Exploring the Impact of Social Influence on Group Well-being in MMO Games: Evidence from *Sky: Children of the Light*

USC Annenberg School for Communication and Journalism | USC Viterbi School of Engineering | International Communication Association

Donggyu Kim[1], Eun Cheol Choi[1], Magdalayna Curry[1], Lei Cao[1], Siyi Zhou[1], Ji Ye Kim[1], Michie Leccese[1], Bumju Jung[1], Natalie Kim[1], Wen Zeng[2], Lizzy Brunn[2], Zituo Wang[1], Aimei Yang[1], Dmitri Williams[1]

[1] Annenberg School for Communication and Journalism | [2] Viterbi School of Engineering

Introduction

- 43% of U.S. adults say they often or sometimes play video games
- 72% of those who play video games, play to spend time with others
- 47% of teen players have made a friend online in games

(Pew Research Center)

Global market for video games industry was $217.06 billion in 2022 and expected to grow by more than 13% every year through 2030 (Statista)

Gaming as a social connection and relationship-building

Methodology & Results

Procedure

Conducted with ***thatgamecompany***, English-speaking adult players of *Sky: Children of the Light*

In-game survey (Oct 15–26, 2024) rewarded with **5 candles** (~$1.70 USD)

10,364 participants (**Response Rate 49.5%**)

Survey Measures (5-point Likert)

Reciprocity: 4 items (α = .75) | Group Well-being: 4 items (α = .83)

Continuation Intention: 3 items (α = .81) | age, gender, gameplay time

Results

H1 (Supported) (β = .353, SE = .011, p < .001)

→ Reciprocity is a core driver of positive group well-being

H2 (Supported) (β = .561, SE = .008, p <.001)

→ Feeling supported in the group makes players likely to stay engaged

Social Value Findings:

Socially influential players (those with high SV) are **more likely to feel positive about their group** (F(1,10360) = 19.35, p < .001) and are **more committed to continuing gameplay** (F(1,10360) = 25.91, p <.001), but being influential alone does not necessarily mean they are more reciprocal.

Implications

Designing games for mutual support matters

→ Game features that encourage prosocial behavior can enhance community dynamics

Excessive gameplay is linked to lower well-being

→ Developers should promote healthy play patterns to sustain both engagement and emotional health.

Literature Review & Hypotheses

Theory of Bounded Generalized Reciprocity

- Players are more likely to return kind actions within their group if they expect the other players to do the same
- Group membership cues activate a heuristic to cooperate with in-group members (Romano et al., 2017)
- Group players are more reciprocal than solo players (Kim et al., 2022)
- Players benefiting from or observing generous acts are likely to be more generous towards others (Bisberg et al., 2022)

Emotional Contagion

- Emotional states of an individual are transferred to others, thereby leading them to experience or express the same emotions.
- In organizations, working groups with more positive emotional atmosphere had improved cooperation, decreased conflict, and increased perceived task performance (Barsade, 2002)
- Emotional contagion happens in computer-mediated settings (Hancock et al., 2008).
- In-person interaction and non-verbal cues are not strictly necessary for emotional contagion (Kramer et al., 2014)

H1: Higher levels of player reciprocity will positively predict perceived group well-being

H2: Higher levels of perceived group well-being will positively predict players' continuation intention

Social Value Algorithm

Social Value (Williams et al., 2023) is a **computational measure of behavioral influence** that captures how much one individual's actions cause others to act within a shared environment.

- **Causal Basis**: SV relies on **time-ordered behavioral data**

1. If **Player A** increases playtime and **Player B** consistently follows, A is inferred to influence B.
2. Influence is **temporal and repeated**—patterns must recur across time to be considered valid

Empirical Requirements:

- Persistent Identifiers (PID) / Timestamped behavioral events (e.g., playtime) / Way to establish social ties (e.g., with-in game interaction)

Social Value ➤ What you cause in others

Following Value ➤ What others cause in you

Non-social Value ➤ What you do on your own

Descriptive Stats | SV Algorithm

Table 1. Descriptive Statistics of the Participants

Variable	Level	*M* (*SD*)	*N*	%
Age	-	24.22 (7.8)	10,364	-
Gender	Female	-	6,721	64.9
	Male	-	2,435	23.5
	Other	-	1,208	11.6
Demographics	White	-	4,134	39.9
	Black or African American	-	482	4.1
	Asian	-	4,918	47.5
	Others	-	884	8.5
Weekly Playtime	Less than 1 hour	-	409	3.9
	1-5 hours	-	3,594	34.7
	6-10 hours	-	2,743	26.5
	11-20 hours	-	1,874	18.1
	21-30 hours	-	861	8.3
	More than 30 hours	-	883	8.5

Note. Self-reported survey data

Table 2. Descriptive Statistics of Player's Social Values Components

	Networked influence in total game playtime				
Metric	Min	Max	Std	Mean	Total
Social Value	0	119.44	1.20	0.59	485,563.7
Non-social Value	0	4.62	1.09	1.30	1,083,713
Network Power	0	120.74	1.73	1.89	1,569,277.7
Total Value	0	123.273	2.18	2.48	2,054,841.4

Note. Unit for playtime is in minutes, log10-transformed
Timeframe for playtime (10/15 - 11/30)

Appendix A. Algorithm for Estimating Social Value

To compute Social Value, a machine learning model M (random forest) is first developed to learn the function $f(d_i) = y_i$ for each user u_i. Next, the data d_i is modified to d'_i by removing instances of u_i's interaction with others. The model M then estimates $y'_i = f(d'_i)$, which represents u_i's expected behavior without influence from neighbors. The difference $D_i = (y_i - y'_i)$ captures the social effect of u_i's neighborhood, called the Receptivity Value $Inf(u_i)$, measuring neighbor influence on u_i. This Receptivity Value is distributed among each of u_i's neighbors, weighted by relationship intensity $e(n_j, u_i)$. Pairwise influence from n_j to u_i, $PairInf(n_j, u_i)$, is calculated as $Inf(u_i) \times e(n_j, u_i) \,/\, \sum_{n \in N(u_i)} e(n_j, u_i)$, assigning greater influence to stronger relationships. Finally, Social Value $SV(u_i)$ is computed by aggregating u_i's pairwise influences over all neighbors, $SV(u_i) = \sum_{n \in N(u_i)} PairInf(n_j, n)$.