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Capability, Opportunity, and Motivation in a Social Multiplayer Online Game: Player Influence Dynamics in *Sky: Children of Light*

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Abstract

This study investigates networked social influence in *Sky: Children of the Light*, a social multiplayer online game. Drawing on survey responses (n = 9,254) and in-game data from over 660,000 players, we use an innovative graph-based machine learning approach to quantify how individuals influence others' playtime, and regression analyses to test predictors from the COM-B model. Results show that *Capability* enhances influence, although excessive task focus correlates negatively with social impact; *Opportunity* emerges as the strongest predictor, with active social interactions significantly boosting influence; and *Motivation* varies by playstyle, with socializers and competitors demonstrating greater influence than narrative-focused players. By applying the COM-B model in a digital gaming context, this research highlights behavioral dimensions of player influence and employs a novel metric for quantifying interpersonal influence. These findings suggest practical implications for game design, particularly by highlighting how social interaction opportunities and different player motivations shape influence within communities.

Keywords

social value algorithm, games, networked social influence, COM-B model, player engagement

Introduction

The widespread adoption of smartphones has led to significant growth in mobile online games, including those often described as massively multiplayer online games (MMOs, i.e., games that

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can be inhabited by numerous players simultaneously, allowing for large-scale social interaction in real-time).[1] At the end of 2020, the total revenue generated by the mobile gaming industry had exceeded $76.7 billion, and there were more than 3.3 billion active mobile gamers globally.[2] In contrast to traditional PC and console MMOs, many mobile multiplayer games emphasize accessibility and social interaction among players (Li & Suh, 2021). While considerable research has been conducted on player interactions in PC-based MMOs (Huang et al., 2019; Williams et al., 2023), the dynamics of player communication and influence within mobile contexts have received less attention. This gap is significant, as socializing and cooperation are central features of mobile multiplayer games (Li & Suh, 2021), and the large number of players worldwide underscores the importance of understanding the factors that drive interpersonal influence within this growing segment of the gaming market.

This study investigates networked social influence dynamics within *Sky: Children of the Light*, a game that centers its gameplay on collaboration. While *Sky* is commonly labeled as an "MMO" in public discourse, in this study, we describe it as a social multiplayer online game, since players primarily interact in small groups. We also clarify that *Sky* was exclusively available on mobile devices during our data collection in late 2020. Although it has since expanded to other platforms, in the context of this study, it represents a case of a mobile-only multiplayer online game. *In Sky,* players must communicate and assist one another in gathering candles (in-game currency), and certain zones only unlock when multiple players work together[3]—making it an ideal context to study interpersonal influence. Using a graph-based machine learning algorithm (Williams et al., 2022), we quantify interpersonal networked influence, offering an innovative approach to measuring how one person's presence or absence can influence others in the network. This approach moves beyond traditional network centrality metrics that don't directly indicate the influence of each entity.

While traditionally used in health contexts (Michie et al., 2011), the COM-B model's adaptability across various fields makes it a valuable tool for studying players' behaviors in the context of mobile gaming, where social interactions are a defining feature of the gameplay experience. As a result, we apply the COM-B model to analyze how a player's Capability (C), Opportunity (O), and Motivation (M) drive Behavior (B)—specifically, networked social influence that occurs through personal connections.

To address this issue, we examine two questions: (1) How does networked social influence emerge within the networks of players, and how does it affect players' time spent in the game? (2) Do one player's capability, opportunity, and motivation predict their networked social influence? By addressing these questions, this study advances the application of the COM-B model to digital contexts and suggests predictors of influence in the mobile context.

By training a graph-based machine learning model (Williams et al., 2022) on a network of 669,836 players, our model yielded an R^2 of 95% and an accuracy of 85%, demonstrating its ability to accurately measure networked social influence. Using the social influence scores derived from the model, we extend the application of the COM-B model to digital contexts. In doing so, we demonstrate the model's applicability for analyzing influence dynamics in online game communities, providing an initial step toward adapting behavioral frameworks to underexplored domains. This study also has potential practical implications for game developers, especially in designing features that foster inclusive and socially engaging gameplay.

Literature Review

Networked Social Influence

A wealth of studies on digital games has demonstrated that peer effects play a significant role in shaping behaviors like gameplay, gaming knowledge, and even addiction to online games (e.g., Jo et al., 2025; Murrian, 2024; Zameri et al., 2024). They emphasize how individual actions impact a wider range of players in multiple ways within online games. However, while peer effects clearly exist within digital games, most prior studies have not directly quantified the degree to which one specific player influences another.

One current way to study the degree of interpersonal influence is to rely on the network attributes, such as centrality, to operationalize influence (Brooks et al., 2011; Guo et al., 2022; Reed et al., 2018). However, while high centrality can reflect structural prominence within a network, it does not necessarily equate to greater interpersonal influence. To address this issue, we investigated which individuals truly exert measurable behavioral impact within the player community by employing the method of Social Value (SV), a network-based machine learning approach developed by Williams et al. (2022). SV quantifies an individual's direct and passive influence by assessing how their actions affect the behavior of others, providing a node-level evaluation of influence in a network of players (Yang & Williams, 2024). In this study, we used SV to measure how a player's presence influences the playtime of others even without explicit interactions like conversations or friend requests. For example, a player with a higher SV is the one who causes others to engage more frequently and for longer durations in *Sky*. This approach seeks to more accurately identify individuals who truly influence the behavior of their peers within the network.

COM-B Model

Our theoretical framework is based on the COM-B model (Michie et al., 2011), which proposes that Behavior (B) is the result of an interaction between three components: Capability (C), Opportunity (O), and Motivation (M). A person must have the capability and opportunity to engage in a behavior and be sufficiently motivated to do so. These components interact dynamically to shape behavior across contexts, including digital gameplay environments. COM-B has proven adaptable for understanding behavior in various contexts. Though initially applied in health (McDonagh et al., 2018; Mersha et al., 2020; Michie et al., 2011), the COM-B model has been used for studying people's behaviors like consumer behavior (Jiang & Farag, 2023), internet usage (Liu et al., 2023), game design (Hedin et al., 2017), and online game-based health promotion (Robertson et al., 2021). Despite its limited application in mobile multiplayer games, COM-B's relevance in digital contexts suggests its potential to reveal factors that predict player behavior in these environments.

Capability

Capability, as defined in the COM-B model, refers to the physical and psychological abilities that enable behaviors. Physical abilities encompass skills and strengths, while psychological abilities involve cognitive processes (Michie et al., 2011).

Existing literature supports the connection between capability and influence. For example, NBA players who have higher win probabilities tend to have higher in-degree centrality among their teammates (Reed et al., 2018), suggesting a positive correlation between the sports players' capability and their potential influence in the teams. Similarly, in corporate networks, professionals with recognized skills among other co-workers are often positioned more prominently within organizational structures (Ahuja, 2000; Borgatti & Cross, 2003).

In the gaming context, gaming capital (Consalvo, 2009) refers to the skills, knowledge, and attitudes that enable players to engage meaningfully with games, game-related content, and other players, which can be an indicator of one player's expertise (Korkeila & Harviainen, 2023). The study of gaming capital has shown that resources like in-game expertise, language proficiency, and strategic insights enhance a player's likelihood of exerting social influence (Korkeila & Harviainen, 2023). Additionally, players who develop effective strategies to optimize their in-game performance gain respect and recognition from the community, as their capability is acknowledged by peers (Barnett & Coulson, 2010). Furthermore, demonstrating gaming skills has been identified as a key factor in building social connections in competitive online settings (Murrian, 2024). Based on this, we propose:

H1: Players with more capabilities have more networked social influence.

Opportunity

Opportunity in the COM-B model refers to external factors that facilitate behavior, including both environmental and social opportunities (Michie et al., 2011). Specifically, environmental opportunities can be time and money, and social opportunities can be networks, cultures, and norms (Botella-Guijarro et al., 2022; Liu et al., 2023; Michie et al., 2011).

Previous studies have highlighted the importance of opportunities in shaping players' gaming experiences (Hsiao & Chiou, 2012; Mao, 2021). Opportunities to socialize and interact with others have been shown to correlate positively with a player's leadership and influence within the gamer community (Goh & Wasko, 2009). Players who are highly active in guilds, for example, are often able to exert leadership and become more influential within the guilds (Goh & Wasko, 2009). Players occupying key positions within a community tend to be regarded as more successful among players, with higher network centrality enabling access to more in-game resources (Hsiao & Chiou, 2012). Moreover, greater social interaction within the game fosters deeper engagement with game content (Mao, 2021). However, many of these studies focus on online games with guild systems, where communication and resource exchange predominantly occur within guilds (Goh & Wasko, 2009; Zhang et al., 2018). The absence of a guild system in games like *Sky: Children of Light* raises the question of whether player dynamics and social interactions would differ in environments lacking such structures.

Socioeconomic status (SES) is a factor that can be related to social and environmental opportunities (Brooks et al., 2011; Lagory et al., 2001). Research suggests that the class a person comes from significantly influences their access to resources and potential accomplishments (Lagory et al., 2001). According to Weber (2009), SES shapes one's quality of life, with inferred class status affecting how individuals are perceived and treated by others (Côté, 2011). Higher SES individuals tend to have larger social networks in digital spaces (Brooks et al., 2011), which may enhance their access to opportunities. Additionally, the social cognitive theory of social class (Kraus et al., 2012) suggests that long-term exposure to a specific SES environment shapes individuals' thought patterns, emotional responses, and behavioral tendencies. Studies indicate that those raised in high-resource environments often develop greater psychological strengths, such as optimism and a strong sense of control over outcomes, which in turn contribute to leadership success in workplace settings (Ali et al., 2005; Duan et al., 2022; Fang & Saks, 2020). Given the strong connection between SES and leadership in professional settings, it is reasonable to expect that higher SES may also provide greater opportunities for leadership and social connectivity in online gaming environments.

Additionally, the link between players' behaviors and their environmental opportunities remains underexplored. For example, the relationship between in-game spending and player influence is inconsistent, with some studies showing no significant connection (Goh & Wasko, 2009; Zhang et al., 2018). However, other research has suggested that players' consumption behaviors can be influenced by the playtime and spending habits of others (Guo et al., 2022). This discrepancy highlights the need for further investigation regarding the extent to which players can influence others within the network through their behaviors. Therefore, we predict that:

H2: Players with (a) more social opportunities, (b) more environmental opportunities, and (c) higher SES have more networked social influence.

Motivation

Motivation encompasses the mental processes that drive and direct behavior (Michie et al., 2011). It includes both automatic motivations, such as emotions and instincts, and reflective motivations, like analytical decision-making (Michie et al., 2011).

Intrinsic motivation has long been a focal point in the study of why people play computer games (Przybylski et al., 2009; Ryan & Deci, 2000; Ryan et al., 2006). Self-Determination Theory (SDT) has been a commonly applied framework for studying automatic motivations, proposing that gameplay behavior is often driven by intrinsic desires for autonomy, competence, and relatedness (Ryan & Deci, 2000; Ryan et al., 2006). These psychological needs—autonomy, competence, and relatedness—are considered essential to understanding the happiness and satisfaction people derive from gaming (Przybylski et al., 2009; Ryan et al., 2006). Specifically, fulfilling the need for relatedness, such as through coordinated team play and communication with others in the game, is believed to enhance people's well-being (Reer & Krämer, 2020). It is reasonable to argue that players who seek relatedness are more likely to engage in cooperative behaviors, thus becoming more influential within their group.

Reflective motivations, on the other hand, differ across player types. The Trojan Player Typology (TPT) (Kahn et al., 2015) identifies players driven by various motivations, including socializing, completion, competition, escapism, narrative curiosity, and intellectual challenge. Different types of games attract players with different motivations: for instance, players of online collectible card games are primarily driven by their desire to compete and deeply engage with the game, while social interaction and strategic complexity play minimal roles in their motivation (Turkay & Adinolf, 2018). In *Sky*, the game design encourages cooperation, as playing with others allows players to explore the maps more easily (Bisberg et al., 2022). Therefore, we hypothesize that players who are motivated by cooperation and social connection within the game are more likely to progress and become more influential. We propose:

H3: (a) Players with higher needs for relatedness and (b) Socializers have greater networked social influence.

Figure 1 showcases the hypotheses listed above.

Control Variables: Age, Race, and Gender

In research on interpersonal influence, demographic characteristics such as age, race, and gender are often associated with how individuals are perceived and how much influence they can exert in social environments (Dennis & Chandler, 2025; Eagly et al., 2003; Hall et al., 2015). For example, healthcare providers often treat patients differently based on age, ethnicity, or gender (Hall et al., 2015). A large body of research shows that racial minorities often face systemic barriers that limit their ability to exert influence. For example, African Americans remain underrepresented in higher education and leadership roles, partly due to persistent structural disadvantages (Dennis & Chandler, 2025).

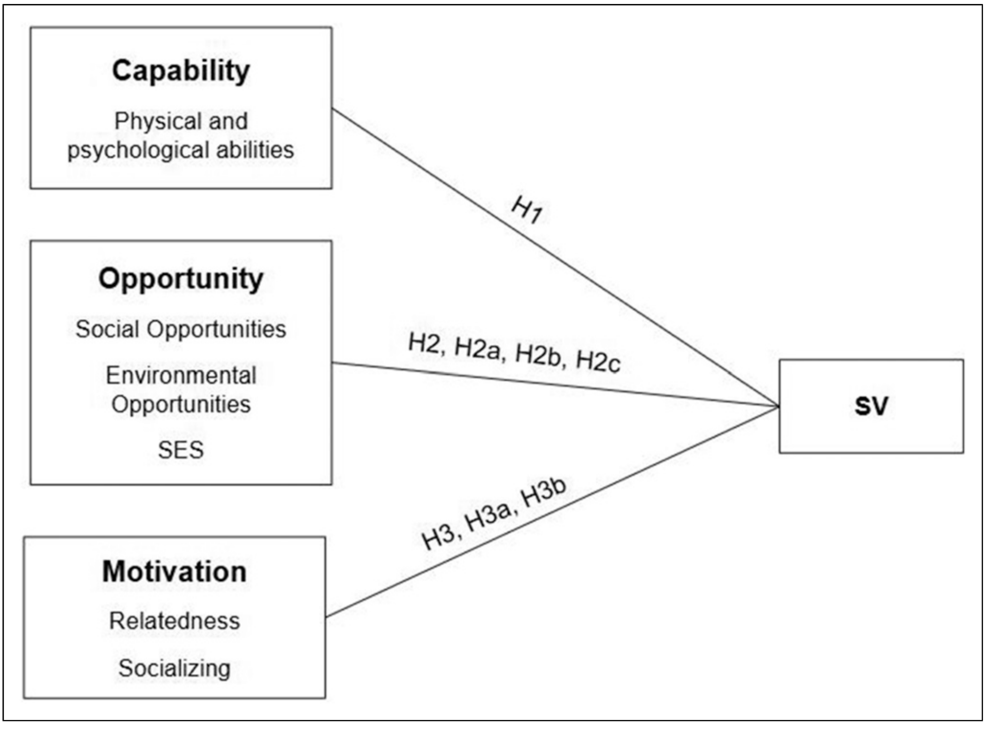

Figure 1. Conceptual Framework and Hypotheses Based on the COM-B Model

Gender further plays a complex role in how influence is perceived and enacted. In offline professional settings, women who exhibit assertive behaviors often face harsher judgments than men displaying the same traits (Eagly et al., 2003). However, in gaming environments, these dynamics may shift. Female players are more likely to engage in prosocial behaviors such as recruiting others, participating in text-based chat, and coordinating with peers (Veltri et al., 2014). These behaviors help build stronger in-game networks and can enhance a player's perceived influence within the community (Hou, 2012; Kneer et al., 2019; Veltri et al., 2014).

Given these documented effects of demographic characteristics on influence and interaction, age, race, and gender were included as control variables in our analysis. This allows us to isolate the effects of capability, opportunity, and motivation on player influence while accounting for potential demographic differences.

Methods

Data for this study was obtained through a collaboration between the authors' institution and *thatgamecompany*, the publisher of *Sky: Children of Light*. We utilized both behavioral data and survey responses from *Sky* players. The survey was distributed in-game between November 20 and 30, 2020, and collected through a collaboration between *thatgamecompany* and the survey designers. The survey was implemented via the SurveyMonkey platform and randomly distributed in-game by *thatgamecompany* to players who had completed the final realm of *Sky*. This recruitment approach emphasized players who had finished the initial storyline—a process that typically takes 2–3 hours—and therefore had the opportunity to engage socially with others in the game. The publisher considered players below this threshold to be unengaged and set this point as the minimum requirement for survey sampling. It reflects the study's focus on socially active participants. As such, our sample is not representative of all players who downloaded the game, especially those who churned early without social engagement, but is representative of the community where networked social influence can occur. Participation was voluntary, with players receiving candles as a reward for completing the survey. The survey sample size was 9,254. The respondents, aged 5 to 70, were from various countries worldwide, including the United States, Canada, and Japan.

In addition to the survey data, we obtained server-side behavioral data from the *Season of Prophecy* in *Sky* (October 5, 2020 – December 13, 2020), which recorded players' in-game behaviors, including playtime, chat activity, and currency collection. In *Sky*, a "season" refers to a content cycle lasting for several months, which typically introduces limited-time seasonal events and storylines. Through an anonymized data matching process, we linked each survey response to the corresponding player's behavioral records from earlier in the season. This retrospective linkage enabled us to reconstruct players' capability, opportunity, and motivation during the first four-fifths of the *Season of Prophecy* and examine how these factors predicted their networked social influence, as calculated at the season's end.

Social Value

Social Value (Williams et al., 2022) is an algorithm designed to estimate the influence of one individual on another within a network. It operates by examining dyadic relationships (edges) over time and assessing whether a focal player's behavior systematically differs when a particular other player is present versus absent. When sufficient observations are available, the model can attribute a portion of the behavioral variation to the presence of that other player in a manner consistent with causal inference. The method is flexible in that it can be applied to any measurable behavior and can be integrated into standard modeling frameworks to incorporate covariates and controls, provided that network data are available.

The implementation of the Social Value algorithm in *Sky* is based on two primary datasets, one for the main variables in a random forest regression model and another for an underlying network graph. The first dataset is a user-level aggregation that contains the dependent variable—playtime (duration_in_sec)—and several behavioral features used to train the machine learning model, such as wax_farmed, chat_msg, and candle exchanges. A complete list and definitions of all user-level variables are provided in Appendix A. The second dataset is an edge list representing social connections between users, where edges are defined by players being in close proximity to one another in-game, where the distance between two players is equal to or less than 4 in-game units (1 unit = height of *Sky* avatar = 1 m). Unlike the user-level dataset, which aggregates individual attributes (e.g., playtime, resources, and communication), this edge-level dataset captures relational ties between pairs of players. This edge-building measure could outline all instances, whether passive or explicit, where interpersonal influence can be detected in the algorithm. This construct of edges reflects the complexity of influence, which can occur even through passive interactions, such as a player noticing another's outfit and feeling motivated to play more to earn in-game currency for a similar purchase, without explicit actions like friend requests, interactions, or conversations.

Data for both user-level and edge-level tables was collected from December 1, 2020, to December 13, 2020, covering the last 1/5 of the *Season of Prophecy*. The edge list dataset recorded interactions among 669,836 users across 853,552 edges. The user-level features table encompasses all users from the edge list and includes variables such as the number of chat messages exchanged, in-game currency collected, and playtime. This comprehensive structure enables a detailed analysis of user behaviors and social interactions.

We then utilized the open-source program developed by Williams et al. (2022) to calculate SV, using the two tables mentioned above. First, we constructed a model that used data up to time t to predict players' total playtime in the interval $\tau = (t, t + \tau)$. This step tracked players' behaviors at each time point, estimated their playtime at subsequent time points, and compared the observations from $t + \tau$ with the predictions to identify errors. Second, we identified all players (U) whose neighbors were absent during the interval τ and analyzed the pairwise networked social influence these players exerted on their neighbors. This step utilized network data to determine which players had the opportunity to influence others within the network. Next, we predicted players' playtime at τ for each player $u \in U$, using the models from Step 1. This step integrated network data into the model estimation from Step 1, enabling further error recording and model refinement. At the last step, for each user $u \in U$, we deducted the combined pairwise networked social influence values of all absent neighbors affecting actor u from the total playtime estimate obtained in the previous step, resulting in the networked social influence-adjusted value:

$$AdjTotalPlaytime_u^\tau(t) = TotalPlaytime_u^\tau(t) - \sum\nolimits_{y \in N(u) \& y\, churned\, in\, \tau} SV_{yu}^\tau(t)$$

In addition, we compared $AdjTotalPlaytime_u^\tau(t)$ with the actual observed data. We expected that $AdjTotalPlaytime_u^\tau(t)$ would be more accurate than $TotalPlaytime_u^\tau(t)$. Through this process, these models generated SV, representing a player's networked social influence, which captured the degree to which the player influenced others' behaviors.

In our model estimation, we utilized random forest regression models within the Social Value algorithm, achieving an R^2 value of 95% and an accuracy of 85%. These models were used to estimate the impact of actors on others. The forests were configured with 100 trees. Figure 2 presents the feature importance of the variables, highlighting the predictors that most significantly influenced model performance.

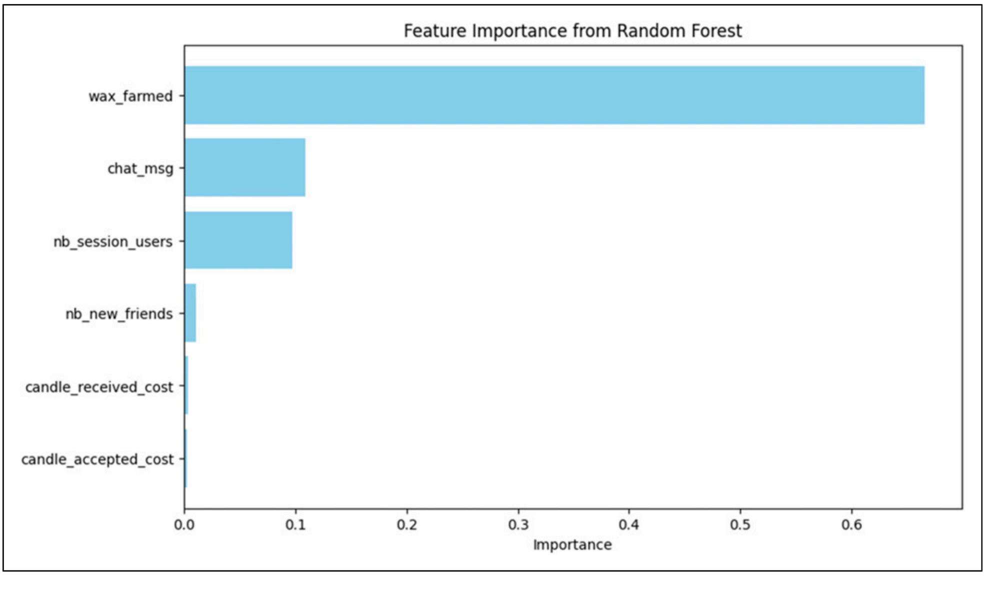

Figure 2. Feature Importance from the Random Forest Model Estimating Social Value

COM-B Model

Operationalization of Variables. Players' capability was assessed through two performance-based metrics: the wax collection rate (total in-game currency collected per unit of playtime) and level completion rate (total levels completed per unit of playtime). Wax is an in-game item that players collect to form candles. Both variables reflect players' overall efficiency in acquiring resources and progressing through the game, encompassing both physical and psychological capability (Michie et al., 2011), consistent with "gaming capital" frameworks (Barnett & Coulson, 2010; Reed et al., 2018).

Opportunity was operationalized through social engagement and playtime. Social engagement was measured by the total number of chat messages sent and received, while playtime was recorded as the total minutes played during the observation period. Social engagement represents a player's social opportunities; a player exchanging more messages in *Sky* has more opportunities to interact with others through the game, mirroring Goh and Wasko's (2009) use of social engagement to capture leadership potential in gaming guilds. Playtime represents a player's environmental opportunities, serving as both a finite resource and a temporal window through which players can explore, interact with, and master the possibilities offered by the game world. The more playtime available, the greater the potential for players to discover and engage with the game and other players. Socioeconomic status (SES) was measured as the respondent's education level, as education is one of the widely-used proxies of SES (Côté, 2011; Soobader et al., 2001). SES was included as a variable under opportunity because it is a background variable highly related to one's access to both social and environmental opportunities and ability to exert interpersonal influence (Fang & Saks, 2020).

Motivation was divided into automatic and reflective components. Automatic motivation was assessed using three factors from Self-Determination Theory (SDT) (Ryan et al., 2006)—autonomy, competence, and relatedness. Reflective motivation was captured using the Trojan Player Typology (Kahn et al., 2015), which categorizes players into six types (e.g., socializer, competitor, and escapist) based on their play preferences. Both SDT and the Trojan Player Typology have been successfully used in previous game studies to categorize players' motivations.

The COM-B predictors in this study vary in their degree of social content: capability measures, such as wax collection and level completion, reflect task efficiency, whereas social opportunity incorporates social engagement through chat activity. Regardless of their social component, all COM-B predictors are treated uniformly as independent variables. Each is used to predict the socially defined outcome of networked social influence, which is calculated separately via the SV algorithm.

Age, gender, and race were included as control variables. Coding schemes for all independent and control variables are provided in Appendix B. Figure 3 presents the operationalized variables of the COM-B model and the corresponding hypotheses.

COM-B Dataset. The processing of the COM-B model variables involved integrating two datasets. The first dataset captured players' behavioral data spanning October 5, 2020, to November 30, 2020, covering the first 4/5 of the *Season of Prophecy* in *Sky*. The second dataset comprised players' self-reported motivations obtained from a survey distributed between November 20, 2020, and November 30, 2020. The two datasets were merged using an inner join, producing a comprehensive sample of 9,254 players. This combined dataset enabled us to examine players' capability, opportunity, and motivation patterns across the first 4/5 of the *Season of Prophecy* (October 5 to November 30, 2020). Figure 3 illustrates the measures derived from behavioral data and those drawn from survey data.

Sample Characteristics. After joining the Social Value dataset and the COM-B model dataset, and completing data cleaning, the final dataset comprised 3,925 players. The size was reduced primarily by

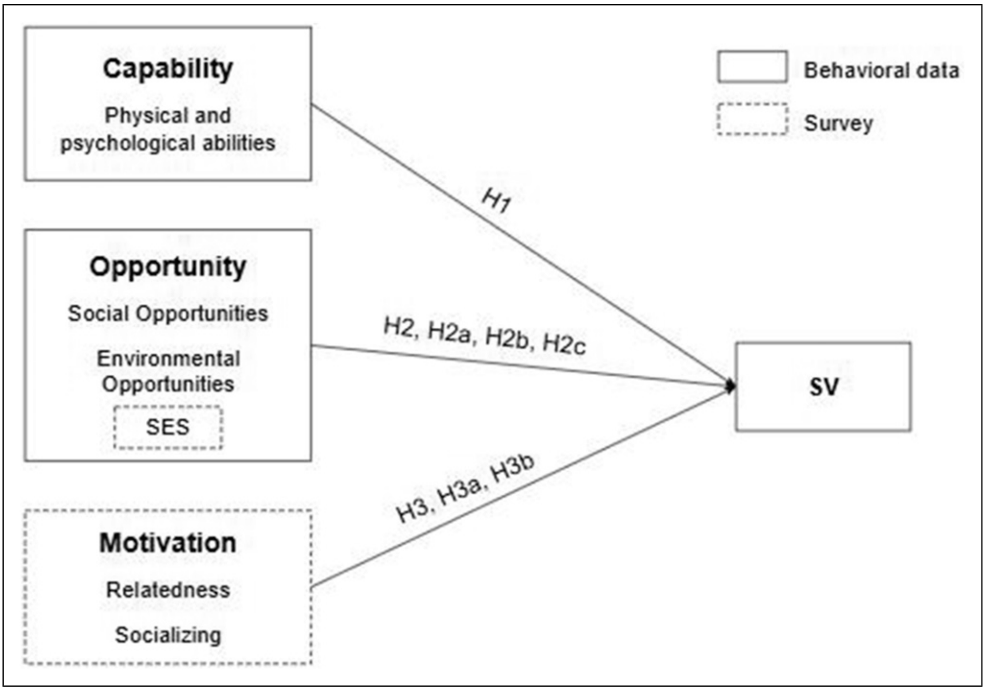

Figure 3. Operationalization of COM-B Constructs and Measurement Sources
Note. Arrow direction reflects measurement order (IV before DV) in lagged regression, enhancing confidence in effect direction while remaining observational

removing low-quality responses—for example, entries like "dog" under gender, which indicated inattention and unseriousness. Excluding these ensured the reliability and quality of the survey results. We also excluded respondents who are under 18. The players in the final dataset aged 18 to 64 years. The sample comprised 25.3% males and 74.7% females. 62.01% of participants identified as Asian, 20.18% as White, and 17.81% as other racial/ethnic groups (e.g., Black, Native or First Peoples, Pacific Islander, Latina/o/x, or Hispanic). To maintain statistical power in subsequent analyses, we conducted analyses using broad racial categories as defined in the survey, rather than disaggregated subgroups. We acknowledge that these categories are not homogeneous and that cultural context (e.g., players in Japan vs. China) may shape behavior differently, which we note as a limitation of this study.

Educationally, 32.48% reported having some college but no degree, 27.97% had a high school or equivalent degree, and 19.90% held a Bachelor's degree. Regarding income, 50% reported earning less than $15,000 annually. Asian was used as the reference group.

Analytical Approach. Due to heteroskedasticity observed among variables (i.e., unequal variance of residuals across observations), Ordinary Least Squares (OLS) regressions with HC3 robust standard errors were employed to examine the predictive (lagged) relationships between COM-B components and player influence. As shown in Figure 3, Capability, Opportunity, and Motivation were measured during the first part of the *Season of Prophecy* (October 5–November 30, 2020), and networked social influence was calculated at the season's end (December 1–13, 2020). This temporal lag design allows us to assess how COM-B factors measured during the first part of the season relate to players' networked social influence (Social Value scores) at the end of the same season. In other words, our model estimates prospective associations within a single season, not forecasts across multiple seasons.

While Structural Equation Modeling (SEM) is useful for modeling latent constructs and complex variable relationships (Kline, 2016), our study focuses on observed, theory-driven variables rather than latent dimensions. Given the large sample size, the linear structure of our hypotheses, and the goal of estimating the relative predictive power of each COM-B component, OLS with robust standard errors provides a more straightforward and interpretable approach.

Results

Capability

To test H1, we examined the relationship between the independent variables (Wax Collection Rate and Level Completion Rate) and the dependent variable (SV) while controlling for age, race, and gender. The model's R^2 value indicated that capability accounts for 14.2% of the variance in SV, with a $p < .001$, confirming the model's overall significance. Detailed regression results are provided in Table 1.

Our analysis revealed several key findings: players identified as White (*coef* = −4.23, $p < .01$) were less likely to exhibit networked social influence compared to the reference group (Race = Asian). Additionally, males were less likely to exert networked social influence within the players community than females (*coef* = −1.95, $p < .05$). Age showed a positive relationship with Social Value, with each year of age corresponding to a 0.21 increase in SV ($p < .01$). Furthermore, a one-unit increase in a player's wax collection rate was associated with a 7.30 increase in networked social influence ($p < .001$). In contrast, a one-unit increase in level completion rate resulted in a significant 453.15 decrease in interpersonal influence ($p < .001$). This indicates that capability predicts influence in mixed ways: wax collection supports the hypothesis, whereas level completion contradicts it. Hence, H1 was only partially supported.

Opportunity

We analyzed the relationship between independent variables (Chat Message, Playtime as Opportunities, and SES) and the dependent variable (SV), controlling for age, race, and gender. The model had an R^2 score of 50.2% with $p < .001$. Detailed regression results are presented in Table 2.

Players identified as White (*coef* = −2.69, $p < .05$) were less likely to exhibit networked social influence than Asians. Males tended to have less networked social influence (*coef* = −1.58, $p < .05$).

Table 1. OLS Regression Model for Networked Social Influence in Terms of Capability

	Coef.	Std. Err.	z	p-value	[0.025	0.0975]
Intercept	92.07	3.26	28.26	0.00***	85.69	98.45
White	−4.23	1.46	−2.81	0.00**	−7.08	−1.38
Male	−1.95	0.81	−2.40	0.02*	−3.54	−0.36
Wax collection rate	7.30	0.93	7.90	0.00***	5.49	9.11
Level completion rate	−453.15	21.12	−21.46	0.00***	−494.55	−411.76
Age	0.21	0.08	2.77	0.01**	0.06	0.35
R-squared	0.142					
Adjusted	0.140					

*$p < .05$. **$p < .01$. ***$p < .001$. The table shows only variables that are statistically significant.

Table 2. OLS Regression Model for Networked Social Influence in Terms of Opportunity

	Coef.	Std. Err.	z	p-value	[0.025	0.0975]
Intercept	11.99	3.91	3.07	0.00**	4.33	19.65
White	−2.69	1.12	−2.42	0.02*	−4.88	−0.51
Male	−1.58	0.63	−2.53	0.01*	−2.81	−0.36
Chat message	11.83	2.68	4.41	0.00***	6.57	17.09
Playtime	0.00	0.00	40.22	0.00***	0.00	0.00
R-squared	0.502					
Adjusted	0.501					

*p < .05. **p < .01. ***p < .001. The table shows only variables that are statistically significant.

For every additional chat message exchanged, a player's networked social influence increased by 11.83 ($p < .001$). Surprisingly, there was no linear relationship between playtime and networked social influence (*coef* = 0, $p < .001$). There was no statistically significant correlation between a player's SES and interpersonal influence.

In conclusion, H2a was supported, suggesting that players with more social opportunities are more likely to have higher networked social influence. H2b was not supported, as playtime—our measure of environmental opportunity—did not show a positive relationship with networked social influence. H2c was not supported, indicating that a player's SES does not significantly correlate with their networked social influence within the game.

Motivation

We examined the relationship between independent variables (SDT variables for automatic motivation and TPT variables for reflective motivation) and the dependent variable (SV), with control variables. The model's R^2 was 5.8% ($p < .001$). Regression results are presented in Table 3.

White individuals exhibited 7.29 lower networked social influence compared to the reference group (Race = Asian) ($p < .001$). Male participants had 3.50 lower networked social influence ($p < .001$), and age was positively correlated with Social Value, with each additional year increasing SV by 0.23 ($p < .01$).

For automatic motivation, each additional unit of relatedness need was associated with a 2.55 increase in networked social influence ($p < .001$). Regarding reflective motivation, players identified as "Socializers" (*coef* = 0.85, $p < .05$) and "Competitors" (*coef* = 1.32, $p < .001$) were more likely to have higher interpersonal influence. Conversely, players with a stronger "Story-Driven" orientation showed a negative relationship with networked social influence, with a decrease of 2.06 ($p < .001$). The "Smarty-Pants" trait had a smaller but still significant positive association (*coef* = 0.86, $p < .01$).

As a result, both H3a and H3b were supported, suggesting that players with higher psychological needs of relatedness or who are motivated to socialize tend to have greater networked social influence.

Discussions

Support of the COM-B Model

This study applies the COM-B model (Capability, Opportunity, Motivation—Behavior) to examine players' networked social influence within the context of a social multiplayer mobile game,

Table 3. OLS Regression Model for Networked Social Influence in Terms of Motivation

	Coef.	Std. Err.	z	p-value	[0.025	0.0975]
Intercept	30.80	3.90	7.72	0.00***	22.47	34.72
White	−7.29	1.52	−4.81	0.00***	−10.26	−4.32
Male	−3.50	0.85	−4.12	0.00***	−5.17	−1.84
Relatedness	2.55	0.53	4.85	0.00***	1.52	3.59
Socializer	0.85	0.37	2.32	0.02*	0.13	1.57
Competitor	1.32	0.35	3.73	0.00***	0.63	2.01
Story-driven	−2.06	0.53	−3.89	0.00***	−3.10	−1.02
Smarty-pants	0.86	0.30	2.89	0.00**	0.28	1.44
Age	0.23	0.08	2.86	0.00**	0.07	0.38
R-squared	0.058					
Adjusted	0.053					

*p < .05. **p < .01. ***p < .001. The table shows only variables that are statistically significant.

Sky: Children of the Light. Our findings generally support the COM-B model, showing that capability, opportunity, and motivation all predict a player's networked influence.

In the first model, ***Capability*** predicts networked social influence, though its impact varies by specific behaviors. Collecting wax is a key activity that contributes to networked social influence in *Sky*. Players who excel at this task demonstrate efficient gameplay and adaptive strategies, gaining respect and influence within the community. This finding aligns with prior research on gaming capital (Consalvo, 2009; Korkeila & Harviainen, 2023), which highlights the importance of strategic skills in building influence. The negative relationship between level completion rate and networked social influence may stem from the time-consuming nature of completing levels, which might be prioritized by highly dedicated players who focus less on other game features, like social interactions, thus having lower influence. It also underscores the dual nature of capability in gaming contexts: while expertise can elevate a player's status, overemphasis on individual achievement may limit their ability to foster social connections.

In the second model, ***Opportunity*** emerges as the most significant predictor. Interaction through sending and receiving chat messages increases players' opportunities for socializing, boosting a player's potential to influence others. This finding resonates with studies emphasizing the role of social opportunities in shaping leadership and influence within gaming communities (Goh & Wasko, 2009; Hsiao & Chiou, 2012). However, increased playtime did not correlate with higher influence, suggesting that the amount of time spent in the game, regardless of whether it involves social interactions, does not directly translate into influence. These findings showcase that social opportunities are translated into networked social influence when further interactions, such as sending messages, occur between players. This further highlights that the quality of interaction may be more critical to building influence than simply spending more time in the game.

This study challenges the assumption that higher ***Socioeconomic Status*** leads to potential leadership positions in online games. While earlier research indicates a correlation between high SES and leadership outcomes in professional settings (Ali et al., 2005; Duan et al., 2022; Fang & Saks, 2020), our findings suggest that this does not hold for networked interpersonal influence within *Sky*. Players from both high and low SES backgrounds had similar, indistinct levels of influence on others within their network. Our results imply that factors other than SES may play a more significant role in determining influence in gaming environments. For example, purchasing or exchanging in-game items can increase one's social attractiveness and visibility to peers (Cai et al., 2022; Wohn, 2014). These findings suggest that offline SES may not be as critical in determining influence within digital contexts, where interaction is mediated by avatars and symbolic displays rather than face-to-face cues.

In the third model, ***Motivation*** also plays a critical role in explaining players' influence. Players who are motivated by their psychological need for relatedness in the *Sky* community and in-game relationships are more likely to engage in social activities, thereby increasing their influence. This aligns with Self-Determination Theory (Ryan & Deci, 2000), which posits that fulfilling psychological needs for relatedness enhances well-being and social engagement (Reer & Krämer, 2020). "Competitor" players are also more influential, as their competitive nature likely enhances their capability (e.g., gaming skills), positioning them as central figures in the community. Conversely, story-driven players, who are more focused on immersion or solo experiences, tend to have lower networked social influence, highlighting how motivations and play styles influence players' roles within the game's social network.

Theoretical Contributions

This study offers substantial theoretical contributions to the COM-B model and the broader understanding of networked social influence in digital environments. First, it extends the COM-B model, initially designed for health behavior research, by applying it in a new context: mobile games, an emerging field that has attracted billions of active game players. It demonstrates the model's versatility and generalizability by revealing how Capability, Opportunity, and Motivation shape players' influence. This research underscores the model's relevance to fields beyond its traditional applications.

Second, our study extends the COM-B model by introducing a new dimension: networked social influence. This dimension captures the extent to which a player's presence and actions influence the behaviors of others within a networked community. By applying the COM-B framework, we demonstrate that Capability, Opportunity, and Motivation not only shape individual behaviors but also are associated with the degree of influence one player exerts over others. It reveals that interpersonal influence—traditionally studied through network centrality or structural metrics—can also be understood and explained through the lens of behavioral dimension.

By integrating networked social influence into the COM-B framework, this study bridges the gap between behavioral study and network science. It provides a theoretical foundation for understanding how individual behaviors ripple through social networks, influencing others in measurable ways. This contribution not only enriches the COM-B model but also opens new avenues for research into networked social influence dynamics across digital and non-digital contexts.

Our analysis revealed gender and racial differences in networked social influence. Female players consistently exhibited stronger influence, aligning with prior research that suggests women excel in social interactions and relationship-building within gaming environments (Xiong, 2012). In terms of race, Asian players had higher levels of networked social influence compared to White players. This finding was unexpected, given that race is not directly disclosed in the game. However, these differences could be attributed to various unobserved factors. For example, Asian players may engage more deeply with the cooperative aspects of the game, which aligns with values emphasizing collaboration and group harmony (Wang et al., 2024). On the other hand, White players may exhibit different engagement patterns, resulting in lower networked social influence scores. However, the exact cause of this difference remains unclear, and more research is needed to understand whether these patterns are related to player behavior or other demographic variables that affect engagement. These findings underscore the importance of considering race and gender when applying the COM-B model to spaces with diverse backgrounds.

Methodological Contributions

This research applies a graph-based machine learning approach to studying networked social influence, demonstrating its utility in the context of digital gaming. It decouples the understanding of influence from traditional network centrality metrics, shifting the focus toward observable behaviors. Specifically, the study measures influence through the impact of a player's presence or absence on others' playtime, offering a more behaviorally grounded and context-sensitive definition of influence. Moreover, the integration of machine learning into the analysis provides a replicable framework for understanding complex social interactions in digital contexts. By quantifying influence, the study illustrates how behavioral and computational methods can be combined to investigate social influence in gaming environments and other digital platforms.

Practical Implications

The lower influence observed among White players compared to Asian players highlights the presence of group-level differences in networked social influence. Although these patterns may stem from real-world factors or social norms, they nonetheless hold meaningful implications for fostering inclusivity in digital environments. While this study doesn't attribute racial bias to the game design, it underscores the importance of considering how offline identities and backgrounds may influence digital interactions.

Beyond inclusivity, our findings also provide design insights. First, because social opportunities emerged as the strongest predictor of influence, developers may wish to prioritize features that lower barriers to interaction. Designing systems that reward prosocial communication can amplify positive engagement across the player base.

Additionally, the results indicate that different playstyles map onto different influence patterns. Socializers and competitors were more influential, while narrative-focused players exhibited lower influence. Developers aiming for more balanced community participation might therefore design narrative-driven events with explicit opportunities for collaboration, ensuring that players who prefer immersion or story engagement can still contribute to and benefit from the community.

Taken together, these implications suggest that effective design involves more than maximizing individual engagement. It requires cultivating inclusive, balanced, and prosocial influence dynamics, thereby creating digital environments that are both socially sustainable and engaging.

Limitations and Future Research

First, the study relies on observational data from *Sky: Children of the Light*, which limits the generalizability of findings to other gaming contexts. The social dynamics and game mechanics unique to *Sky* may not fully translate to other environments, particularly those with different player interaction structures or competitive elements (Kim, 2025). Future research could extend this analysis to a broader range of games, including more competitive multiple-player or single-player games with social features, to examine whether the observed patterns hold across diverse gaming ecosystems.

Second, the study duration was confined to a single game season (the *Season of Prophecy*). Networked social influence may take longer to develop and become apparent in games like *Sky*, where networks are gradually built over extended periods. A limited timeframe may not fully capture how influence accumulates and evolves in dynamic gaming environments. Longitudinal studies tracking player interactions over multiple seasons could provide deeper insights into the long-term development of influence and network structures.

Third, although this study included gender and race and found significant differences in social influence, our data did not include measures that would allow us to explain why these differences emerged. Future research should explore how offline cultural norms, identity-based behaviors, and socialization patterns shape in-game interactions and influence. These factors are often invisible in online environments like *Sky*, where avatars lack real-world identifiers, yet they may profoundly affect how players engage with others. Understanding how offline identity and cultural background manifest in digital behaviors could provide deeper insights into the origins of networked social influence and inform more inclusive and culturally aware game design practices.

Fourth, our analysis relied on broad racial/ethnic categories (such as Asian, White, Black) that collapsed diverse cultural backgrounds into simplified groups. This approach was necessary to maintain statistical power, but it does not capture within-group heterogeneity. For example, players in Japan and China were both classified as Asian, though cultural differences may shape gameplay and influence in distinct ways. Future research should employ finer-grained cultural or regional distinctions to better understand how social influence varies across different player communities.

Despite these limitations, our findings contribute to a growing understanding of networked social influence in digital spaces and highlight opportunities for future research to build upon this work. Expanding the scope of game environments, incorporating additional psychological and behavioral factors, and utilizing mixed-method approaches will help further refine our understanding of how networked social influence emerges and evolves in online communities.

Moreover, future research could extend this work by applying affordance theory to better explain how game design enables or constrains social interactions (Gibson, 2013; Norman, 1999). This is relevant given our finding that social opportunities were the most significant predictor of social influence. Features like in-game chat, collaborative missions, and shared objectives function as social affordances that shape how players engage with others (Sumayah Abu-Dawood, 2016). Exploring how these affordances are designed, perceived, and acted upon across different games and communities may reveal how interactions become influence. Such work could help developers create socially responsive environments that foster meaningful participation.

Conclusions

This study examined networked social influence dynamics within mobile social multiplayer online games, specifically through the lens of the COM-B model in *Sky: Children of the Light*. By integrating a graph-based machine learning approach to measuring networked social influence, we demonstrate that, within the scope of our COM-B–based model, a player's influence is shaped by their capability, opportunity, and motivation, each contributing uniquely to behavioral outcomes in the digital ecosystem.

Capability enhances social standing, while excessive focus on task completion diminishes influence. Opportunity emerges as the most impactful factor, with active communication significantly bolstering player influence, highlighting the pivotal role of social interaction within gaming networks. Meanwhile, the nuanced influence of motivation underscores the diversity of player engagement.

Moreover, this study offers insights for fostering inclusive and engaging gaming environments. Enriching social affordances within games can provide players with more opportunities for meaningful engagement, while preserving their autonomy in how and when they choose to interact.

In sum, this research contributes by applying the COM-B framework to the gaming context and demonstrating how behavioral and computational approaches can be integrated. While limited to one game and dataset, the findings highlight directions for future research and suggest considerations for developers.

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Ethical Consideration

This research adhered to the ethical guidelines set forth by the Institutional Review Board (IRB) at the University of Southern California, with approval granted under protocol number UP-20-00363.

Consent to Participate

Informed consent was obtained from all participants, and steps were taken to protect their confidentiality and ensure the anonymity of their data.

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Declaration of Conflicting Interests

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Data Availability Statement

Research data are not available at this time.

Notes

1. From *MMORPG Games Market Forecasts Significant Growth with a CAGR of 10.50% by 2028*, by Research and Markets. 2024 (https://www.globenewswire.com/news-release/2024/01/25/2816729/28124/en/MMORPG-Games-Market-Forecasts-Significant-Growth-with-a-CAGR-of-10-50-by-2028.html).
2. From *2025 Gamers Report: Age, Gender, Location, Habits*, by A. Knezovic. 2025, Udonis (https://www.blog.udonis.co/mobile-marketing/mobile-games/modern-mobile-gamer).
3. From *"Sky: Children Of The Light" Teaches The Importance Of Collaboration* (And The Joy Of Isolation), by A. Meader. 2020, The Daily Fandom (https://thedailyfandom.org/sky-teaches-importance-of-collaboration/).

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Author Biographies

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Appendix

Appendix A

User-Level Features

Dependent variable.

Duration_in_sec: Total playtime (in seconds).

Model features.

Wax_farmed: Amount of wax collected by the player.
Chat_msg: Count of chat messages exchanged by the player.
Nb_session_users: Average number of users in the players' play sessions.
Nb_new_friends: Number of in-game friends added.
Candle_received_cost: Number of candles received from other players.
Candle_accepted_cost: Number of candles accepted from other players.

Appendix B

Measurement Scales and Items

Capability.

Wax Collection Rate (in-game currency)**:** total number of wax collected during October 5, 2020-November 30, 2020, divided by total playtime during this period.

Level Completion Rate**:** total number of level completions during October 5, 2020-November 30, 2020, divided by total playtime during this period.

Opportunity.

Chat Message**:** total number of messages the players have sent or received during October 5, 2020-November 30, 2020.

Playtime**:** total minutes the players have played during October 5, 2020-November 30, 2020.

Socioeconomic Status (SES).

-Education Level.

"Please indicate your highest completed level of education." (Scale: 1 = "Less than high school," 2 = "High school or equivalent," 3 = "Some college but no degree," 4 = "Associates degree," 5 = "Bachelor's degree," 6 = "Master's degree," 7 = "Professional degree, e.g., MD, JD," 8 = "Doctoral degree")

Motivation.

Automatic Motivation

Self-Determination Theory (SDT) (five-point Likert scales).

- *Autonomy:*

"When I am playing *Sky*, I feel free to be who I am."
"When I am playing *Sky*, I have a say in what happens, and I can voice my opinion."
"When I am playing *Sky*, I feel controlled and pressured to be certain ways."

- ***Competence:***

"When I am playing *Sky*, I feel like a competent person."
"When I am playing *Sky*, I do not feel very competent."
"When I am playing *Sky*, I feel very capable and effective."

- ***Relatedness:***

"When I am playing *Sky*, I feel cared about in the gaming community."

"When I am playing *Sky*, I often feel a lot of distance in the gaming community."
"When I am playing *Sky*, I feel a lot of closeness in the gaming community."

Reflective Motivation

Trojan Player Typology (5-point Likert scales).

- *Socializer:*
"I like to chat with other players while playing *Sky* (either through the game or some outside method)."
"I like to use some voice system to talk with other people when I play *Sky*."
"It's important to me to play *Sky* with a tightly knit group."

- ***Completionist:***
"I like to master every part of the *Sky* experience."
"I like to figure out all of the small details of *Sky*."
"I like to try everything that is possible to do in *Sky*."

- ***Competitor:***
"Progressing through content more than other players is a big reason for me to play *Sky*."
"I play *Sky* to accomplish more than others."
"It is important to me to be the most skilled person playing *Sky*."

- ***Escapist:***
"I like to do things in *Sky* that I cannot do in real life."
"*Sky* allows me to pretend I am someone else."

- *Story-driven:*
"I like the feeling of being part of the story."
"I like the storylines that play out during *Sky*."

- *Smarty-pants:*
"Playing *Sky* makes me smarter."
"I play *Sky* to enhance my intellectual abilities."

Control Variables.

Age

Race: (0 = Asian, 1 = White, 2 = Black, 3 = Native or First Peoples, 4 = Others, 5 = Pacific Islander, and 6 = Latina/o/x or Hispanic).

Gender: (0 = Female. 1 = Male).