previous research has provided robust correlational evidence that PIU and loneliness are linked, but controversy over the directionality of this relationship remains (e.g., Moretta et al., 2022; Zhang et al., 2024). Both directions have received theoretical and empirical support (e.g., Tóth-Király et al., 2021; Zhao et al., 2024). Moreover, these processes may interact dynamically, potentially forming a self-reinforcing feedback loop where increased loneliness fuels PIU, further exacerbating loneliness (e.g., Wang & Zeng, 2024; Zhang et al., 2024).

However, it remains unclear whether these reciprocal relationships occur simultaneously (contemporaneous effects) or unfold over longer periods (lagged effects). Thus, we hypothesize:

Hypothesis 1a (H1a): PIU has a positive contemporaneous within-person effect on loneliness.

Hypothesis 1b (H1b): PIU has a positive lagged within-person effect on loneliness.

Hypothesis 2a (H2a): Loneliness has a positive contemporaneous within-person effect on PIU.

Hypothesis 2b (H2b): Loneliness has a positive lagged within-person effect on PIU.

In addition to reciprocal effects, assessing the dynamic relationship requires considering the stability, i.e., autoregressive tendencies, of each variable over time (Lucas, 2023). In other words, one must consider whether PIU and loneliness are determined solely by their absolute values at each measurement occasion, or whether prior states of PIU and loneliness influence future changes. Prior studies on PIU suggest that symptoms show moderate stability over time, but that it also varies within individuals (e.g., Boer et al., 2022). PIU can be an adaptive response to stressful life events (Xiao et al., 2019), as it can be used for mood modification and to cope with difficult emotions, but time-invariant factors, such as genetics, probably also play a role (Hahn et al., 2017).

Similarly, loneliness tends to remain relatively stable, although fluctuations within individuals over time are common (see Mund, Freuding, et al., 2020). For example, negative or positive life events can affect the within-person trajectories of loneliness (e.g., Fried et al., 2015). Short-term increases in loneliness may even motivate for reconnection (Qualter et al., 2015), whereas long-term loneliness tends to become maladaptive and affect negatively people's social skills and relational abilities (Maes & Vanhalst, 2024). Stable traits also at least partially explain the differences in experienced loneliness between individuals (Mund, Lüdtke, et al., 2020).

Considering this, individuals with higher levels of PIU or loneliness at one time point are also more likely to report higher levels at subsequent time points. Therefore, we hypothesize:

> *Hypothesis 3 (H3):* PIU and loneliness demonstrate stability such that each construct shows positive autoregressive effects over time.

Method

Participants and Procedure

We used a balanced six-wave (T1–T6) panel dataset comprising 753 individuals (T1: $N = 1530$; $M_{age} = 46.67$; Females = 49.44%) residing in Finland. Data were collected every six months over a three-year period, spanning spring 2021 to fall 2023. The response rate of the T1 survey was 31.32%, and the response rates remained high across the following waves (T2: 78.30%; T3: 71.57%; T4: 65.62%; T5: 61.00%; T6: 58.10% of T1 respondents). The data collection was a part of a larger research project, for which the initial sample size was set to ensure broad population coverage and to maintain sufficient statistical power to detect changes in variables across repeated measures, even after expected panel attrition. Despite attrition, the final analytical sample (N = 753) remains comparatively large for a longitudinal study, allowing us to estimate within-person changes. When comparing the sociodemographic characteristics of the participants to the broader Finnish adult population, no significant biases were found. To maintain data quality and integrity, thorough checks (i.e., attention checks, patterned responses) were performed after each data collection. The study protocol was reviewed by the Academic Ethics Committee of the Tampere region, Finland, which confirmed prior to implementation that the study did not include any ethical concerns.

Measures

Compulsive Internet Use Scale (CIUS)

PIU was measured with the Compulsive Internet Use Scale (CIUS) (see Meerkerk et al., 2009). The scale has demonstrated strong reliability and validity across various populations and settings (Lopez-Fernandez et al., 2019; Sarmiento et al., 2021; Savolainen et al., 2020). The respondents rated their responses to the items (e.g., "How often do you think about the Internet, even when not online?") on a 5-point scale, ranging from 0 (*never*) to 4 (*very often*), with higher scores indicating a greater degree of compulsive internet use. Total scores ranged from 0 to 56. Internal consistency of the scale based on McDonald's omega (ω) was excellent: .95 for all six time points. We tested longitudinal measurement invariance of the CIUS across all time-points, and the results supported scalar invariance (see Supplementary material).

Loneliness

We measured loneliness with a widely used 3-item scale (Hughes et al., 2004). This measure has been widely used in prior studies and has shown good validity and reliability (Latikka et al., 2022; Sirola et al., 2019; Surkalim et al., 2022). The measure includes statements about perceived loneliness (e.g., "How often do you feel left out?"), and it captures unidimensional subjective experience of loneliness. Response options ranged from 0 (*almost never*) to 2 (*often*). Internal consistency of the scale was good: ω,T1 = .86; ω,T2 = .85; ω,T3 = .86; ω,T4 = .86; ω,T5 = .84; ω,T6 = .86. Measurement invariance analyses for the loneliness scale confirmed scalar invariance across waves (see Supplementary material).

Demographics

We provide descriptive statistics for the demographic variables (i.e., age, sex, education, and income) in Supplementary material (Table SB1) to characterize the sample.

Analytical Strategy

Longitudinal panel data analysis offers a rigorous alternative for strengthening causal inference by capturing temporal dynamics and controlling for time-invariant unobserved heterogeneity (Allison et al., 2017; Zyphur et al., 2020). Time-invariant unobserved heterogeneity refers to omitted variables that differ across respondents but remain constant over the study period, including demographic and socioeconomic characteristics, personality traits, cognitive ability, and other genetic factors (Leszczensky & Wolbring, 2022). As both PIU and loneliness can be affected by stable dispositions of individuals, the statistical models that are used to model the influence of these variables on each other should control out these unobserved qualities.

Fixed-effects (FE) regression model and its extensions are a typical way to account for the non-independence of repeated measures in panel data, while also controlling for both measured and unmeasured stable differences between individuals (Allison, 2009). However, FE models cannot be used when *reverse causality* (i.e., the possibility that past values of the dependent variable affect future values of the independent variables) is present and cannot account for the *autoregressive element* of the dependent variable (i.e., the possibility that the past values of the dependent variable are affecting future values of the dependent variable) (Leszczensky & Wolbring, 2022). These issues are particularly relevant for psychological studies, as research often focuses on intra-individual processes that are characterized by reciprocal causation and autoregressive dynamics.

A common solution for these problems is to use CLPMs and their extensions (Zyphur et al., 2020). However, it is well-established that traditional CLPM cannot control for the influence of time-invariant unobserved confounders and often produce biased estimates when there are stable differences between individuals (e.g., Hamaker et al., 2015; Lucas, 2023). Recently, random-intercept cross-lagged panel model (RI-CLPM) has emerged as popular alternative to traditional CLPM, as it can be used to estimate within-person reciprocal causation while accounting for between-person differences (Hamaker et al., 2015).

Yet another approach suggested by the literature is to use dynamic panel models (DPMs; Allison et al., 2017). DPMs are a class of statistical models designed for longitudinal panel data that explicitly account for both the temporal ordering and the autoregressive nature of variables. They estimate the dependent variable y_t as a function of its own prior value y_{t-1}, as well as the contemporaneous and lagged values of independent variable x_t and x_{t-1}, allowing for both the contemporaneous (within-wave) and cross-lagged (cross-wave) effects between the variables (Moral-Benito et al., 2019). While also RI-CLPMs account for the influence of stable individual traits, DPMs are well suited for situations where the psychological process is still evolving or where the data includes a relatively large number of time points (Andersen, 2022; Murayama & Gfrörer, 2024). Another limitation of RI-CLPMs is their assumption of no contemporaneous (i.e., same-wave) associations between the variables, an assumption that may not reflect the realities of psychological processes where variables often influence each other within the same time point (Muthén & Asparouhov, 2024).

In this study, we employed three stepwise DPMs (M1a–M1c) with loneliness as a dependent variable and three DPMs (M2a–M2c) with CIUS as a dependent variable. The first model (M1a/M2a) accounts for the contemporaneous relationship between the independent and dependent variables (x_t -> y_t). The second model (M1b/M2b) adds a six-month lagged effect of the independent variable (x_{t-1} -> y_t), and the third model (M1c/M2c) includes a 12-month lagged effect (x_{t-2} -> y_t). All models used a six-month lag of the dependent variable to account for the autoregressive effects (y_{t-1} -> y_t). To clarify the model structure, an example DPM depicting the paths estimated when loneliness is treated as the dependent variable is provided in Figure 1. Full model structure is illustrated in Supplementary material (Figure SA1).

We also conducted a post-estimation analysis of long-run effects. The classical econometric long-run effect captures the cumulative impact of a sustained deviation in the independent variable over time (see Shamsollahi et al., 2022). The long-run effect was calculated from the model estimates as

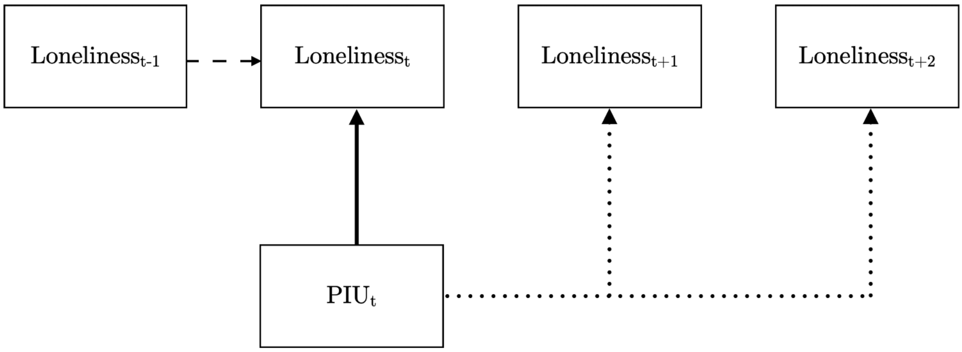

Figure 1. DPM with loneliness as dependent Variable. *Note*. Solid line = contemporaneous effect; dashed line = autoregressive effect; dotted line = lagged effect.

long-run effect = (short-run effect)/(1 − ρ), where the short-run effect is the contemporaneous coefficient and ρ is the autoregressive coefficient of y_{t-1}.

In all models, PIU (CIUS) and loneliness were standardized within wave to have a mean of 0 and a standard deviation of 1. Model fit was evaluated using the root mean square error of approximation (RMSEA), the standardized root mean square residual (SRMR), the comparative fit index (CFI), and the Tucker-Lewis Index (TLI). Following Hu and Bentler (1999), we used cut-off values of RMSEA < .06, SRMR < .08, and CFI > .95 to indicate good fit; for TLI, values > .95 similarly indicate excellent fit.

DPMs were estimated using the xtdpdml (Williams et al., 2018) command in Stata 18 (StataCorp, 2023). All other analyses were done in R (R Core Team, 2025). Appendices A–E, complete model outputs, and Stata and R code used to reproduce all analyses are available at https://osf.io/4a63f/.

Results

Descriptive statistics for main variables are presented in Table 1, and within-person correlations between CIUS and loneliness at T1-T6 are reported in Supplementary material (Table SB2). ICCs demonstrated that 76.5% of the variation in loneliness and 78.9% of the variation in CIUS scores were attributable to between-person differences, suggesting that both constructs reflect individual trait-like stability over the study period. Nonetheless, a meaningful proportion of variance occurred within individuals, supporting the use of DPMs to analyze within-person processes.

Table 1. Descriptive statistics of the main variables.

Variable	N	*M*	*SD*	Min	Max	SD (Between)	SD (Within)	ICC
CIUS	4,518	7.26	8.80	0	56	8.00	3.69	0.789
Loneliness	4,518	1.66	1.66	0	6	1.49	0.74	0.765

Note: ICC = Intraclass Correlation Coefficient.

Tables 2 and 3 provide within-person parameters estimated with DPMs. Each table displays three different DPMs with contemporaneous and lagged effects. All models fit the data well (RMSEA = .007–.039; SRMR = .008–.014; CFI = .994–1.000; TLI = .989–1.000).

In Table 2, the first model (M1a) shows a positive and statistically significant contemporaneous effect of CIUS on loneliness (β = 0.138, *SE* = 0.032, p < .001). The second model (M1b) adds a one-period lag of CIUS (CIUS$_{t\text{-}1}$), while the contemporaneous effect remains significant (β = 0.121, *SE* = 0.037, p < .001); the lagged effect of CIUS$_{t\text{-}1}$ is negative but not statistically significant (β = −0.037, *SE* = 0.028, p = .187). In model M1c, a two-period lag of CIUS (CIUS$_{t\text{-}2}$) is included. The contemporaneous effect of CIUS remains significant (β = 0.144, *SE* = 0.073, p = .049), while both CIUS$_{t\text{-}1}$ and CIUS$_{t\text{-}2}$ are non-significant (β = 0.001, *SE* = 0.048, p = .986; β = 0.055, *SE* = 0.037, p = .135). The one-period lagged effect of loneliness (Loneliness$_{t\text{-}1}$) is significant in models

Table 2. Estimated within-person effects on loneliness from dynamic panel models.

	M1a			M1b			M1c		
Predictor	*β*	*SE*	*p*	*β*	*SE*	*p*	*β*	*SE*	*p*
CIUS (lag0)	0.138	0.032	<.001	0.121	0.037	<.001	0.144	0.073	.049
CIUS$_{t\text{-}1}$ (lag1)	–	–	–	−0.037	0.028	.187	0.001	0.048	.986
CIUS$_{t\text{-}2}$ (lag2)	–	–	–	–	–	–	0.055	0.037	.135
Loneliness$_{t\text{-}1}$ (lag1)	0.047	0.022	.029	0.053	0.022	.017	0.045	0.027	.104
N	4518			4518			4518		
χ2	45.25			44.78			16.66		
df	21			24			16		
RMSEA	.039			.034			.007		
SRMR	.014			.013			.008		
CFI	.994			.995			1.000		
TLI	.989			.991			1.000		

Note. lag0 = contemporaneous effect. CIUS and loneliness are standardized (*M* = 0 and *SD* = 1). RMSEA = Root Mean Square Error of Approximation, SRMR = Standardized Root Mean Square Residual, CFI = Comparative Fit Index, TLI = Tucker-Lewis Index.

Table 3. Estimated within-person effects on CIUS from dynamic panel models.

	M2a			M2b			M2c		
Predictor	*β*	*SE*	*p*	*B*	*SE*	*p*	*β*	*SE*	*p*
Loneliness (lag0)	0.118	0.030	<.001	0.185	0.039	<.001	0.168	0.073	.021
Loneliness$_{t\text{-}1}$ (lag1)	–	–	–	0.038	0.028	.171	0.045	0.049	.355
Loneliness$_{t\text{-}2}$ (lag2)	–	–	–	–	–	–	−0.009	0.032	.769
CIUS$_{t\text{-}1}$ (lag1)	0.083	0.022	<.001	0.086	0.023	<.001	0.117	0.029	<.001
N	4518			4518			4518		
χ2	44.45			48.07			22.21		
df	21			24			16		
RMSEA	.039			.037			.023		
SRMR	.008			.008			.008		
CFI	.995			.995			.998		
TLI	.991			.991			.996		

Note. lag0 = contemporaneous effect. CIUS and loneliness are standardized (*M* = 0 and *SD* = 1). RMSEA = Root Mean Square Error of Approximation, SRMR = Standardized Root Mean Square Residual, CFI = Comparative Fit Index, TLI = Tucker-Lewis Index.

M1a and M1b ($\beta = 0.047$, $SE = 0.022$, $p = .029$; $\beta = 0.053$, $SE = 0.022$, $p = .017$), but becomes non-significant in M1c

($\beta = 0.045$, $SE = 0.027$, $p = .104$).

Table 3 shows the results of the models predicting CIUS. The first model (M2a) indicates a positive contemporaneous effect of loneliness on CIUS ($\beta = 0.118$, $SE = 0.030$, $p < .001$). The second model (M2b) introduces a one-period lag of loneliness ($\text{Loneliness}_{t\text{-}1}$) while maintaining a strong contemporaneous effect of loneliness on CIUS ($\beta = 0.185$, $SE = 0.039$, $p < .001$). The lagged effect of $\text{Loneliness}_{t\text{-}1}$ was positive but nonsignificant ($\beta = 0.038$, $SE = 0.028$, $p = .171$). The third model (M2c) adds a two-period lag of loneliness ($\text{Loneliness}_{t\text{-}2}$), with the contemporaneous effect of loneliness still significant ($\beta = 0.168$, $SE = 0.073$, $p = .021$), while $\text{Loneliness}_{t\text{-}1}$ ($\beta = 0.045$, $SE = 0.049$, $p = .355$) and $\text{Loneliness}_{t\text{-}2}$ ($\beta = -0.009$, $SE = 0.032$, $p = .769$) both remain nonsignificant.

The one-period lagged effect of CIUS ($\text{CIUS}_{t\text{-}1}$) was consistently positive and significant across all models ($\beta = 0.083$, $SE = 0.022$, $p < .001$; $\beta = 0.086$, $SE = 0.023$, $p < .001$; and $\beta = 0.117$, $SE = 0.029$, $p < .001$, respectively).

Additional Analyses

We conducted a decomposition of the total effects of CIUS and loneliness into their short-run and long-run components for the base models (M1a and M2a; see Supplementary material). Models with lagged predictors yielded no significant cross-lagged effects and therefore are not included in this analysis. In M1a, the short-run effect of CIUS on loneliness was $\beta = 0.138$, while the long-run effect was estimated at $\beta = 0.145$. This decomposition reveals that 95.3% of the total effect is short-run, while only 4.7% accrues over time. Similarly, M2a estimates the short-run effect of loneliness on CIUS at $\beta = 0.118$, and the long-run effect was $\beta = 0.129$. The decomposition indicates that 91.7% of the total effect of loneliness on CIUS occurs in the short term, with 8.3% accumulating over time.

We also estimated additional models including general mental health and perceived stress as time-varying covariates to test the robustness of our findings (see Supplementary material). Given that both PIU and loneliness have a strong negative association with mental health (e.g., Cai et al., 2023; Leigh-Hunt et al., 2017), it is plausible that fluctuations in mental health problems or life stressors could confound their relationship (i.e., increases in depression might simultaneously increase both loneliness and PIU). While the estimates for the main predictors changed slightly, they remained robust, which indicates that recent stressors and mental health explain only part of the within-person variation in PIU and loneliness.

Table 4. Summary of hypothesis support.

Hypothesis	Description	Supported
H1a	Contemporaneous PIU → Loneliness	+
H1b	Lagged PIU → Loneliness (6 or 12 months later)	–
H2a	Contemporaneous Loneliness → PIU	+
H2b	Lagged Loneliness → PIU (6 or 12 months later)	–
H3	Autoregressive effects PIU → PIU/Loneliness → Loneliness (6 months later)	+/–

Note: + = supported; – = not supported; +/– = partially supported (i.e., not consistent across models).

Discussion

The purpose of the present longitudinal study was to test a dynamic, reciprocal within-person process between problematic internet use (PIU) and loneliness. Using fixed-effects dynamic panel models (DPMs; Allison et al., 2017), we examined whether increases in PIU predicted current and subsequent increases in loneliness, and vice versa. We also explored whether deviations in PIU and loneliness predicted their own future values, capturing autoregressive dynamics. Table 4 summarizes the main results of our study.

In line with recent meta-analytic results (see Zhang et al., 2024), we found that PIU and loneliness had a positive, reciprocal, and contemporaneous within-person effect on each other (H1a/H2a). However, we did not find any support for lagged within-person dynamics, as deviations from an individual's average level of PIU or loneliness did not predict changes in the other variable 6 or 12 months later (H1b/H2b). The results strongly imply that when individuals experienced higher-than-usual levels of PIU, they were also experiencing higher-than-usual levels of loneliness, and vice versa.

In addition, we found that past values of PIU and loneliness positively predicted their current values in all models except M1c, providing rather strong support for our hypothesis (H3). Significant autoregressive effects suggest that when individuals deviate from their typical level of loneliness or PIU, they tend to remain elevated relative to their own average over the six-month observation period. Using the formula provided by Shamsollahi et al. (2022), we calculated classic econometric long-run effects of both variables on each other. The results showed that most of the effect of PIU on loneliness (and loneliness on PIU) is contemporaneous (within-wave), and only small part of the total effect is attributable to long-run dynamics.

Theoretical and Practical Implications

The main results of the present study add nuance to the widely cited notion of reciprocal longitudinal relationship between PIU and loneliness (see Zhang et al., 2024 for a review). Although we observed robust within-person reciprocal relationship between PIU and loneliness, these effects were contemporaneous rather than lagged. This deviation from earlier studies may partly reflect methodological differences, as our study controlled for all stable between-person differences and focused on within-person changes and dynamic relationships between the variables. However, the null lagged effects are also interesting considering earlier research often cites social displacement as a potential mechanism through which PIU might increase loneliness (Hall & Liu, 2022). If PIU gradually eroded social resources through time displacement or long-term displacement of face-to-face relationships, we would expect to observe delayed increases in loneliness.

The lack of lagged effects suggests that displacement may operate more at the level of attention, as preoccupation with the internet use reduces the perceived quality of the close relationships in the moment (Roberts & David, 2016). For example, in romantic relationships, PIU primarily reduces the relationship satisfaction of the partner experiencing problematic use (Kerkhof et al., 2011). Likewise, the contemporaneous but not lagged effect of loneliness on PIU suggests that increases in loneliness may not signify a loss of actual social ties, but a temporary decline in perceived belonging or emotional connection. The lack of lagged effects of loneliness on PIU could also reflect how lonely states heighten the motivation to find online social rewards in the short term, and that even temporary dips in perceived belonging can trigger internet use to cope with emotional disconnection (e.g., Hawkley & Cacioppo, 2010).

Together, the results suggest that increases in emotional rather than social loneliness may be driving the effect, though our unidimensional measure of loneliness cannot directly test this possibility. For example, lonely individuals may turn to the internet to regulate distress or restore a sense of belonging, yet this use can expose them to curated portrayals of others' lives or amplify fear of missing out, thereby reinforcing perceptions of social inadequacy and disconnection (e.g., Taylor & Choi, 2024; Wang et al., 2025). In this way, PIU may initially function as a compensatory strategy, but as its effects backfire it can further intensify loneliness, creating a self-reinforcing cycle between the two. While plausible, these mechanisms remain speculative in the context of our study and require direct examination in future research.

Another explanation for null cross-lagged effects is that a six-month interval between waves may be too coarse to capture the temporal dynamics between PIU and loneliness. As Gollob and Reichardt (1987) noted, the detection of causal effects can depend critically on timing. Using their example, taking an aspirin has no effect within minutes, a strong effect after a few hours, and little effect the next day. Similarly, some researchers have noted that contemporaneous (lag0) effects in longitudinal data do not necessarily reflect instantaneous reciprocal causality but may represent unmeasured lagged processes occurring between the measurement points (see Marsh et al., 2024, for a discussion).

To illustrate, imagine an individual reports low PIU and loneliness at T1. Four months later, they begin to use Internet extensively (e.g., to cope with their stress), and by the fifth month, they feel lonelier than usual. At T2 (six months after the initial measurement), their scores in both PIU and loneliness are still lingering higher than their average. In our models, the reciprocal relationship is interpreted as contemporaneous, even though it could actually causally be a sequential one. Consequently, future studies with shorter intervals between waves would be better positioned to detect fast-moving, reciprocal within-person dynamics between PIU and loneliness.

Regarding effect sizes, the standardized estimates for the contemporaneous effect of PIU on loneliness (β = 0.138) and loneliness on PIU (β = 0.118) are relatively small by conventional standards. However, as the models control for the dependent variables' past values, effect sizes in autoregressive models are expected to be smaller (see Adachi & Willoughby, 2015). Orth et al. (2024), for example, suggest 0.03 (small effect), 0.07 (medium effect), and 0.12 (large effect) as recommended thresholds for interpreting effect sizes of CLPMs and RI-CLPMs. As DPMs fit in the same family as those statistical methods, our results can be interpreted by these standards also, although caution is probably useful here.

Even though our results highlight absence of cross-lagged effects, our analyses still provide information about within-person temporal dynamics of PIU and loneliness. To aid the interpretation of these long-run dynamics (see Shamsollahi et al., 2022, for a discussion), Figure 2 illustrates cumulative effects if PIU or loneliness is sustained at +1SD level across the whole observation period.

The left panel shows that continued PIU is associated with persistent feelings of loneliness, which stabilizes at ~0.15 SD above the individual's baseline loneliness. Furthermore, we can see that most of this effect is realized contemporaneously (within-wave), and loneliness stabilizes quite early. The right panel shows similar, although slightly weaker effect, as sustained loneliness leads to increased PIU, stabilizing at ~0.13 SD higher PIU over time. The fact that long-run effect is only marginally larger than short-run effect suggests that neither PIU nor loneliness exert cumulative influence on each other over time. Practically, this pattern indicates that sustained PIU leads to a persistent elevation in loneliness (and vice versa), but these elevated states do not continue to intensify, and they reach a new equilibrium rather than spiraling further.

Considering practical implications, our findings suggest that interventions should target PIU and loneliness simultaneously rather than separately, given their concurrent reinforcement. Digital wellbeing programs could integrate strategies addressing both problematic use and social isolation, while healthcare providers might screen for both issues together. Moreover, since much internet use occurs on social media platforms, addressing these issues requires attention to platform design features that may exacerbate both PIU and

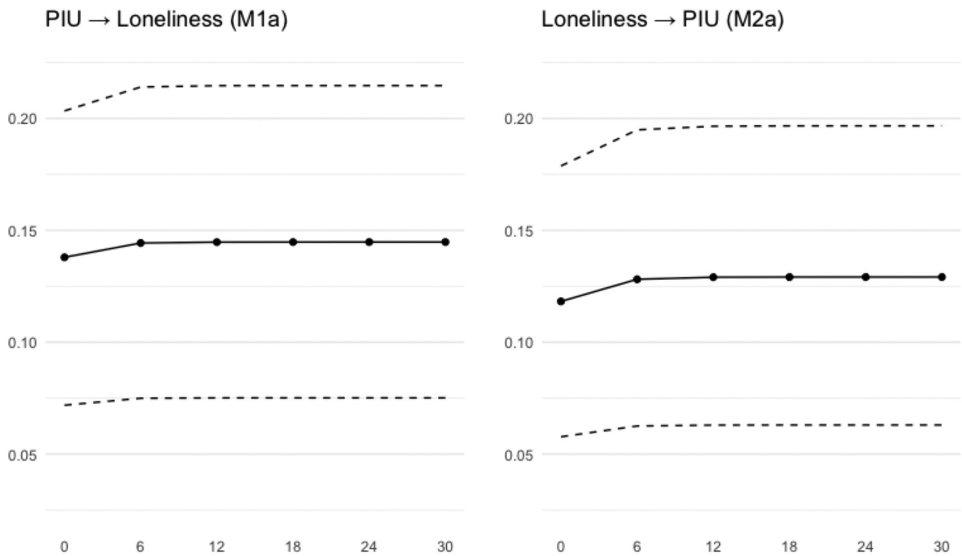

Figure 2. The long-run effects of loneliness and PIU. *Note*: The y-axis shows standardized effect estimates, and x-axis time in six-month intervals (0–30 months). Solid lines indicate the estimated long-run effect, dashed lines show 95% confidence intervals.

loneliness. This points to the need for collaboration among clinicians, researchers, policymakers, and platform designers in developing effective interventions.

Limitations and Future Directions

The main strength of our study is the use of within-person longitudinal data based on a relatively large sample of adult population. This contrasts with much of the existing literature, which often relies on between-person analyses or samples of children or adolescents. While the within-person approach increases the robustness of our findings, it also limits our ability to examine between-person differences. As a significant proportion of variation in loneliness and PIU is attributable to stable individual differences, future research could analyze the moderating effects of different factors that may explain differences between individuals. Related to this, within-person fixed effects estimate only average effects of deviations over time and offer no information on individual trajectories. This may leave out important variation in how PIU and loneliness evolve within individuals over time.

In addition, while we controlled for all stable between-individual differences, there are several time-varying unmeasured factors that could conflate our estimates. For example, stressful and adverse life events–such as job loss, divorce, and major health challenges–increase both PIU (Xiao et al., 2019) and loneliness (Buecker, Denissen, et al., 2021). Therefore, it is plausible that negative life events might act as confounders, which increase both feelings of loneliness and PIU. Even though our robustness checks cleared these worries to some extent, future studies should systematically explore how different kinds of life events and stressors might be associated with loneliness and PIU. Another caveat of this study is that we used unidimensional 3-item measure of loneliness (Hughes et al., 2004), which does not distinguish between social and emotional dimensions. Future research using multidimensional measures of loneliness could provide more nuanced insights on the relationship between PIU and loneliness.

Last, specifying the right or optimal lag structure is particularly difficult (Gollob & Reichardt, 1987). This might also bias our results, even though a recent simulation study showed that DPMs in a structural equation framework might be more robust toward bias caused by the wrong lag structure (Leszczensky & Wolbring, 2022).

Conclusion

This study used dynamic panel models (DPMs) with fixed effects to examine the reciprocal within-person relationship between problematic internet use (PIU) and loneliness in a longitudinal sample of Finnish adults. We theorized and tested both contemporaneous and lagged effects between the two constructs. The results showed that increases in PIU were associated with contemporaneous (within-wave) increases in loneliness, and vice versa. However, we found only limited evidence for lagged effects once contemporaneous associations were accounted for. These findings suggest that the link between PIU and loneliness is primarily short-run and reactive.

Author contributions

CRediT: **Eetu Marttila:** Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing; **Aki Koivula:** Conceptualization, Writing – original draft, Writing – review & editing; **Iina Savolainen:** Writing – original draft, Writing – review & editing; **Anu Sirola:** Writing – original draft, Writing – review & editing; **Atte Oksanen:** Funding acquisition, Investigation, Writing – original draft, Writing – review & editing.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

Funding

Data collection was supported by the Finnish Foundation for Alcohol Studies (Gambling in the Digital Age Project, 2021–2024, PI: A. Oksanen).

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