MHDT
2,4

Received 19 June 2025
Revised 21 August 2025
Accepted 23 August 2025

Bridging digital and physical worlds: longitudinal effects of online gaming and in-person social networks on mental health outcomes

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Abstract

Purpose – Online gaming has emerged as a significant avenue for social connection, yet questions remain about how changes in gaming-related social networks influence mental health and social connectedness over time. This study aims to examine how changes in online gaming and in-person network characteristics were associated with changes in mental health outcomes (depression, anxiety) and social connectedness (isolation, social support) over a six-month period.

Design/methodology/approach – Participants ($n = 236$) completed surveys assessing their online gaming and in-person social networks, mental health symptoms and social connectedness at two time points.

Findings – Partial least squares regression models explained modest variance in outcome changes (R^2: depression$n = 0.146$; anxiety $= 0.076$; isolation$n = 0.134$; support $= 0.146$). Increases in the diversity of how participants met their in-person network was associated with decreases in depressive symptoms ($ß = −3.74$), while increases in online interaction frequency was associated with increases in symptoms ($ß = 1.34$). For anxiety, increased in-person relationship heterogeneity was associated with higher symptoms ($ß = 2.88$), while online relationship heterogeneity was associated with lower symptoms ($ß = −3.51$). Changes in relationship quality metrics were consistently associated with outcomes as opposed to changes in network size or interaction frequency. Notably, improvements in both online ($ß = 1.83$) and in-person ($ß = 2.53$) relationship quality were associated with increased social support.

Originality/value – These findings suggest that while online gaming relationships may complement in-person connections, they may not effectively substitute for diverse in-person interaction. Results emphasize the importance of maintaining varied in-person social connections while leveraging online gaming relationships as supplementary rather than primary sources of social support.

Keywords Social network analysis, Mental health, Social connectedness, Gaming communities

Paper type Research paper

Introduction

Online gaming has evolved into an opportune and accessible social platform, fundamentally transforming how millions of people worldwide connect and build communities. Recent statistics indicate that 64% of adults in the USA engage in gaming, with 65% playing with others online and spending an average of 6.6 h per week in multiplayer environments (Entertainment Software Association, 2019). For many players, gaming represents more than entertainment – 80% report mental stimulation benefits, 63% cite problem-solving

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Funding: This study was supported by the JP Bramhall Faculty Research Seed Grant Program through the Huffines Institute at Texas A&M University.

Mental Health and Digital Technologies
Vol. 2 No. 4, 2025
pp. 300-316
Emerald Publishing Limited
2976-8756
DOI 10.1108/MHDT-06-2025-0039

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advantages, and 55% value gaming for connecting with friends, while 79% use gaming for relaxation and stress relief (Entertainment Software Association, 2019). This surge in social gaming coincides with broader societal changes in how people form and maintain relationships, particularly as research shows decreasing social connectedness threatens wellbeing across developed nations, with estimates suggesting socially isolated individuals have a 30% increased risk of mortality (Holt-Lunstad *et al.*, 2015; Holt-Lunstad, 2022).

The relationship between online gaming and mental health outcomes presents a complex picture that defies simple categorization. Research has identified multiple pathways through which gaming might influence well-being – from facilitating meaningful social support and combating loneliness (Cole *et al.*, 2017; Prochnow *et al.*, 2023; Prochnow *et al.*, 2020b; Prochnow *et al.*, 2020a; Prochnow and Patterson, 2024; Prochnow *et al.*, 2021; Colder Carras *et al.*, 2017) to potentially exacerbating psychological issues when gaming patterns become problematic (González-Bueso *et al.*, 2018; O'Farrell *et al.*, 2020). While studies have examined the cross-sectional relationships between gaming networks and mental health, a significant gap exists in understanding how changes in gaming relationships over time predict changes in psychological outcomes. This longitudinal perspective is crucial, as the quality and impact of these relationships may evolve substantially as they develop (Cole *et al.*, 2020; Cole *et al.*, 2017). Further, understanding these relationships in the context of a gamer's larger social network including in-person relationships are vital.

The present study addresses these gaps by examining the temporal dynamics between social network characteristics (both through online gaming and in-person) and mental health outcomes among online gamers. By using a longitudinal design and comprehensive social network analysis, we can better understand how changes in both online and offline social capital predict changes in mental health outcomes over time. This approach moves beyond static associations to understand the developmental trajectories of gaming relationships and their implications for mental health. Such knowledge is crucial for designing interventions that can effectively promote healthy gaming experiences while supporting beneficial social connections both online and offline.

Literature review

The relationship between social connections and mental health has particular relevance to online gaming communities, especially as traditional face-to-face interaction patterns continue to evolve in contemporary society (Halbrook *et al.*, 2019). Research indicates that loneliness has reached concerning levels, with approximately 57% of adults reporting chronic feelings of social disconnection – a trend that carries significant public health implications (Holt-Lunstad *et al.*, 2015). Against this backdrop, gaming environments have emerged as distinctive social ecosystems that offer structured opportunities for connection that may be particularly valuable for those experiencing barriers to traditional social engagement (Halbrook *et al.*, 2019).

Multiple studies suggest that the quality of relationships formed through gaming carries greater significance than their quantity in determining mental health outcomes (Mandryk *et al.*, 2020; Cole *et al.*, 2020). This qualitative dimension appears particularly important in fostering positive outcomes, with research demonstrating that harmonious gaming passion – characterized by autonomous engagement that complements rather than conflicts with other life domains – consistently predicts increased social capital development and enhanced psychological well-being (Mandryk *et al.*, 2020; Cole *et al.*, 2020). The positive effects manifest most strongly when gaming facilitates meaningful interactions that provide genuine emotional support and connection rather than merely superficial contact (Mandryk *et al.*, 2020; Cole *et al.*, 2020).

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Gaming relationships demonstrate considerable heterogeneity in their functions and impacts across different individuals and contexts (Snodgrass *et al.*, 2018; Di Blasi *et al.*, 2020). Recent research has identified several moderating factors that influence these relationships, including pre-existing social anxiety, the robustness of offline social networks and individual motivations for gaming engagement (Di Blasi *et al.*, 2020; Kowert and Oldmeadow, 2015; Prochnow and Patterson, 2024). For individuals with elevated social anxiety, gaming environments may provide a controlled social context with reduced evaluation concerns, potentially serving as a "training ground" for developing interpersonal skills (Dechant *et al.*, 2020; Kowert and Oldmeadow, 2015). Conversely, for those with strong existing social connections, gaming relationships may function primarily as complementary social ties that broaden rather than replace traditional support networks (Prochnow and Patterson, 2024; Depping *et al.*, 2018). This contextual sensitivity underscores the need for nuanced approaches to understanding how gaming relationships contribute to or potentially detract from overall social well-being.

Social capital theory provides a valuable framework for understanding the dynamics of online gaming relationships, offering conceptual clarity for analyzing how virtual interactions build different types of interpersonal resources (Claridge, 2018; Putnam, 2000). Research has identified two distinct forms of social capital in gaming contexts: bridging and bonding capital, each with unique characteristics and outcomes for psychological well-being (Claridge, 2018; Putnam, 2000).

Bonding social capital develops through close, emotionally supportive relationships characterized by high trust and reciprocity, often formed within stable gaming groups or guilds where players interact consistently over time (Perry *et al.*, 2018b). This form of capital manifests through deeper connections that provide emotional support and identity reinforcement (Claridge, 2018). Studies demonstrate that bonding capital in gaming contexts has been associated with increased emotional support, improved self-esteem and reduced loneliness, particularly when these relationships foster genuine intimacy and meaningful disclosure (Cole *et al.*, 2017; Halbrook *et al.*, 2019; Trepte *et al.*, 2012). Research by Cole and Griffiths (2007) found evidence that MMORPG players discussed sensitive issues with their gaming friends that they might not discuss with in-person friends, highlighting how these virtual relationships can facilitate important emotional connections.

In contrast, bridging social capital emerges from broader, more diverse connections that expose players to different perspectives and resources, often through more casual gaming interactions that span different social groups (Depping *et al.*, 2018; Mandryk *et al.*, 2020). Steinkuehler and Williams (2006) demonstrated that multiplayer gaming environments function as "third places" that facilitate bridging connections across socioeconomic, geographic and demographic boundaries that might otherwise remain uncrossed. These connections have been shown to expand players' worldviews and access to information networks, with studies indicating that bridging capital developed through gaming correlates with increased civic engagement and broader social identities (Prochnow *et al.*, 2021; Prochnow and Patterson, 2024; Zhong, 2011). Research by Trepte *et al.* (2012) found that bridging capital in gaming was positively associated with information benefits and social embeddedness beyond gaming contexts, suggesting these connections provide valuable resources beyond immediate emotional support. Additionally, Kobayashi (2010) demonstrated that engaging with diverse players in gaming contexts was associated with increased political participation and tolerance, highlighting how bridging capital facilitates broader societal integration.

The interaction between these two forms of social capital in gaming environments creates complex patterns of social connection that can simultaneously address different

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psychological needs (Claridge, 2018). Research suggests that many games are particularly effective at facilitating bridging capital through their structural features that encourage interaction with diverse others, while more sustained engagement within gaming communities can eventually transform bridging relationships into bonding ones as trust develops over time (Depping *et al.*, 2018; Steinkuehler and Williams, 2006; Williams, 2006). Understanding how these distinct forms of social capital develop and function in gaming contexts provides essential theoretical grounding for examining their differential impacts on mental health outcomes and social connectedness (Korkeila and Harviainen, 2023).

The evolution of gaming relationships over time presents challenges for research and theory development. While studies indicate that online gaming relationships may complement rather than replace traditional social connections, questions remain about how these relationships develop and change over time (Mandryk *et al.*, 2020). Research suggests that the benefits of gaming relationships often depend on how well they complement existing social networks and the quality of interactions they facilitate (Prochnow *et al.*, 2020b; Prochnow *et al.*, 2020a; Prochnow *et al.*, 2021; Halbrook *et al.*, 2019; Depping *et al.*, 2018). Understanding how changes in online and offline social networks influence mental health requires a longitudinal perspective that can capture the evolution of these relationships over time. This is particularly important given evidence that the quality and nature of gaming relationships may change substantially as they develop (Cole *et al.*, 2017). Furthermore, research suggests that the impact of gaming relationships on wellbeing may depend on complex interactions between online and offline social networks, gaming motivations and individual characteristics (Mandryk *et al.*, 2020).

Social network analysis (SNA) offers a methodologically rigorous approach to operationalizing and measuring social capital in gaming contexts (Borgatti *et al.*, 2018; Valente, 2010; Perry *et al.*, 2018a). While traditional measures of social capital often rely on self-reported perceptions, SNA provides specific metrics that capture the structural and compositional features of relationships that constitute both bonding and bridging forms of social capital (Perry *et al.*, 2022; Burt, 1995; Lin, 2017). This approach enables researchers to move beyond general assessments to examine precise network characteristics that may differentially impact mental health outcomes (Lin, 2017).

The structural dimensions of social networks reveal important aspects of bridging capital through metrics such as network size, density and heterogeneity (Lin, 2017; Perry *et al.*, 2022). Network size quantifies the number of connections an individual maintains, while density measures the interconnectedness among these contacts. Heterogeneity captures the diversity of relationship types within the network, a key indicator of bridging capital's resource-diversification function (Peng *et al.*, 2021). These structural metrics allow researchers to assess how individuals' access to diverse perspectives and resources through gaming evolves over time and correlates with psychological outcomes.

Complementing these structural measures, SNA also captures the quality dimensions of relationships that constitute bonding capital through metrics such as tie strength, interaction frequency, and emotional closeness (Lin, 2017; Perry *et al.*, 2018a). In gaming contexts, these indicators allow researchers to distinguish between peripheral connections and the deeper, emotionally supportive relationships that provide psychological sustenance (Cole *et al.*, 2017; Prochnow *et al.*, 2023). By simultaneously measuring these multiple dimensions across both online and offline networks, SNA provides a comprehensive framework for examining how different forms of social capital develop through gaming and interact with existing relationship patterns to influence mental health trajectories (Prochnow and Patterson, 2024; Snodgrass *et al.*, 2018).

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Hypotheses

Based on social capital theory and prior research on gaming relationships, this study tested several key hypotheses regarding the longitudinal relationship between changes in social network characteristics and mental health outcomes. First, we hypothesized that changes in relationship quality metrics would be more predictive of mental health outcomes than changes in network size or interaction frequency, reflecting the primacy of connection quality over quantity. Second, we hypothesized that increases in diverse in-person social connections (measured through relationship heterogeneity) would predict mental health outcomes. Third, we hypothesized that online gaming relationships would demonstrate differential effects based on network characteristics – specifically, that improvements in online relationship quality would predict increased social support and decreased isolation, but that increased online interaction frequency without corresponding quality improvements might predict increased symptoms of depression and anxiety. Finally, we hypothesized that complementary patterns of social capital development across both online and offline contexts would yield the most positive mental health outcomes, supporting the theory that gaming relationships function optimally as supplements rather than replacements for in-person social connections.

Methods

Participants and procedure

The study recruited online gamers ($n = 300$) from various gaming platforms and communities using CloudResearch Connect. Participants anonymously completed surveys at two time points, approximately 6 months apart (T1 and T2). The six-month interval between assessments provides sufficient time for meaningful changes in gaming relationships while minimizing participant attrition (Trepte *et al.*, 2012; Cole *et al.*, 2017). This timeframe captures typical cycles of game engagement and social network development while aligning with research showing clinically significant fluctuations in depressive and anxiety symptoms often emerge within 3–6 months (Mandryk *et al.*, 2020; Cuijpers *et al.*, 2023). Eligibility criteria included being at least 18 years old, currently engaging in online gaming activities and being able to provide informed consent. To minimize attrition, participants who completed the T1 survey received email reminders one month before T2 data collection. Each survey took 20–30 min to complete. Participants received $10 compensation for completing T1 and $15 for completing T2. Quality checks were performed at both time points, with participants needing to pass three of four quality checks for inclusion. All procedures were approved by the approved by the [Institution name] IRB (Protocol [ID], approval date [DD-MMMYYYY]) and participants were required to view an informed consent page prior to participation. All research was conducted in accordance with the Declaration of Helsinki.

The final analytical sample consisted of 236 participants who completed both the baseline (T1) and follow-up (T2) surveys. Initially, 300 participants were recruited and completed the T1 assessment. Of these, 64 participants (21.3%) did not complete the T2 survey, representing an attrition rate of 21.3% over the six-month study period. To assess potential attrition bias, we conducted comparative analyses between those who completed both waves of data collection ($n = 236$) and those who only completed the baseline assessment ($n = 64$). These analyses examined demographic characteristics (age, gender, race/ethnicity, education level, income), baseline gaming behaviors and baseline mental health measures (depressive symptoms, anxiety, social isolation and social support). No statistically significant differences were observed between completers and non-completers on any of these variables (all $p > 0.05$), suggesting that attrition occurred randomly rather than systematically. This indicates that the final analytical sample remains representative of the initial cohort, minimizing concerns about selection bias affecting the longitudinal results.

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Participants ($n = 236$) were predominantly men (66.5%, $n = 157$) and White or Caucasian (78.8%, $n = 186$), with 13.1% ($n = 31$) identifying as Black or African American, 7.6% ($n = 18$) as Asian and 14.4% ($n = 34$) identifying as Hispanic, Latino/a/x or Spanish origin. The average age was 34.92 years (SD = 8.71; range = 18–65). Most participants reported having at least some college education, with 37.3% holding a Bachelor's degree ($n = 88$) and 7.2% holding graduate degrees ($n = 17$). The majority were employed (63.1% employed for wages, 15.7% self-employed), with a modal household income between \$50,000 and \$74,999 (23.0%). Regarding relationship status, 38.6% reported not dating ($n = 91$), while 30.9% were married ($n = 73$). See Table 1 for more information about the sample.

Measures

Depressive symptoms. The eight-item Patient Health Questionnaire (PHQ-8) measured depressive symptoms at both time points (Kroenke *et al.*, 2009). Participants indicated

Table 1. Participant demographics ($n = 236$)

Characteristic	*n* (%)
Gender	
Man	157 (66.5)
Woman	78 (33.1)
Other	1 (0.4)
Race/Ethnicity	
White or Caucasian	186 (78.8)
Black or African American	31 (13.1)
Asian	18 (7.6)
American Indian/Alaska Native	4 (1.7)
Native Hawaiian/Pacific Islander	2 (0.8)
Other	6 (2.5)
Hispanic or Latinx	34 (14.4)
Education	
High school or less	54 (22.8)
Some college/technical training	49 (20.8)
Associates degree	28 (11.9)
Bachelor's degree	88 (37.3)
Graduate degree	17 (7.2)
Employment	
Employed for wages	149 (63.1)
Self-employed	37 (15.7)
Unemployed	29 (12.3)
Student	9 (3.8)
Other	12 (5.1)
Annual household income	
Less than \$24,999	48 (20.4)
\$25,000–\$49,999	51 (21.7)
\$50,000–\$74,999	54 (23.0)
\$75,000–\$99,999	33 (14.0)
\$100,000 or more	49 (20.8)

Note(s): Percentages may not sum to 100 due to rounding and participants being able to select multiple racial categories
Source(s): Authors' own work

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frequency of problems over the past 2 weeks from “not at all” (0) to “nearly every day” (3). Items (e.g., “Feeling down, depressed, irritable or hopeless”) were summed for a total score ranging from 0 to 24. While results should be verified by clinicians, meta-analyses support the scale’s diagnostic properties (Wu *et al.*, 2020; Thombs *et al.*, 2014). Cronbach’s α was 0.76 at T1 and 0.78 at T2. In this sample depressive symptoms had a mean score of 6.82 (SD = 6.14) at T1 and 6.60 (SD = 6.21) at T2.

Symptoms of anxiety. We used the state subscale of the State-Trait Anxiety Inventory (STAI) validated short form to assess anxiety at both time points (Spielberger, 1970). The state subscale contains 10-items and uses a four-point Likert scale and summed, with higher scores indicating greater state anxiety. Participants were asked to rate how often they generally feel a certain way (e.g. “I feel nervous and restless”) with response options of almost never, sometimes, often, and almost always. The STAI demonstrates strong reliability, with internal consistency coefficients reported between 0.86 and 0.95 (Spielberger, 1970). Over a two-month period, test-retest reliability coefficients have been observed to range from 0.65 to 0.75 (Spielberger, 1970). Additionally, substantial evidence supports the scale’s construct and concurrent validity (Seligman *et al.*, 2004; Metzger, 1976). For this sample, the mean was 24.79 (SD = 6.42) at T1 and 24.15 (SD = 6.40) at T2.

Social isolation. The shortened UCLA Loneliness Scale (Hughes *et al.*, 2004) measured social isolation at both time points. Three items (e.g. “How often do you feel alone”) were scored on a three-point scale from “Hardly ever” (1) to “Often” (3). The three items were summed (range 3–9); higher scores indicated greater loneliness. The UCLA-3 shows good reliability (α = 0.84; (Hughes *et al.*, 2004). In this study, social isolation scores had a mean of 5.14 (SD = 2.13) at T1 and 5.21 (SD = 2.19) at T2.

Social support. We assessed perceived social support using an abbreviated version of the Multidimensional Scale of Perceived Social Support (MSPSS) assessed social support at both time points (Zimet *et al.*, 1990). The 16-item scale (e.g. “I get the emotional help and support I need from my family.”) uses a four-point response format from “strongly disagree” to “strongly agree.” Subscales for family, friends, significant others and online support were summed for a total score ranging from 16 to 64. The MSPSS demonstrates good internal consistency (Cronbach’s α ranging 0.84–0.92) and test-retest reliability (0.72–0.85) (Zimet *et al.*, 1990; Dahlem *et al.*, 1991). At T1, the mean score for social support was 48.48 (SD = 10.81), while at T2, the mean was 48.60 (SD = 11.19). The scale was modified to include an online subscale as an exploratory measure.

Social networks. At both time points, participants listed up to five people they interacted with most through online gaming and up to five people they interacted with most in-person over the last 30 days (Prochnow *et al.*, 2020b; Prochnow and Patterson, 2024). Networks were limited to five members to capture the most salient relationships (Adams, 2019; Perry *et al.*, 2018a). Participants could list members in both networks if applicable. For each network member, participants provided comprehensive relationship information. This information included the type of relationship, frequency of contact, frequency of confiding about difficult issues, how they met, how good the network member makes them feel about themselves, perceived closeness and whether network members know each other.

From these responses, we generated network composition and structure variables related to social bridging and bonding measures for both in-person and online networks at each time point (Perry *et al.*, 2022). The bridging social capital measures included four key components. Network size was calculated as the number of network members reported, with a maximum of five. Effective size represented the number of non-overlapping groups within each participant’s network (Borgatti, 1997). Heterogeneity was computed as the number of unique relationship types divided by network size (Peng *et al.*, 2021). Additionally,

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heterogeneity in how participants met those in their networks (in-person or online) was also calculated. The presence of weak ties was determined by the frequency of minimum-value closeness ratings (Sandstrom and Dunn, 2014).

The bonding social capital measures consisted of four distinct metrics (Perry *et al.*, 2022). Mean tie strength was calculated as the average of closeness ratings on a 1–5 scale. The proportion of active engagement represented the proportion of network members with whom participants interacted frequently (3–5 days/week). The proportion of frequent confiding was calculated as the proportion of relationships involving frequent confidant interactions. Mean quality of connection was determined by averaging the "feeling good" ratings on a 1–5 scale for all network members (Prochnow and Patterson, 2024).

Data analysis

Change scores were calculated for all network variables and mental health outcomes by subtracting T1 from T2 values. Partial least squares (PLS) regression using a latent variable path modeling approach was used to examine how changes in network variables were associated with changes in feelings of social connectedness and mental health outcomes. PLS regression was selected because it effectively handles multicollinearity among predictor variables and can accommodate situations where the number of predictors is large relative to the sample size (Wold *et al.*, 2001). This approach is particularly appropriate for our analysis as network variables often show substantial intercorrelation despite representing unique concepts, and we examined multiple network variables simultaneously. The PLS regression extracted orthogonal latent factors that maximize the covariance between predictor variables (network variable changes) and the response variable (e.g. PHQ-8 change scores). The structural model can be conceptualized as a two-stage process: first, latent components were derived from the predictor matrix using weighted linear combinations; second, these components were used to predict the outcome variables through regression. The number of components retained was determined by examining the cumulative proportion of variance explained in both predictor and response variables. Variable importance in projection (VIP) scores were calculated to assess the relative contribution of each predictor to the model; a score of 1.0 or greater was used as a heuristic for variable importance. All data were analyzed using SPSS v.29 (IBM, 2022).

Results

Depressive symptoms (PHQ-8)

For depressive symptoms, the PLS regression model explained 14.6% of the variance in PHQ-8 change scores. Changes in in-person meeting heterogeneity (i.e. meeting people both online and in-person) emerged as the strongest predictor (VIP = 1.99), with increases in diverse meeting contexts predicting significant decreases in depressive symptoms ($\beta = -3.74$). Other in-person network changes were associated with decreases in depressive symptoms such as relationship heterogeneity (VIP = 1.10, $\beta = -0.54$), number of weak ties (VIP = 1.10, $\beta = -0.72$), average frequency of network members making the participant feel good about themselves (VIP = 1.15, $\beta = -0.40$), average closeness (VIP = 1.01, $\beta = -0.45$) and effective size (VIP = 1.23, $\beta = -0.06$). However, increases in in-person network size were associated with increased depressive symptoms (VIP = 1.31, β = 0.17). For the online network, increased online interaction frequency significantly was associated with changes in depressive symptoms (VIP = 1.48), with more frequent online interactions associated with increased depressive symptoms (β = 1.34). Additionally, increases in the frequency of online confiding (VIP = 1.16, β = 0.78) was also associated with increased depressive symptoms. See Table 2 for full model results.

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Table 2. PLS regression results predicting changes in mental health outcomes from changes in network characteristics

Network characteristic	Depressive symptoms	Anxiety	Social isolation	Social support
Model fit				
R^2	0.15	0.08	0.13	0.15
Adjusted R^2	0.13	0.05	0.11	0.13
In-person network parameters				
Relationship heterogeneity	−0.54 (1.10)*	2.88 (1.45)*	−0.86 (1.13)*	−2.13 (0.48)
Meeting heterogeneity	−3.74 (1.99)*	2.28 (1.20)*	−0.17 (0.87)	0.18 (0.33)
Weak ties	−0.72 (1.10)*	−0.003 (0.64)	−0.17 (0.66)	0.89 (0.88)
Average closeness	−0.45 (1.01)*	−0.03 (0.25)	−0.22 (1.25)*	0.63 (1.34)*
Percent frequent interaction	0.39 (0.65)	2.35 (1.26)*	0.11 (0.62)	1.80 (0.45)
Percent frequent confiding	−0.26 (0.51)	−2.68 (1.95)*	0.15 (0.54)	−1.48 (0.62)
Average feeling good	−0.40 (1.15)*	0.33 (1.08)*	−0.14 (1.56)*	2.53 (2.20)*
Network size	0.17 (1.31)*	0.75 (1.74)*	0.11 (0.96)	−0.10 (0.36)
Effective size	−0.06 (1.23)*	0.24 (1.50)*	−0.07 (0.93)	−0.31 (0.46)
Online network parameters				
Relationship heterogeneity	0.97 (0.87)	−3.51 (1.42)*	0.27 (0.38)	1.52 (0.39)
Meeting heterogeneity	0.47 (0.64)	−0.37 (0.70)	0.41 (0.45)	0.48 (0.29)
Weak ties	0.33 (0.79)	0.19 (0.83)	−0.09 (0.80)	0.33 (1.07)*
Average closeness	0.30 (0.65)	0.27 (0.55)	0.05 (0.85)	1.83 (1.80)*
Percent interaction	1.34 (1.48)*	0.51 (0.39)	0.09 (0.89)	−1.88 (0.73)
Percent confiding	0.78 (1.16)*	0.07 (0.41)	0.58 (1.03)*	−1.68 (0.61)
Average feeling good	−0.004 (0.33)	0.43 (0.66)	−0.81 (2.36)*	1.33 (1.91)*
Network size	0.08 (0.34)	−0.42 (0.94)	0.22 (1.01)*	0.75 (0.84)
Effective size	−0.04 (0.35)	−0.12 (0.86)	−0.01 (0.70)	−0.83 (0.88)

Note(s): Values represent standardized coefficients with Variable Importance in Projection (VIP) scores in parentheses. *VIP scores > 1.0 was used as a heuristic for variable importance
Source(s): Authors' own work

Anxiety
For anxiety symptoms, the model explained 7.6% of the variance in STAI change scores. Changes in in-person confiding frequency emerged as the strongest predictor (VIP = 1.95), with increased confiding associated with decreases in anxiety symptoms ($\beta = -2.68$). Changes in in-person network size (VIP = 1.74, β = 0.75), in-person interaction frequency (VIP = 1.26, β = 2.35), average frequency of network members making the participant feel good about themselves (VIP = 1.08, $\beta = 0.33$), in-person relationship heterogeneity (VIP = 1.45, β = 2.88), in-person meeting heterogeneity (VIP = 1.20, β = 2.28) and effective size (VIP = 1.50, β = 0.24) were associated with increased anxiety. Meanwhile, changes in online relationship heterogeneity strongly was associated with decreased anxiety (VIP = 1.42, $\beta = -3.51$). See Table 2 for full model results.

Social isolation
The model for social isolation explained 13.4% of the variance in UCLA Loneliness Scale change scores. Changes in online average frequency of network members making the participant feel good about themselves emerged as the strongest predictor (VIP = 2.36), predicting decreased isolation ($\beta = -0.81$). However, increases in online confiding frequency (VIP = 1.03, $\beta = 0.58$) and network size (VIP = 1.01, $\beta = 0.22$) were associated with increases in feelings of social isolation. Changes in in-person relationship heterogeneity (VIP = 1.13,

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$\beta = -0.86$), in-person average closeness (VIP = 1.25, $\beta = -0.22$) and in-person average frequency of network members making the participant feel good about themselves (VIP = 1.56, $\beta = -0.14$) were all associated with decreased feelings of isolation. See Table 2 for full model results.

Social support

For social support, the model explained 14.6% of the variance in MSPSS change scores. Changes in in-person average frequency of network members making the participant feel good about themselves emerged as the strongest predictor (VIP = 2.20), with improved relationship quality predicting substantially increased social support (β = 2.53). Additionally, changes in in-person average closeness (VIP = 1.34, β = 0.63), was associated with increased feelings of social support. Similarly, changes in online average closeness (VIP = 1.80, β = 1.83), online average frequency of network members making the participant feel good about themselves (VIP = 1.91, β = 1.33) and number of online weak ties (VIP = 1.07, β = 0.33) were associated with increased social support. Changes in online relationship heterogeneity (VIP = 1.39, β = 1.52) was also associated with increased social support. See Table 2 for full model results.

Discussion

The temporal relationship between changes in gaming-related social networks and mental health outcomes reveals complex patterns that challenge simplistic views of online gaming's impact. Our findings demonstrate that mental health effects cannot be reduced to simple linear associations, but rather depend on intricate interactions between online and offline social capital development. Findings also suggest differences in the impact of network dynamics on depressive symptoms and anxiety. This aligns with emerging literature showing the necessity of examining both quantity and quality of social connections in gaming spaces (Mandryk *et al.*, 2020; Cole *et al.*, 2017). While the observed associations are theoretically grounded and consistent with prior literature, these findings should be interpreted as hypothesis-generating rather than definitive. Given the exploratory nature of the PLS regression and the complexity of social network dynamics, the implications are best viewed as preliminary insights that warrant further investigation. Future research should incorporate additional robustness checks, such as cross-validation or bootstrapping procedures, to further assess the stability and generalizability of these findings across diverse samples and contexts.

Changes in network characteristics and depressive symptoms

Our findings demonstrate that increases in in-person meeting heterogeneity was associated with decreases in depressive symptoms, while increased online interaction frequency was associated with increased depressive symptoms. It is likely that if a gamer is meeting people from various contexts, that they are less constrained to their network members, and therefore are not confined to one homogenous group of network members, particularly if that group is distressing (Burt, 1992). This aligns with recent research suggesting that diverse in-person social connections may be particularly protective against depressive symptoms (Trepte *et al.*, 2012; Halbrook *et al.*, 2019; Prochnow *et al.*, 2020b; Prochnow *et al.*, 2021). The importance of meeting heterogeneity supports social capital theory's emphasis on diverse connections as crucial for psychological wellbeing (Williams, 2006). The results suggest that while online gaming relationships can provide valuable social connections, they may not effectively substitute for varied face-to-face interactions and may inherently create more constrained networks. Instead, this research furthers the idea of the protective and unique value of face-to-face interaction for mental health (Depping *et al.*, 2018; Perry *et al.*, 2018b).

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The observation that increased online interaction frequency was associated with higher depressive symptoms requires careful interpretation within the broader context of gaming and mental health research. Rather than suggesting that online gaming cause depressive symptoms, this may reflect what Lieberman and Schroeder (2020) describe as a compensatory response - individuals experiencing increased depressive symptoms may turn to online gaming for social connection. This interpretation aligns with recent research showing that psychosocially vulnerable individuals may use online gaming to compensate for existing difficulties rather than gaming directly causing negative outcomes (Kardefelt-Winther, 2014; Di Blasi *et al.*, 2020). There is also research that shows when experiencing depressive symptoms, people initially seek support online and overtime turn to more in-person sources of support (Alavi *et al.*, 2023). Furthermore, studies have shown that the relationship between gaming and depressive symptoms often depends on factors such as gaming motivation, play style and the quality of social interactions (Kowert and Oldmeadow, 2015; Snodgrass *et al.*, 2018).

Anxiety and network changes

The relationship between network changes and anxiety showed a more complex pattern, with increased in-person relationship heterogeneity predicting higher anxiety symptoms while online relationship heterogeneity was associated with lower symptoms. This seemingly counterintuitive finding may reflect the unique characteristics of online gaming environments, which can provide structured social interactions that may be less anxiety-provoking for some individuals compared to diverse in-person relationships (Park *et al.*, 2016; Mandryk *et al.*, 2020). People experiencing anxiety often seek more controlled and stable environments, which may be difficult in more diverse in-person social networks (Benedetti *et al.*, 2024). The controlled nature of online gaming interactions may offer opportunities for social engagement that feel more manageable for individuals prone to anxiety, supporting previous research on gaming as a potential pathway for social connection among socially anxious individuals (Dechant *et al.*, 2020; Kowert and Oldmeadow, 2015). This aligns with research showing that online environments can provide safe spaces for social interaction and relationship building, particularly for individuals who might find face-to-face interactions challenging (Depping *et al.*, 2018; Cole and Griffiths, 2007).

Social isolation and network change

Our findings revealed complex relationships between network characteristics and social isolation over a six-month period. Changes in online gaming relationships showed mixed effects, with improvements in the quality of online relationships (as measured by network members making the participant feel good about themselves) strongly predicting decreased isolation. However, increases in online confiding frequency and network size were associated with greater feelings of isolation. This paradoxical finding aligns with Mandryk *et al.* (2020) showing that while gaming relationships can build social capital, their effectiveness in combating isolation depends heavily on the quality rather than quantity of connections, and supports previous research that indicates isolation can at times be more of a feeling or perception as opposed to a quantity or threshold of relationships in a person's life (Taylor *et al.*, 2023). The positive association between increased online confiding and isolation may reflect what Lieberman and Schroeder (2020) describe as compensatory behavior, where individuals experiencing greater isolation may turn to online connections for support. Meanwhile, changes in in-person network characteristics was consistently associated with decreased isolation, particularly through greater relationship heterogeneity and improved relationship quality. This supports previous findings that diverse, high-quality

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in-person relationships remain crucial for combating social isolation (Cole *et al.*, 2020). Overall, this study suggests that relationship quality, whether experienced online or in-person, is related to social isolation scores among online gamers, with evidence to suggest that online gaming relationships appear most effective when complementing rather than replacing varied in-person social connections. This aligns with recent work emphasizing the importance of maintaining balanced social portfolios across both online and offline contexts (Depping *et al.*, 2018). Game developers and mental health practitioners should therefore focus on helping individuals leverage online gaming relationships to supplement, rather than substitute for, meaningful in-person connections.

Social support and relationship quality

Our results emphasize that changes in relationship quality metrics were consistently more predictive of outcomes than changes in network size or interaction frequency. This builds on our previous findings related to isolation and aligns with recent research suggesting that the quality of gaming relationships, rather than their quantity, is crucial for positive psychological outcomes (Williams, 2006; Depping *et al.*, 2018; Cole *et al.*, 2020). The finding that improvements in both online and in-person relationship quality were associated with increased social support suggests that gaming relationships can meaningfully contribute to individuals' support networks when they facilitate high-quality connections. This supports previous work on the potential for online gaming to build both bridging and bonding social capital (Prochnow *et al.*, 2023; Prochnow *et al.*, 2020a) and aligns with research showing that online relationships can provide genuine social support when they develop sufficient depth and quality (Perry *et al.*, 2018b).

Implications for theory and practice

These findings have important implications for understanding how online gaming relationships influence mental health and social connectedness. The results support a more nuanced theoretical framework that moves beyond examining gaming relationships in isolation to consider how they interact with broader social networks over time. This aligns with recent work suggesting that gaming relationships' impact on well-being depends heavily on how well they complement existing social connections (Raith *et al.*, 2021; Kowert and Oldmeadow, 2015). The findings add to our understanding of social capital development in digital spaces (Steinkuehler and Williams, 2006) and support theories about the importance of maintaining diverse social portfolios across both online and offline contexts (Putnam, 2000; Depping *et al.*, 2018).

For mental health practitioners, these findings suggest the importance of assessing both the quality and diversity of clients' social connections across online and offline contexts. Rather than universally encouraging or discouraging online gaming relationships, interventions should focus on helping individuals develop balanced social portfolios that leverage the unique benefits of both online and in-person connections while maintaining healthy boundaries. This recommendation aligns with recent research on therapeutic applications of gaming (Iacovides and Mekler, 2019) and the role of digital spaces in mental health support (Collins *et al.*, 2019; Reinecke, 2009). Practitioners should consider how gaming relationships might complement traditional therapeutic approaches, particularly for clients who struggle with conventional social interactions or face barriers to in-person support networks (González-Bueso *et al.*, 2018; Kowert and Oldmeadow, 2015).

Game developers and platform designers can benefit substantially from these insights. The finding that relationship quality was consistently associated with positive outcomes suggests the value of designing features that facilitate meaningful connections rather than

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simply maximizing interaction frequency or network size. This aligns with recent research emphasizing the importance of designing for social connectedness in gaming environments (Depping *et al.*, 2018). Specific design recommendations might include implementing systems that encourage sustained interactions between players, providing tools for meaningful communication beyond gameplay mechanics, and creating spaces for community building that extend beyond immediate gameplay (Trepte *et al.*, 2012; Perry *et al.*, 2018b). Additionally, developers should consider implementing features that help players maintain healthy gaming habits and balance their online and offline social interactions (Przybylski *et al.*, 2009).

Limitations and future directions

While this study advances our understanding of how gaming relationships influence mental health over time, several limitations should be noted. The six-month timeframe, while providing valuable longitudinal data, may not capture longer-term patterns of social network development. Future research could benefit from extended longitudinal designs that track relationships and outcomes over multiple years, allowing for examination of how gaming relationships evolve and potentially mature over time (Williams, 2006; Cole *et al.*, 2020). Similarly, there are limitations to the use of change scores in determining longitudinal effects that may require more advanced study designs to further assess. Additionally, our study's sample demographics, while representative of many gaming communities, may limit generalizability to other populations. Further, there may be cross-cultural variation in gaming, socialization and the combination of the two that are not captured fully in these results. Future research should explicitly examine how these relationships manifest across different demographic groups, particularly considering factors such as age, gender and cultural background (Frostling-Henningsson, 2009; Halbrook *et al.*, 2019). The role of gaming relationships in supporting mental health may vary significantly across different life stages and social contexts.

Further research could also benefit from examining potential moderating factors such as gaming motivation, play style and individual differences in social needs. Studies investigating how personality traits, attachment styles and pre-existing mental health conditions influence the relationship between gaming connections and psychological outcomes would be particularly valuable (Przybylski *et al.*, 2009; Mandryk and Birk, 2017). Additionally, examining different game genres and gaming contexts could help clarify how specific gaming environments and mechanics influence social capital development (Perry *et al.*, 2018b; Depping *et al.*, 2018). Future studies should also consider employing mixed-method approaches that combine quantitative network analysis with qualitative investigation of relationship development processes. This could provide richer insight into how and why some gaming relationships develop into meaningful sources of social support, while others remain superficial (Steinkuehler and Williams, 2006; Iacovides and Mekler, 2019). Understanding these mechanisms could inform both clinical interventions and game design practices aimed at promoting healthy social connection through gaming.

Conclusion

This study provides crucial insights into how gaming relationships influence mental health by demonstrating their dynamic and context-dependent nature. Rather than viewing online gaming as uniformly beneficial or harmful, our findings suggest that its impact depends heavily on how gaming relationships integrate with broader social networks. The results emphasize that quality of connections consistently outweighs quantity in predicting positive mental health outcomes (Cole *et al.*, 2020). These findings provide concrete direction for

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mental health professionals, game developers, and players themselves in promoting healthy social connection through gaming while maintaining balanced social portfolios across both online and offline contexts (Raith *et al.*, 2021). Future research building on these findings could further enhance our understanding of how to optimize gaming environments for social wellbeing while mitigating potential risks of over-reliance on digital connections.

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