It's not just a game: social networks, isolation and mental health in online gamers

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Received 6 November 2023
Revised 14 March 2024
26 March 2024
Accepted 11 April 2024

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

Conflict of interest: Authors have no conflicts to disclose.

Research data: Data generated from this study can be made available upon reasonable request.

Ethics: Research was approved by the Texas A&M University Institutional Review Board.

Abstract

Purpose – *Online gaming has emerged as a popular activity providing a social outlet for millions. However, implications of online game networks for mental health remain disputed. Concepts of bridging social capital and bonding social capital may help characterize protective factors within social networks. This study aims to examine the associations between social capital derived from online versus in-person networks and mental health indicators among gamers.*

Design/methodology/approach – *Online gamers (n = 301) completed an online survey assessing their social networks (both in-person and through online gaming) and mental health indicators (depressive symptoms, anxiety, social isolation, perceived social support). Social network analysis was used to analyze bridging (network size, effective size, heterogeneity, weak ties) and bonding (closeness, frequent contact, confiding, connection quality) social capital. Separate linear regression models evaluated associations between bridging and bonding social capital for both online and in-person networks and depressive symptoms, anxiety, social support and social isolation.*

Findings – *In-person network characteristics showed the strongest associations with mental health outcomes. Greater average closeness and frequent confiding in the in-person network predicted lower isolation and fewer depressive symptoms. More diverse relationship types also correlated with lower depression. For online networks, closeness and confiding ties associated only with less isolation and greater support, not depressive symptoms, or anxiety.*

Originality/value – *While online gaming networks provide some degree of social support, in-person social capital exhibited stronger associations with mental health. This reinforces the importance of face-to-face relationships for emotional well-being. Findings suggest helping gamers cultivate close bonds offline. However, online connections still matter and should not be discounted.*

Keywords *Social network analysis, Social capital, Online gaming*

Paper type *Research paper*

Introduction

Online gaming has emerged as a popular activity that can foster social connections and community engagement for millions of users (Carras *et al.*, 2018). Online gaming involves playing video games with other people over the internet, allowing gamers to interact and build virtual communities (Kowert *et al.*, 2014b). Popular online game genres include multiplayer battle arenas, massively multiplayer online role-playing games (MMORPGs) and shooters; however, online games range from casual smartphone apps to immersive virtual worlds. Some industry estimates place global revenue from online gaming to reach US $175bn in 2021, reflecting massive growth and participation (Wijman, 2021). Playing online has become a primary pastime and social outlet for millennials and Gen Z generations (typically those born between 1981 and 2012; Serbanescu, 2022, Nigam, 2022, Bassiouni and Hackley, 2014). However, consequences of online gaming for social relationships and mental health remain disputed. Some studies suggest that online gaming can provide opportunities for social connection, support and a sense of community, which may positively influence mental health (Trepte *et al.*, 2012, Lu *et al.*, 2022). On the other hand, excessive gaming has been associated with negative outcomes such as social isolation, decreased life satisfaction and increased risk of addiction-like behaviors (Lemmens *et al.*, 2011, Männikkö *et al.*, 2017).

Mental health encompasses emotional, psychological and social well-being. It includes not only the absence of psychopathology but also the presence of positive functioning and psychological thriving (Keyes, 2005). Key indicators include anxiety, depression, social isolation and perceived social support. Anxiety involves excessive apprehension, worry and activation of the fight-or-flight response, which can become pathological at high levels (Porter *et al.*, 2017). Depression is characterized by persistent low mood, loss of interest and other cognitive and somatic disturbances that impair functioning. However, researchers have called for an expanded understanding of mental health considering both the perspective of dysfunction and the perspective of how well a person is doing and thriving psychologically (Keyes, 2005, Hides *et al.*, 2020). These positive aspects of mental health reflect an individual's ability to cope with daily stressors, work productively, contribute to their community and realize their full potential (Keyes, 2005, Hides *et al.*, 2020). A comprehensive understanding of mental health should encompass both the absence of psychopathology and the presence of positive psychological functioning, such as help seeking or positive coping (Keyes, 2005, Hides *et al.*, 2020). This balanced perspective is crucial when examining the relationship between social capital and mental health outcomes in the context of online communication and gaming communities (Meier and Reinecke, 2020).

Multiplayer online games provide virtual spaces for regular social interaction, which may have implications for players' well-being and mental health (Prochnow *et al.*, 2020b, Prochnow *et al.*, 2020c, Prochnow *et al.*, 2023, Prochnow *et al.*, 2021a). In particular, the concepts of bridging social capital and bonding social capital within gaming communities may be linked to mental health outcomes. Bridging and bonding social capital emerge from distinct network patterns (Szreter and Woolcock, 2004). Bonding social capital refers to the close ties between similar or homogenous individuals, which provide emotional support and access to scarce resources (Szreter and Woolcock, 2004). These strong, redundant ties are characterized by high levels of trust, intimacy and reciprocal obligation (Geys and Murdoch, 2010). Bonding capital functions as a "sociological superglue" that reinforces exclusive group identity and homogeneous norms (Claridge, 2018). By contrast, bridging social capital involves loose connections between dissimilar individuals from different backgrounds (Szreter and Woolcock, 2004, Claridge, 2018). Bridging capital provides linkages to external assets and information diffusion through weak ties between diverse groups (Claridge, 2018, Granovetter, 1973). It enables cooperation between distinct social clusters and expanded access to new perspectives and ideas. This social "sociological WD-40" lubricates integration in heterogeneous societies (Claridge, 2018). Both forms of capital have implications for well-being that likely depend on context (Claridge, 2018). While research has examined social capital across contexts like neighborhoods and workplaces (Eagle *et al.*, 2010, Han and Chung, 2022), less is known about its operation within online gaming communities specifically from a network perspective. These virtual spaces allow forming diverse ties unconstrained by geography. Clarifying bridging and bonding social capital dynamics can inform promoting positive gaming experiences.

Prior work shows the importance of social relationships for wellbeing more broadly. For instance, social isolation and loneliness elevate risks for adverse mental and physical health outcomes (Holt-Lunstad *et al.*, 2015). Social isolation refers to a deficiency in quality relationships and objective lack of social connectedness (Holt-Lunstad *et al.*, 2015). By contrast, social integration and support are linked to better mental health (Umberson and Karas Montez, 2010). These mechanisms likely involve both structural (network connections) and functional (emotional support) social resources (Holt-Lunstad *et al.*, 2017).

Social network analysis (SNA) comprises theories and methods for understanding social structures based on patterns of relationships between individuals or groups (Valente, 2010). It enables empirically mapping and analyzing networks by quantifying properties like density, centrality, subgroups and position (Valente, 2010). Applying SNA techniques can elucidate the configuration of bridging and bonding social capital within a community (Perry *et al.*, 2022). Unlike traditional social capital scales that primarily focus on an individual's perception of their social resources, SNA allows for a more comprehensive and objective examination of the structural and relational aspects of social capital within a network (Perry *et al.*, 2022). By mapping and quantifying the actual connections and patterns of relationships among individuals, SNA provides a more advanced and nuanced understanding of how social capital is distributed and operates within a given context (Perry *et al.*, 2022). Moreover, SNA has been increasingly applied to mental health research, particularly through the network episode model, which posits that individuals' health and illness experiences are shaped by their social networks and the dynamic interactions within these networks over time (Perry and Pescosolido, 2015).

This cross-sectional study uses SNA to examine the distribution of bridging and bonding social capital among online gamers. It investigates how these network patterns relate to mental health indicators, including anxiety, social isolation, depression and perceived social support. Specifically, this study aims to:

- characterize the social network structure and distribution of bridging and bonding social capital among online gamers; and
- examine associations between social network characteristics and mental health indicators.

Clarifying dynamics of social connections, social capital and mental health in the context of online gaming can inform promotion of healthy gaming and communities. Examining both online and in-person networks will reveal their relative implications.

Methods

Participants and procedure

The study recruited online gamers (n = 301) from various gaming platforms and communities using CloudResearch Connect. CloudResearch Connect is a specific survey tool similar to that of MTurk. Eligibility criteria will include being at least 18 years old, currently engaging in online gaming activities and being able to provide informed consent. Participants completed a 20–30 min online survey assessing their social networks, social capital, mental health indicators and covariates. Once completed, a quality check was performed. Participants who passed three of four quality checks were compensated US$10 for their time. All procedures were approved by the referent Institutional Review Board, and participants were required to view an informed consent page prior to participation in the study. All research was conducted in accordance with the Declaration of Helsinki.

Measures

Depressive symptoms. The eight-item Patient Health Questionnaire (PHQ-8) was used to measure depressive symptoms (Kroenke *et al.*, 2001). Using this scale, participants were asked the frequency with which they had been bothered with certain problems over the past two weeks ranging from "not at all," "several days," "more than half the days," to "nearly every day." Responses are then scored from 0 to 3 and subsequently summed to create a total scale score. Example items include, "Little interest or pleasure in doing things," "Feeling down, depressed, or hopeless" and "Feeling bad about yourself – or that you are a failure or have let yourself or family down." While results from the questionnaire should be verified by a clinician, two meta-analyses concluded this scale to have acceptable diagnostic properties for detecting depressive episodes (Manea *et al.*, 2012, Manea *et al.*, 2015). For this specific study, depressive symptoms will be presented as a continuous variable and not used for any diagnostic calculations. Cronbach's α values for the PHQ-8 have been reported at 0.89 (Shin *et al.*, 2019) and was 0.76 in the present sample.

Symptoms of anxiety. The State-Trait Anxiety Inventory (STAI) is a self-report questionnaire designed to assess anxiety levels (Spielberger, 1970, Spielberger *et al.*, 1973). Trait (general predisposition to experience anxiety across various situations, irrespective of specific events) subscale was used consisting of 20 items, which are summed to provide a scale score. The inventory uses a three-point Likert scale and can provide valuable insights into anxiety symptoms, helping professionals assess and monitor anxiety levels over time. The STAI has been widely used in research and clinical settings to evaluate anxiety symptoms, assess treatment outcomes and identify individuals at risk for anxiety disorders and has been suggested to be valid and reliable (Seligman *et al.*, 2004, Metzger, 1976).

Social isolation. The shortened UCLA Loneliness Scale includes three items (Hughes *et al.*, 2004) such as, "How often do you feel alone" and "How often do you feel that there is no one you can turn to." Items are scored on a three-point Likert-type scale ranging from 1 (hardly ever) to 3 (often). Items are averaged, with higher scores indicating higher social isolation. The UCLA-3 has good reliability with Cronbach's alpha value of 0.84 (Hughes *et al.*, 2004).

Social support. An abbreviated version of the Multidimensional Scale of Perceived Social Support (MSPSS) was used to measure social support (Zimet *et al.*, 1990). The MSPSS is a widely used instrument that assesses perceived social connections and support from various sources, including family, friends and significant others. It measures the individual's subjective perception of the availability of support, the level of satisfaction with the support received and the adequacy of support in different domains of their life. The MSPSS consists of 12 items rated on a four-point Likert scale, ranging from "strongly disagree" to "strongly agree." The scale captures dimensions of social connectedness, such as emotional support, tangible support and social companionship and suggested to have good internal reliability and factorial validity (Zimet *et al.*, 1990, Dahlem *et al.*, 1991). This scale was adapted to include subscales for family, friends, significant others and online support, which were summed to develop a scale score.

Social networks. Participants (also termed "egos" in SNA) were asked to list up to five people they interacted with most through online gaming over the past 30 days and up to five people they interacted with most in-person over the past 30 days (Prochnow *et al.*, 2020a, Prochnow *et al.*, 2021b, Prochnow *et al.*, 2022b, Prochnow *et al.*, 2020d, Prochnow *et al.*, 2022a, Reich *et al.*, 2012). Participants were informed that people could be used in both networks if they fit the description. Networks were limited to five to capture the most salient relationships as suggested in previous work (adams, 2019). For each person/account (termed "alter" in SNA) listed, participants were then asked questions to better understand their relationship with each specific alter as well as if the alters they listed know each other. For each alter, participants identified their relationship to the alter, frequency of contact, frequency of confiding in the alter about a difficult issue, how they met the alter, how good the alter makes them feel about themselves and how close they feel to the alter. This method of collecting networks has been used previously (Prochnow *et al.*, 2020a, Prochnow *et al.*, 2021b, Prochnow *et al.*, 2022b, Prochnow *et al.*, 2020d, Prochnow *et al.*, 2022a, Reich *et al.*, 2012). From these questions, network composition variables related to social bridging and social bonding measures were generated for both in-person and online networks (Perry *et al.*, 2022).

Measures operationalizing social bridging include network size, effective size, heterogeneity and presence of weak ties. These measures capture the extent to which participants have extensive wide-reaching networks. *Network size* is the number of alters reported in the participant's network. It should be noted network size was limited to five; however, participants reporting more alters is still hypothesized to have a role in bridging networks. *Effective size* refers to the number of non-overlapping groups with which a person interacts; it is calculated as the number of alters minus the mean number of ties that each alter has to all other alters (Borgatti, 1997). Higher values indicate presence of structural holes (Burt, 1995). *Heterogeneity* refers to the number of unique relationship types in a person's network (e.g. friend, family member, person they do not know well) and where they met (e.g. online, in-person). We count the number of unique relationship types in each respondent's network and divide by network size to avoid conflating diversity with overall size of the network (Peng *et al.*, 2021). *Presence of weak ties* in the network will be assessed using frequency of alters reported at the minimum value of the closeness of ties. This measure follows the tradition of using emotional closeness to operationalize weak ties between individuals (Sandstrom and Dunn, 2014).

Measures operationalizing social bonding include mean tie strength, proportion active engagement, proportion frequent confiding and mean quality of connection. These measures capture the extent respondents have close personal bonding networks. *Mean tie strength* refers to the average closeness of the tie between ego and each of the alters (range: 1–5). *Proportion active engagement* is the proportion of alters in the network with whom ego frequently interacts (seeing or talking to the alter at least 3–5 days per week). *Proportion frequent confiding* is the proportion of alters in the network in whom ego frequently confides (speaking to the alter about difficult issues alter at least 3–5 days per week). While active engagement and confiding frequencies may be similar, the latter implies a degree of intimacy absent from simple contact measures; we use both to capture distinct phenomena. *Mean quality of connection* refers to the average of the participant's response to "how good does this person make you feel about yourself" for each alter (range: 1–5).

Data analysis

First, descriptives are provided to shed light on what online gaming networks look like in this context. Within this step, network density was calculated to describe the networks. Network density was calculated by dividing the sum of existing ties by the total number of possible ties within each participant's online and offline networks separately. Next, network variables created in Step 1 will be used as independent variables with model covariates in separate multiple linear regression models for each dependent variable (social support, social isolation, anxiety and depressive symptoms). In this manner, we can detect significant associations between specific network composition variables and social support, social isolation and mental health outcomes while controlling for other effects. There was less than 5% missing data on any of the variables included in the analyses with no identifiable pattern to the missingness. Multiple imputation was used to simulate the missing data using the mice package in R (Van Buuren and Groothuis-Oudshoorn, 2011). To control for the increased likelihood of making a Type I error when conducting multiple hypothesis tests, a Bonferroni correction was applied, dividing the desired familywise error rate ($\alpha = 0.05$) by the number of tests ($n = 4$), resulting in a more stringent significance level ($\alpha' = 0.0125$) for each individual test.

Results

The sample consisted of 301 online gamers with a mean age of 34.72 years (SD = 8.78). The majority of participants were men (67.4%) and white or Caucasian (75.7%), with 15.0% identifying as black or African American. Most respondents had at least some college education, with 38.5% holding a bachelor's degree. Over half worked full-time (65.8%) with a modal income between US$50,000 and US$74,999 (23.3%). Just over one-third were married (33.9%), while 38.2% reported being single. On average, participants played video games for 22.79 h per week (SD = 11.99). The most frequently played genres were role-playing (35.9%), shooters (20.6%) and multiplayer online battle arenas (11.6%). Mean levels of trait anxiety (M = 22.18, SD = 4.44), depressive symptoms (M = 6.83, SD = 5.98) and social isolation (M = 5.17, SD = 2.13) were in the moderate ranges. Participants reported an average social support score of 48.33 (SD = 10.49), indicating moderately high perceived support. See Table 1 for more information.

On average, participants listed 4.05 alters (SD = 1.08) in their online gaming networks, with a mean online network density of 0.52 (SD = 0.37). The online networks showed moderate levels of relationship heterogeneity (M = 0.43, SD = 0.20) and meeting heterogeneity (M = 0.40, SD = 0.17). Around 45% of online networks contained weak ties. Participants rated their average closeness to online alters as 3.24 (SD = 0.97) on a five-point scale. They interacted frequently (3–5 days per week) with about 55% of online alters (SD = 0.34) and confided frequently in around 26% (SD = 0.31). The mean rating for how good online alters make participants feel was 4.04 (SD = 0.67) on a five-point scale. Effective size, measuring lack of network constraint, averaged 1.89 (SD = 1.52).

On average, participants listed four in-person alters (SD = 1.14) in their networks, with a mean in-person network density of 0.70 (SD = 0.34). The in-person networks showed moderate heterogeneity in relationships (M = 0.43, SD = 0.20) but lower meeting heterogeneity (M = 0.30, SD = 0.14). Only around 21% of in-person networks contained weak ties. Participants rated their average closeness to in-person alters as 3.84 (SD = 0.91) on a five-point scale. They interacted frequently (3–5 days per week) with about 63% of in-person alters (SD = 0.33) and confided frequently in around 37% (SD = 0.34). The mean rating for how good in-person alters make participants feel was 4.12 (SD = 0.70) on a five-point scale. Effective size averaged 1.17 (SD = 1.31).

Social isolation

A linear regression examined associations between social network factors and social isolation. The model was significant ($F(25,275) = 3.81$, $p < 0.001$) and accounted for 26.2% of the variance in social isolation. In the online network, higher average closeness to alters predicted lower social isolation ($\beta = -0.25$, $p = 0.01$). For the in-person network, greater average closeness ($\beta = -0.63$, $p < 0.01$) and more frequent confiding ($\beta = -0.18$, $p = 0.011$) were associated with lower isolation. Table 2 provides full regression results.

Social support

A linear regression examined social network factors related to social support. The overall model was significant ($F(25, 275) = 8.61$, $p < 0.001$) and explained 44.5% of the variance in social support. Within online networks, participants who reported more of their alters made them feel good about themselves ($\beta = 3.42$, $p < 0.01$) reported greater feelings of support. Likewise, for in-person networks, higher average good feeling from alters ($\beta = 3.59$, $p < 0.01$) and percent often confide ($\beta = 3.82$, $p < 0.01$) were associated with higher support. Table 2 provides full regression results. It should be noted that participants reporting more frequent confiding in alters ($\beta = 1.48$, $p = 0.04$) also reported greater feelings of support; however, based on multiple testing significance correction this result should be interpreted with caution.

Table 1 Sample demographics, social capital and mental health measures

Variable	n	%	Mean	*SD*
Gender				
Female	97	32.2		
Non-binary	1	0.3		
Male	203	67.4		
Marital status				
Single	115	38.2		
Dating one or more people	79	26.3		
Married/partnered	102	33.9		
Divorced/widowed	5	1.6		
Race				
American Indian or Alaska native	3	1.0		
Asian	20	6.6		
Black or African American	45	15.0		
White	228	75.7		
Other	5	1.7		
Ethnicity				
Hispanic	48	15.9		
Non-Hispanic	253	84.1		
Household income				
Less than $24,999	52	17.3		
$25,000–$49,999	64	21.3		
$50,000–$74,999	70	23.3		
$75,000–$99,999	44	14.6		
$100,000–$1,24,999	29	9.6		
$1,25,000–$1,49,999	17	5.6		
More than $1,50,000	24	8.0		
Highest educational level				
High school diploma, GED	63	20.9		
Some college or technical training	63	20.9		
Associates degree	32	10.7		
Bachelor's degree	116	38.5		
Masters or doctoral degree	27	9.0		
Employment				
Unemployed	36	12.0		
Student	10	3.3		
Employed	198	65.8		
Self-employed	42	14.0		
Retired	3	1.0		
Age			34.72	8.78
Weekly hours spent playing online games			22.79	11.99
Social isolation			5.17	2.13
Social support			48.33	10.49
Trait anxiety			22.18	4.44
Depressive symptoms			16.83	5.98

Source: Table by authors

Symptoms of anxiety

A linear regression analysis found that the model for social network variables predicting trait anxiety was significant ($F(25, 275) = 1.93$, $p = 0.006$), accounting for 15.3% of variance. Online network size ($\beta = 0.99$, $p = 0.01$) was associated with higher anxiety symptoms. Meanwhile in-person often interaction ($\beta = -1.93$, $p = 0.04$) was associated with lower anxiety scores, and the online bridging social capital variable of relationship heterogeneity ($\beta = 3.68$, $p = 0.02$) was associated with higher anxiety symptoms; however, these

Table 2 Linear regression results for social support, social isolation, anxiety and depressive symptoms

Effect	Social isolation $R^2 = 0.26$ Estimate	SE	p	Social support $R^2 = 0.45$ Estimate	SE	p	Anxiety $R^2 = 0.15$ Estimate	SE	p	Depressive symptoms $R^2 = 0.23$ Estimate	SE	p
Intrapersonal variables												
Age	−0.01	0.01	0.21	−0.01	0.05	0.75	−0.01	0.03	0.80	−0.03	0.03	0.36
Gender (referent female)	0.16	0.12	0.21	−0.99	0.54	0.06	0.38	0.29	0.18	0.67	0.36	0.06
Educational attainment	−0.07	0.06	0.28	0.51	0.29	0.07	−0.21	0.15	0.16	−0.23	0.19	0.24
Income	−0.01	0.07	0.92	0.32	0.30	0.28	−0.16	0.16	0.31	−0.24	0.20	0.23
Hours spent online gaming	0.01	0.01	0.29	−0.01	0.04	0.74	−0.01	0.02	0.89	0.02	0.02	0.34
Online bonding social capital												
Average closeness	−0.25	0.10	0.01**	0.92	0.87	0.29	−0.29	0.46	0.52	0.13	0.59	0.82
Percent often interaction	−0.22	0.41	0.59	−1.30	1.77	0.46	0.56	0.94	0.54	1.52	1.19	0.20
Percent often confide	−0.41	0.51	0.41	1.48	0.71	0.04*	−2.13	1.15	0.06	−2.62	1.46	0.07
Average feeling good	−0.45	0.29	0.12	3.42	1.26	<0.01**	0.07	0.67	0.91	0.09	0.85	0.91
Online bridging social capital												
Relationship heterogeneity	1.09	0.71	0.12	−1.53	3.03	0.61	3.68	1.61	0.02*	3.48	2.04	0.10
Meeting heterogeneity	−0.15	0.90	0.86	−1.57	3.84	0.68	0.50	2.04	0.80	0.12	2.60	0.96
Weak tie presence	−0.04	0.17	0.79	−0.47	0.72	0.51	−0.34	0.38	0.37	0.24	0.49	0.61
Effective size	0.07	0.08	0.40	−0.36	0.35	0.29	0.04	0.18	0.83	−0.04	0.23	0.86
Network size	0.07	0.16	0.66	0.26	0.71	0.71	0.99	0.37	0.01**	0.90	0.48	0.06
In-person bonding social capital												
Average closeness	−0.63	0.22	<0.01**	0.64	0.96	0.50	−0.58	0.51	0.25	−1.29	0.65	0.04*
Percent often interaction	−0.22	0.41	0.60	0.67	1.77	0.70	−1.93	0.94	0.04*	−3.08	1.20	0.01**
Percent often confide	−0.18	0.08	0.01**	3.82	1.12	<0.01**	0.79	1.13	0.48	2.18	1.43	0.13
Average feeling good	−0.32	0.30	0.28	3.59	1.27	<0.01**	−0.99	0.68	0.14	−2.19	0.86	0.01**
In-person bridging social capital												
Relationship heterogeneity	−0.35	0.63	0.57	−0.61	2.67	0.82	−0.03	1.42	0.98	−1.66	1.80	0.35
Meeting heterogeneity	0.11	0.89	0.89	1.62	3.79	0.66	−2.15	2.02	0.28	1.84	2.56	0.47
Weak tie presence	−0.31	0.24	0.20	−0.22	1.05	0.83	−0.39	0.56	0.48	−1.02	0.71	0.14
Effective size	0.01	0.09	0.97	−0.12	0.41	0.75	0.03	0.22	0.88	0.08	0.28	0.75
Network size	0.087	0.125	0.48	0.66	0.52	0.20	−0.18	0.28	0.52	0.18	0.35	0.60

Notes: *Indicates statistically significant at $p < 0.05$; **indicates statistically significant at the corrected $p < 0.0125$
Source: Table by authors

variables were not deemed statistically significant after correction. Table 2 provides full regression results.

Depressive symptoms

The regression model examining links between social networks and depressive symptoms was significant ($F(25, 275) = 3.16$, $p < 0.001$), explaining 22.8% of the variance in depressive symptoms. For the in-person network, more frequent in-person interaction ($\beta = -3.08$, $p = 0.01$) was associated with lower symptoms. Further, reporting that alters made participants feel better about themselves ($\beta = -2.19$, $p = 0.01$) was also associated with fewer depressive symptoms. Average closeness with in-person network members ($\beta = -1.29$, $p = 0.04$) was associated with lower symptoms; however, it was deemed not significant after correction. Table 2 provides full regression results.

Discussion

This study aimed to characterize the social networks and capital distributions among online gamers and examine associations with mental health indicators. Bridging and bonding social capital were assessed for both online and in-person networks using SNA. By using SNA, this study moves beyond individual perceptions of social capital and provides a more comprehensive understanding of the structural and relational aspects of social capital within online gaming communities, addressing a gap in the literature. Similar to past research within a gaming community (Prochnow *et al*., 2021a, Prochnow *et al*., 2020b, Prochnow *et al*., 2020c, Prochnow *et al*., 2023), results indicate that while online social connections play a role in feelings of support and mental health, social capital from in-person sources proved to be more beneficial for participants in this sample.

Social bonding

The findings for social bonding align with prior work emphasizing the mental health benefits of emotionally close relationships that provide intimacy and support (Holt-Lunstad *et al*., 2017, Holt-Lunstad *et al*., 2015, Sandstrom and Dunn, 2014). Greater average closeness and more frequent confiding ties in the in-person network were linked to lower isolation, greater support, lower anxiety and fewer depressive symptoms. This reinforces the importance of strong ties that engender trust, self-disclosure and attachment for well-being outcomes (Lakey and Orehek, 2011, Sandstrom and Dunn, 2014). Such emotionally close relationships are thought to influence mental health through mechanisms like provision of social support during times of stress, having a reliable confidant and meeting needs for belonging and meaning (Peng *et al*., 2021, Perry *et al*., 2022, Pescosolido, 2021). The current study extends this understanding by demonstrating the specific network characteristics, such as average closeness and frequency of confiding ties, that are associated with mental health outcomes in the context of online gamers' in-person social circles. The current results corroborate these connections in the context of online gamers' in-person social circles.

Social bridging

In line with research on the value of network diversity (Eagle *et al*., 2010, McCarty *et al*., 2019), higher relationship heterogeneity in the in-person network also predicted fewer depressive symptoms. This suggests that access to varied social circles can be protective, consistent with the concepts of bridging capital (Lee *et al*., 2018). Bridging ties, characterized by weak connections between diverse individuals, have been extensively studied in relation to mental health and well-being. These ties are thought to provide informational support, expose individuals to new perspectives and link them to external assets that can promote well-being, such as job opportunities or creativity (Lee *et al*., 2018, Granovetter, 1973). In the context of mental health, bridging ties have been found to play a crucial role in recovery from severe mental illness (Salehi *et al*., 2019). Moreover, the benefits of online bridging ties for mental health have been recognized for decades, with research highlighting the positive effects of network heterogeneity on social tolerance within gaming communities (Kobayashi, 2010). The current findings align with this existing body of research, suggesting that the protective effects of bridging capital measured through SNA also extend to depressive symptoms in the context of online gaming. The convergence of our results with previous studies that used different methodologies lends credence to the validity of using SNA to measure social capital and its relationship to mental health outcomes in online contexts. However, given the complex nature of social capital and mental health, further investigation is warranted to deepen our understanding of the specific mechanisms through which bridging ties influence depressive symptoms in online gaming communities.

Online network results

For online gaming networks, higher closeness and more frequent confiding were associated with lower isolation and greater support, but not anxiety or depression. This indicates online relationships may provide some degree of social support but do not substitute for in-person ties regarding mental health symptomology. This aligns with models arguing online and offline interactions uniquely contribute to well-being rather than displacing one another (Valkenburg and Peter, 2007). Prior research similarly found online friendships enhance but do not replace offline ties (Domahidi *et al.*, 2018). It may be that while emotional support transfers effectively online, other benefits of in-person bonding like physical touch and oxytocin release remain important for mood and anxiety (Holt-Lunstad *et al.*, 2017, Holt-Lunstad *et al.*, 2015, Jaremka *et al.*, 2013). The present study adds to this literature by demonstrating that specific online network characteristics, such as closeness and frequency of confiding, are associated with reduced isolation and increased support, but not with anxiety or depression. The current results underscore key distinctions between online versus in-person relationships regarding mental health benefits, suggesting that interventions aimed at promoting mental health among gamers should prioritize fostering in-person connections while also supporting healthy online interactions.

In-person network results

In contrast to online networks, in-person social network characteristics showed robust associations across all mental health outcomes. This highlights that face-to-face relationships remain most relevant for symptomology, though online connections still matter. Evolutionary psychology perspectives contend that in-person interaction has inherently greater impact due to its prominence in human history (Kanai *et al.*, 2012). Related neuroscience research also demonstrates specific biomarkers like increased oxytocin that accompany in-person contact (Holt-Lunstad *et al.*, 2017, Holt-Lunstad *et al.*, 2015, Jaremka *et al.*, 2013). Considering these biological and evolutionary factors, it is unsurprising that in-person relationships exhibited stronger ties to mental health. However, online relationships should not be discounted, as they still offered some degree of perceived support.

Implications

Future research directions include longitudinal and experimental studies to establish causality and directionality of effects between social capital and mental health over time. Analyses distinguishing structural versus functional network properties would also prove informative, as they may differentially influence mental health outcomes (Berkman *et al.*, 2000). Further research could explore moderators like game genre that may influence the extent of mental health benefits derived from the online community, as different game types foster distinct social interactions and norms (Domahidi *et al.*, 2018). In addition, direct comparison of online versus offline relationships using dyadic data would clarify relative impacts and provide insights into the interplay between virtual and real-world connections (Snodgrass *et al.*, 2011).

The current findings suggest implications for promoting healthy gaming experiences. Gamers may benefit from cultivating close bonds and diverse ties in their in-person circles, as these connections demonstrated stronger associations with mental health outcomes. However, online connections still matter and should not be discounted. Interventions could focus on supporting healthy online community engagement while encouraging gamers to maintain and develop offline relationships. For example, gaming platforms could incorporate features that facilitate the formation of diverse and supportive online communities, such as matchmaking based on shared interests or promoting positive social norms (Seabrook *et al.*, 2016). At the same time, gamers could be encouraged to engage in offline activities and social interactions to foster in-person connections. Mental health professionals working with gamers could assess their online and offline social networks and provide guidance on building and maintaining a balanced social support system. Outright discouraging online play may backfire (Kowert *et al.*, 2014a); instead, a nuanced approach that recognizes the potential benefits and risks of online gaming is needed. Multi-faceted interventions could include active coaching to foster in-person social skills alongside gaming, tailored to individual risk factors and gaming motivations (Kuss and Griffiths, 2012).

Limitations

The cross-sectional design prevents causal conclusions. The use of self-report measures and egocentric network data could contribute to bias. While the use of clickworkers (individuals who participate in online surveys and panels as a primary source of income) allows for efficient data collection from a diverse sample, it is important to acknowledge potential limitations such as self-selection bias, data quality concerns and the ethical considerations of fair compensation and informed consent (Chandler and Shapiro, 2016). Another limitation is that the study did not assess the potential overlap between participants' online and offline networks, which may have influenced the observed associations between social capital and mental health outcomes, as individuals who interact with the same people both online and offline may have different experiences compared to those with distinct online and offline social circles (Domahidi, 2018). This overlap between online and in-person worlds is an area for future research in understanding the impact of our highly connected worlds. In addition, imputed data was used in this study as the rate of missing data was less than 5% with no discernable pattern; however, it is possible this simulated data may have biased results.

Conclusions

This work provides initial evidence that social capital available through online gaming interacts with mental health, though not to the same extent as in-person capital. Results can help inform promotion of healthy gaming experiences. Findings suggest online and offline social connections have complementary effects, arguing for a nuanced approach in research and practice.

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