Online Appendices for “Interlopers or Catalysts? Dissecting the Impact of Incorporating AI Players on Multiplayer Online Games”

Online Appendix A: Evidence of the Skill Disparity Among Players Before Policy and the Low Competence of AI players

We present a histogram depicting the distribution of player skill levels before the policy. Specifically, we measure player skill levels using the average distance of eliminating an opponent. As shown in Figure A.1, the distribution indicates a significant skill disparity among players prior to the policy.

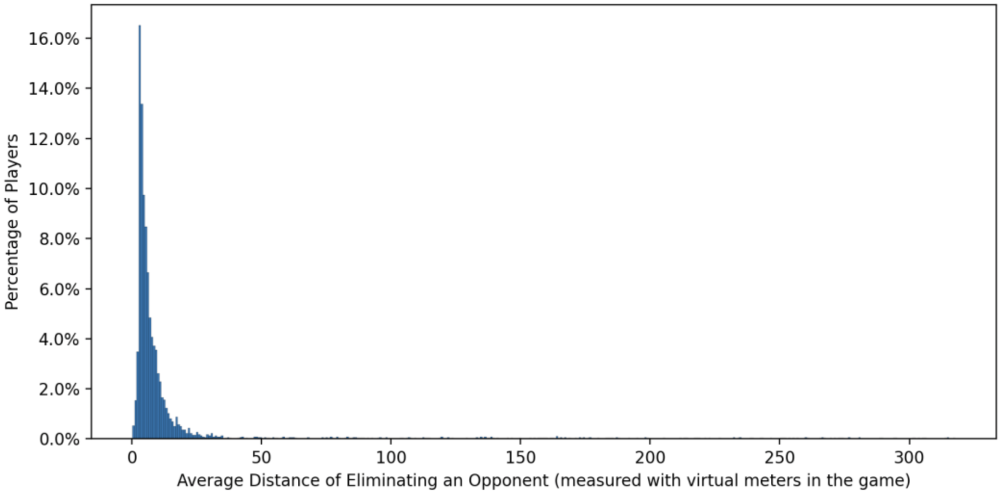

Figure A.1. Distribution of Player Skill Levels Before the Introduction of AI Players

Similarly, we use the average distance of eliminating an opponent to measure the skill level of AI players. Based on our dataset, we find that the average distance at which an AI player eliminates an opponent is 2.686 meters (virtual meters in the game). Among the 3,798 players in our sample, about 92.5% (3,514) can eliminate an opponent from a greater distance on average before the introduction of AI players. This indicates that AI players are designed to have a lower level of competence. In addition, we conducted qualitative interviews with PUBG players to help clarify the details of our research context. During the interview, all participants noted that AI players are relatively less competent. For example, one player mentioned, “*The AI players are generally less challenging than human players.*”

Online Appendix B: Post-Analysis Interview

B.1 Interview Supporting the Research Motivation

In the Introduction, we highlight a key distinction: while defeating weak human opponents can increase self-efficacy, eliminating AI opponents may not yield the same effect due to the ambiguity in the interpretation of performance (Bandura 1989; Compeau et al. 1999). As such, AI opponents may generate different outcomes compared to weak human players. To support this research motivation, we conducted interviews with PUBG players to explore their perceptions of AI versus human opponents. Interestingly, players initially held low expectations for AI opponents, assuming matches would be unexciting. However, after gameplay, many described AI players as unexpectedly smart and capable. These responses suggest that AI may produce different outcomes when it is perceived as human-like, underscoring the distinction between modern AI and traditional bots or NPCs. This shift in player perception also helps explain why our findings diverge from earlier literature (e.g., Liu et al. 2013; Hamari and Keronen 2017). Below, we present excerpts from players' narratives that support our motivation.

> "*Honestly, **I didn't think I would enjoy playing against AI at first. I thought it would be too easy or kind of boring**. But once I finished my first AI match, I was actually really surprised. They were smarter than I expected! It didn't feel like I was just steamrolling bots; I still had to think and play well. The whole match just felt smoother and more fun.*"

> "***I didn't expect much going into my first AI match. Based on my past experience with games, bots were usually pretty dumb.** They act like machines, barely react, and could not really keep up. So I just thought, 'It is AI; how challenging can it be?' But I was actually surprised. The AI looked pretty smart. They were not just standing around or doing random stuff. The match ended up being really fun, and I did not feel like I was wasting my time at all. It did not even feel that different from playing against real people, to be honest. I think that made a big difference. It didn't feel like the old*-school *bots I remember.*"

B.2 Interviews Supporting the Hypothesis Regarding Self-efficacy

Our empirical analysis indicates that the introduction of AI players can enhance game engagement and motivate friend team-ups. While the mediation analysis supports our underlying mechanism, there is a need for direct evidence to substantiate that AI players improve engagement and friend team-ups by enhancing player self-efficacy and team responsibility. To address this gap, we conducted interviews with players to explore their experiences of interacting with AI players. We interviewed ten players who participated in at least ten AI matches and ten non-AI matches. These ten players also vary in skill levels. The interview questions were open-ended, allowing players to share their opinions and experiences regarding both AI and non-AI matches.

In our research, we empirically show distinct behaviors among human players participating in AI matches compared to non-AI matches. This observation is further validated by the feedback from the players we interviewed, all of whom express differing mindsets toward the two types of matches. Below, we present excerpts from their narratives that exemplify the phenomenon of self-efficacy.

> "*In non-AI matches, the competition can get pretty frustrating, especially when I am up against really skilled players or stuck in a losing streak. So I like jumping into AI matches instead. Playing against AI players helps me* ***gain some confidence****, especially after a rough series of games. It is nice to* ***score easy kills and build some momentum****.*
>
> ***No, it is hard to figure out which opponents are AI players, but I can tell which opponents are AI players when reviewing game records after the match****.*"

> "*Playing PUBG in AI matches versus non-AI matches gives me different vibes. I feel more relaxed in AI matches, knowing that the AI players are generally less challenging than human players. This setup lets me try different strategies, weapons, and tactics without the pressure of a competitive environment. It's a great way to* ***build confidence****. I can see myself* ***improving in specific areas****. Non-AI matches, on the other hand, are a whole different experience. I'm playing*

> *against other skilled players. Every match feels like a serious competition. It can be frustrating at times.*
> *Usually, I cannot tell AI players from human players.*"

> "*I prefer playing AI matches with friends because it's way more chill. There's no pressure to perform, so it's just fun and relaxed. I can mess around with game mechanics, try out different strategies, and get better without stressing over mistakes. But I'm a bit wary about jumping into non-AI matches with friends. This mode is super competitive, and every player's performance really matters for the team's rank. I'm worried* **my inexperience might drag the team down**. *This pressure makes me hesitant to join non-AI matches with friends until I feel more confident in my skills.*"

To explain the observed increase in game engagement and friend team-ups following the introduction of AI players, we propose that players experience enhanced self-efficacy and team responsibility in AI matches compared to non-AI matches. To investigate the roles of self-efficacy and team responsibility in our study, we presented interviewees with a hypothetical scenario: assuming all other factors are equal, we asked whether players would be more inclined to continue playing and teaming up with friends after consistently eliminating opponents in several matches, or after achieving no eliminations in several consecutive matches. Notably, all respondents selected the first scenario, highlighting how the confidence gained from repeated success in eliminating opponents influenced their motivation and decision-making.

> "*Honestly, I'd probably be more inclined to continue playing or teaming up with friends after eliminating opponents in several matches in a row. After zero eliminations, it can be pretty frustrating to keep playing and not see any success. When consistently not eliminating anyone, I feel like I am* **not contributing much to the team**, *and that can be a bit demotivating.*"

> "*If I had to choose, I tend to keep playing the game or teaming up with friends after a bunch of matches with eliminations. It's way more exciting and keeps the energy up. It makes me proud to know I'm* ***capable*** *and I can* ***contribute to the team's performance.*** *But when I do not get any eliminations, it is like I'm not really doing good and helping out in the game.*"

In conclusion, the qualitative insights obtained from PUBG players anchor our study in real-world contexts and offer supplementary support for our results and our proposed mechanism.

Online Appendix C: Additional Explanations

C.1 Distinctions Between AI Players and Traditional NPCs

In our research context, we define NPCs as *non-player characters* to highlight the focus of our paper (Thorne 2008). We refer to the AI-controlled NPCs in PUBG as AI players to align with the terminology commonly used by gaming communities and developers (Correa 2024; Inworld Team 2024; Lindsey 2024). It's important to distinguish AI players in PUBG from traditional NPCs. Traditional NPCs, based on straightforward algorithms, follow predetermined paths and remain unchanged in response to player actions, leading to static and predictable interactions (Warpefelt and Verhagen 2015). In contrast, AI players in PUBG employ more advanced AI technologies and possess learning capabilities (Hossam 2020). These AI players can mimic human actions and adapt in real time, making interactions more dynamic and engaging. Hence, human players often believe they are competing against other human opponents rather than AI, which can fundamentally alter the gaming experience.

C.2 Reasons for Using Eliminating Distance to Assess Player Skills

We use the average distance for eliminating an opponent to assess player skills for several reasons. In games such as PUBG, long-distance shooting presents greater challenges than short-distance engagements due to the added complexity of environmental factors (Biswas 2020) and bullet mechanics, including bullet drop and travel time (Knight 2017). Accurate identification of distant opponents requires heightened situational awareness and in-depth knowledge of the map (Biswas 2020). Engaging effectively in long-range combat demands not only precise aiming but also strategic decision-making and a refined understanding of tactical positioning, which are less critical in close combat situations. Successfully neutralizing a distant opponent involves advanced skills, such as mastering bullet trajectory and timing, making long-range shooting a distinct marker of expertise in multiplayer online shooting games (Reeves et al. 2009; Neri et al. 2024). These complexities underscore long-range shooting as a key indicator of player skill levels.

More importantly, we avoid using more direct measurements in the main manuscript, such as the average number of opponents eliminated per match, to mitigate potential bias in evaluating player skill levels after introducing AI players. On the one hand, the number of total opponents eliminated in a match, if including AI opponents, cannot precisely measure the actual performance of a player since defeating AI players does not require advanced skills. On the other hand, using the number of human opponents eliminated in a match can be biased. The presence of AI players reduces the number of human players in a match, thereby decreasing the maximum number of human opponents that can be eliminated and potentially distorting the true measure of performance. Nevertheless, we have explored these direct measurements and obtained substantially similar results.

C.3 Clarification on the Missing Values

In our context, $BotsInteractionNum$ and $WeeksSinceFirstInteraction$ are undefined for players who only engage in human-only matches (i.e., control players). For these players, both variables are set to zero throughout the observation window. Since control players never encounter AI players, they naturally have zero interactions. Likewise, $WeeksSinceFirstInteraction$ measures the time elapsed since first exposure to the treatment. For control players, this duration is zero as the treatment period never begins. This approach is consistent with standard practice in staggered-adoption settings, where units not yet (or never) treated carry zero values for exposure-related measures (Goodman-Bacon 2021).

To ensure robustness, we also re-estimate our models without these two control variables and obtain consistent results, as shown in Table C.1.

Table C.1. Impact of AI Players on Human Player Engagement and Friend Team-ups (Excluding Interaction-related Controls)

Variables	(1) $\log(GameNum)$	(2) $\log(GameTime)$	(3) $\log(GameNumFriend)$	(4) $\log(GameTimeFriend)$
$AIPlayer_{it}$	0.177^{***} (0.005)	0.521^{***} (0.016)	0.092^{***} (0.004)	0.291^{***} (0.012)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.058	0.061	0.056	0.060
Observations	136,728	136,728	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

C.4 Theoretical Definitions and Behavioral Manifestations of Self-efficacy and Team Responsibility

Self-efficacy refers to an individual's belief in their ability to succeed and perform effectively (Bandura 1989; Compeau et al. 1999). According to social cognitive theory, the most influential source of self-efficacy is mastery experience, in which successful performance outcomes are interpreted as evidence of personal competence (Bandura 1997). In gaming contexts, observable indicators of skill and success represent such mastery experiences. Players who perform well are likely to perceive these outcomes as validation of their growing capability and control. Accordingly, we operationalize self-efficacy through behavioral manifestations of performance proficiency, measured by the average distance of eliminating an opponent. Greater elimination distances imply higher mastery and stronger confidence in personal ability.

Team responsibility refers to an individual's perceived obligation to contribute meaningfully to collective success (Morrison and Phelps 1999; Zhang et al. 2017). In interdependent settings such as multiplayer online games, this belief is behaviorally expressed through cooperative actions that contribute to team performance (Zhou et al. 2022). For instance, in squad matches in PUBG, success depends on coordinated action. Players must align their movements and tactical decisions, such as providing cover fire, distracting opponents, or attacking from various angles, to eliminate opponents while maintaining team survival. For example, one team member, A, may deliberately shoot an opponent from one direction to draw attention and cause damage, while team member B attacks from another direction to eliminate that opponent. Such coordinated actions are collaborative and reflect a player's willingness to contribute to collective success (Morrison and Phelps 1999; Zhou et al. 2022).

This collaboration can be captured through the assist mechanism. In PUBG, an assist is recorded when a player inflicts damage on an opponent who is subsequently eliminated by a teammate. In the example above, player A is credited with one assist. Although the immediate goal of each action is combat, the resulting assist captures a coordinated contribution to a shared team outcome. Prior research shows that such contribution-based indicators can reflect collaborative behavior in team-based digital environments (Liu et al. 2013; Depping and Mandryk 2017). Accordingly, frequent assists indicate a player's internalized sense of accountability for team outcomes. Hence, we operationalize team responsibility through team contribution, measured by the average number of assists per match. This measure represents proactive and coordinated behaviors that manifest players' perceived obligation to support their team.

While both constructs (self-efficacy and team responsibility) are inherently belief-based, their behavioral representations (player skill level and team contribution) are consistent with the mechanisms described in social cognitive theory (Bandura 1997) and related empirical work (Santhanam et al. 2016; Zhou et al. 2022). In data-intensive gaming contexts, where self-perceptions evolve through repeated performance feedback, such behavioral measures provide meaningful manifestations of underlying belief constructs. Therefore, we view these proxies as theoretically grounded and empirically suitable for capturing self-efficacy and team responsibility during gameplay.

Online Appendix D: Development of Competing Hypotheses

D.1 AI Players and Player Engagement

Introducing AI players might discourage human participation if it fails to align with the need for competence and mastery. Although AI players are designed with programmable skill levels that make success more attainable and with indistinguishability that introduces interpretive ambiguity, these features may also generate adverse psychological consequences. Specifically, when players cannot determine whether successful eliminations stem from their own ability or from facing AI opponents, interpretive ambiguity may activate a self-effacing attributional bias (Bond et al. 1982; Mezulis et al. 2004). Under this orientation, players attribute success to external conditions (i.e., the presence of less-skilled AI players) and discount their competence. That is, attainable success does not translate into meaningful mastery experiences and fails to satisfy the need for competence and mastery. As a result, self-efficacy is weakened, which may reduce players' motivation to persist in gameplay and ultimately lower overall engagement. Accordingly, we present the following hypothesis, which is a competing perspective to Hypothesis 1.

Hypothesis 1a. *The introduction of AI players has a negative impact on human players' game engagement.*

D.2 AI Players and Friend Team-ups

AI players might discourage human players from teaming up with friends if they do not meet the need for social interaction. In squad matches, players' willingness to form teams with friends depends largely on their perceived contribution to team success (Zhang et al. 2017). When interpretive ambiguity leads players to adopt a self-effacing attribution, they may question whether their actions meaningfully influence team outcomes. Even when joint eliminations occur, players may attribute these successes to the presence of less-skilled AI opponents rather than to their own competence or coordination with teammates. Consequently, attainable success fails to reinforce team responsibility or satisfy the need for social interaction. This diminished sense of responsibility toward teammates may discourage players from initiating or sustaining gameplay with friends (Chen et al. 2024). Thus, we have the following hypothesis, a competing perspective to Hypothesis 2.

Hypothesis 2a. *The introduction of AI players discourages human players from actively engaging in games with friends.*

Online Appendix E: Alternative Explanations

E.1 More Games Set Up and Reduced Wait Times

Introducing AI players can possibly enhance matchmaking efficiency by allowing games to start even when the minimum number of human players is not met. In traditional multiplayer games, long waiting times due to insufficient players can lead to frustration and disengagement, particularly during off-peak hours (Inworld Team 2024). AI players might mitigate this issue by ensuring matches form quickly, reducing waiting times, and maintaining a continuous gameplay experience.

We examine the possibility of this avenue. First, we find that there were sufficient active players to sustain match formations throughout our observation window (from December 2, 2019, to August 3, 2020). There were almost no instances where games failed to start due to insufficient human players. As one of the most popular multiplayer online games, PUBG consistently maintained a strong player base. According to Steam Charts,[1] during the observation window, the game's average concurrent player count ranged from 192,492 to 308,445, with peak counts exceeding 900,000. These numbers indicate that there were always enough players online simultaneously to fill matches and ensure games could start without delay.

Second, during the interviews, we asked players about any differences in waiting time when they engage in AI versus non-AI matches. Most participants report no noticeable difference. For example, one player stated, "*I did not notice a difference in waiting times between AI and non-AI matches. Typically, I can jump into either one fairly quickly*." This evidence can effectively rule out the possibility that the introduction of AI players increased the number of matches human players joined by facilitating quicker game initiation.

Third, we conduct an empirical analysis to examine the impact of introducing AI players on waiting times. Specifically, we have introduced a new dependent variable: the average time player i waits between two consecutive matches in week t ($AvgWaitTime_{it}$). We estimate specification (1) and report the results

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[1] https://steamcharts.com/app/578080, last accessed on May 5, 2025.

in Table E.1. The insignificant coefficient of $AIPlayer_{it}$ indicates that the introduction of AI players does not significantly affect the waiting time for players to start a match, ruling out this potential explanation. A possible reason for this is that the large and stable player base ensured that matchmaking delays remained minimal, regardless of whether AI players were introduced.

Table E.1. Impact of AI Players on Waiting Times

Variables	(1) log($AvgWaitTime$)
$AIPlayer_{it}$	-0.102 (0.246)
Control Variables	Yes
Player FE	Yes
Weekly FE	Yes
Observations	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

E.2 Accounting for the Potential Impact of COVID-19

We account for the potential impact of COVID-19 by conducting a subsample analysis and controlling for the COVID-19 severity.

Subsample analysis: To mitigate the potential impact of COVID-19 on our findings, we conduct a subsample analysis. This analysis focuses on players who started playing the game before the pandemic. In other words, these players did not join due to the pandemic, thus ruling out the impact of the influx of new players. Specifically, we include only those players who started playing before the federal government implemented COVID-19 stay-at-home orders on March 1, 2020 (Moreland et al. 2020). This means that we exclude players whose first match occurred after March 1, 2020, in our observation window. The subsample includes 3,756 players, representing approximately 98.9% of our total sample. We employ the same regression model as in our main analysis, and the results are reported in Table E.2, which are consistent with our main results. Thus, our findings are robust when using a subsample analysis to control for the possible impact of COVID-19.

Table E.2. Impact of AI Players Using Subsamples

Variables	(1) $\log(GameNum)$	(2) $\log(GameTime)$	(3) $\log(GameNumFriend)$	(4) $\log(GameTimeFriend)$
$AIPlayer_{it}$	0.168^{***} (0.005)	0.496^{***} (0.016)	0.088^{***} (0.004)	0.279^{***} (0.012)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.065	0.066	0.058	0.062
Observations	135,216	135,216	135,216	135,216

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Controlling for the COVID-19 severity: We account for the severity of COVID-19 by controlling for the number of confirmed positive cases in week t ($PositiveCases_t$). While we recognize the importance of including local COVID-19 severity as a control variable, our current dataset does not contain information on the players' specific locations. As a result, we use the total number of confirmed cases across the U.S. as a proxy. The data on COVID-19 positive cases is sourced from Data.gov, a U.S. Government platform that provides access to high-value public datasets. We then estimate the regression in Equation (E.1). The results, presented in Table E.3, are consistent with our main findings, indicating that the impact of COVID-19 does not significantly contaminate the estimation.

$$\log(y_{it}) = \beta_0 + \beta_1 AIPlayer_{it} + \beta_2 WeeklyConfirmedCases_t + X_{it} + \alpha_i + \varepsilon_{it}, \tag{E.1}$$

Table E.3. Impact of AI Players After Controlling for the COVID-19 Severity

Variables	(1) $\log(GameNum)$	(2) $\log(GameTime)$	(3) $\log(GameNumFriend)$	(4) $\log(GameTimeFriend)$
$AIPlayer_{it}$	0.079^{***} (0.004)	0.284^{***} (0.013)	0.044^{***} (0.003)	0.163^{***} (0.011)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.050	0.057	0.052	0.057
Observations	136,728	136,728	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

E.3 Faster Game Completion Against AI Opponents

Another explanation for the increased engagement in AI matches could be that AI players, being weaker, allow players to finish games faster, thus enabling more games to be played in the same amount of time. This could lead to a higher frequency of game engagement.

To examine this, we analyze the impact of AI players on match duration (the duration of a single match from start to finish). Specifically, we introduce a new dependent variable $AvgMatchDuration_{it}$, which captures the average match duration for player i in week t. We estimate specification (1) using this dependent variable and present the results in Table E.4. The significantly negative coefficient of $AIPlayer_{it}$ suggests that the introduction of AI players reduces the average match duration. This finding supports the idea that AI players lead to faster match completion.

Table E.4. Impact of AI Players on Average Match Duration

Variables	(1) $\log(AvgMatchDuration)$
$AIPlayer_{it}$	-0.239*** (0.014)
Control Variables	Yes
Player FE	Yes
Weekly FE	Yes
Adjusted R^2	0.095
Observations	50,353

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

While we confirm that AI players reduce average match duration, this does not fully explain the observed increase in engagement. Our main analyses indicate that AI players also lead to an increase in total time spent in the game. This implies that players are not just fitting in more matches due to shorter durations but are also choosing to spend more time engaging in gameplay. Given the reduction in match length, the observed increase in total gameplay time necessarily implies an even greater increase in gameplay frequency. This suggests that the engagement effect is not solely driven by faster matches but reflects an overall increase in players' willingness to stay and play longer.

E.4 Fear of Judgment

An alternative explanation is that players may feel safer competing against AI, knowing they will not be judged if they lose, and therefore may be more willing to participate. However, in our context, players are matched with a mix of human and AI opponents and cannot accurately distinguish between the two during gameplay. As a result, they are unaware whether they are eliminated by a human or an AI. While fear of judgment may influence behavior in settings where opponents are clearly identified, it is less likely to play a significant role in our setting.

Online Appendix F: Additional Context Information

Data clarification: Our data specifically focuses on the PC version of PUBG. While we recognize that PUBG exists in multiple versions and that these variations could introduce different confounding factors, we have deliberately focused on the PC version to maintain consistency in our analysis. This approach allows us to control for potential discrepancies that might arise from diverse game versions, thereby ensuring the robustness and relevance of our findings.

Indistinguishability of AI players: Typically, players cannot distinguish between AI and human opponents during the match. However, after the match, when reviewing game records, players are able to identify which opponents are bots.

About team composition: In a squad match in PUBG, players are randomly paired with three other human players to form a team unless they opt to join the match alone or form a team with friends.

Clarification on the strategy employed by AI players: We provide additional details on the strategy employed by AI players regarding their drop locations. In PUBG, AI players do not have a specific or consistent drop location within a match (Hossam 2020). Their drop locations are typically randomized, near human players but not too close. Since AI players are designed to mimic human behavior, including the drop locations, we believe that the potential influence of AI player drop locations is small in our research context.

Online Appendix G: Repeating the Process of Identifying Friends with A Criterion of $p = q$ More Than Twice

We repeat the process of identifying friends and redefine players p and q as friends if they team up more than twice for robustness. We then re-estimate the regression models and present the results in Table G.1. The significantly positive coefficients of $AIPlayer_{it}$ indicate that after the introduction of AI players, human players are more likely to team up with friends, which aligns with our main results and suggests that our findings are robust when applying a stricter criterion for identifying friends.

Table G.1. Impact of AI Players on Friend Team-ups Using New Criterion

Variables	(1) $\log(GameNumFriend)$	(2) $\log(GameTimeFriend)$	(3) $GameNumFriendRatio$	(4) $GameTimeFriendRatio$
$AIPlayer_{it}$	0.066^{***} (0.003)	0.214^{***} (0.011)	0.086^{***} (0.004)	0.086^{***} (0.004)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.061	0.063	0.060	0.060
Observations	136,728	136,728	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Online Appendix H: Correlation Analysis and VIFs

We perform a correlation analysis to assess the correlation among the main variables. The correlation table is presented in Table H.1. It is important to note that variables (1) – (4) are our main dependent variables, which express relatively high correlations among them. However, the correlations among covariates, as well as between the dependent variables and covariates, are relatively low, which suggests that multicollinearity may not be a serious concern.

Table H.1. The Correlation Table

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DV	(1) $GameNum$	1									
	(2) $GameTime$	0.807	1								
	(3) $GameNumFriend$	0.671	0.573	1							
	(4) $GameTimeFriend$	0.560	0.706	0.834	1						
Covariates	(5) $AIPlayer$	0.118	0.115	0.093	0.092	1					
	(6) $WeeksSinceFirstIntearction$	0.018	0.021	0.019	0.021	0.315	1				
	(7) $BotsInteractionNum$	0.109	0.092	0.070	0.060	0.172	0.050	1			
	(8) $MatchDifficulty$	0.002	0.006	0.002	0.004	0.082	0.021	0.019	1		
	(9) $AvgDistLastMonth$	-0.001	-0.001	-0.003	-0.003	0.023	0.008	0.001	0.052	1	
	(10) $AvgTeamworkLastMonth$	0.091	0.165	0.101	0.155	0.046	0.018	0.010	0.016	-0.010	1

We then address the issue of multicollinearity by examining the variance inflation factors (VIFs), which measure the extent of multicollinearity among the independent variables. When these variables are correlated, the estimated standard errors of the coefficients are inflated, making VIFs a useful tool for detecting multicollinearity (Chatterjee and Hadi 2015; Khurana et al. 2019). A VIF_i value of one indicates no linear relationship between a specific independent variable i and the others, while a VIF_i value greater than one suggests a tendency of multicollinearity. VIFs are widely applied in the information systems literature to check whether multicollinearity is a concern (Singh et al. 2014). Typically, a VIF value greater than 10 implies potential multicollinearity issues (Chatterjee and Hadi 2015; Fan et al. 2023). We analyze the VIFs to evaluate possible multicollinearity among the covariates. As shown in Table H.2, all VIFs are below 2, which is below the generally accepted threshold ($VIF < 10$), suggesting that multicollinearity is not a concern in our analysis and does not significantly affect our results.

Table H.2. Collinearity Diagnostics

Variables	VIF
$AIPlayer$	1.151
$WeeksSinceFirstIntearction$	1.111
$BotsInteractionNum$	1.031
$MatchDifficulty$	1.010
$AvgDistLastMonth$	1.003
$AvgTeamworkLastMonth$	1.002
Mean VIF	1.051

Online Appendix I: Additional Analysis to Capture the Interaction Intensity with AI

We conduct additional analysis to capture the impact of interaction intensity with AI. Specifically, we introduce a new independent variable: the accumulated number of AI matches that player i joins in until week t ($AccNumAIMatch_{it}$). We employ the specification in Equation (I.1) and present the estimated results in Table I.1. The significant coefficients suggest that our findings are robust when considering the interaction intensity with AI players.

$$\log(y_{it}) = \beta_0 + \beta_1 AccNumAIMatch_{it} + X_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{I.1}$$

Table I.1. Impact of Accumulated Number of AI Matches

Variables	(1) $\log(GameNum)$	(2) $\log(GameTime)$	(3) $\log(GameNumFriend)$	(4) $\log(GameTimeFriend)$
$AccNumAIMatch_{it}$	0.038^{***} (0.001)	0.113^{***} (0.003)	0.023^{***} (0.001)	0.071^{***} (0.003)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.067	0.068	0.060	0.064
Observations	136,728	136,728	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Additionally, to account for the impact of the number of AI players, we use the average number of AI players in a match during a week ($AIPlayerNum$) as an independent variable and employ the specifications in Equation (I.2).

$$\log(y_{it}) = \beta_0 + \beta_1 AIPlayerNum_{it} + X_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{I.2}$$

The results reported in Table I.2 indicate that more AI players can contribute to more human player engagement and friend team-ups, which suggests that our findings are robust when considering the impact of the number of AI players.

Table I.2. Impact of the Number of AI Players

Variables	(1) $\log(GameNum)$	(2) $\log(GameTime)$	(3) $\log(GameNumFriend)$	(4) $\log(GameTimeFriend)$
$AIPlayerNum_{it}$	0.025^{***} (0.000)	0.083^{***} (0.000)	0.013^{***} (0.000)	0.044^{***} (0.000)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.195	0.193	0.117	0.120
Observations	136,728	136,728	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Online Appendix J: Alternative Approach to Measuring Playing with Friends

We perform additional analysis to simplify the approach to measuring playing with friends. Specifically, we introduce a new dependent variable, $WithFriend_{it}$, which is a dummy variable and indicates whether player i engages in any match with friends during week t. We employ the specification in Equation (J.1).

$$WithFriends_{it} = \beta_0 + \beta_1 AIPlayer_{it} + X_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{J.1}$$

The estimated results, reported in Table J.1, suggest that the introduction of AI players can encourage human players to engage in the game with friends.

Table J.1. Impact of AI Players on Friend Team-ups

Variables	(1) $WithFriends_{it}$
$AIPlayer_{it}$	0.120^{***} (0.005)
Control Variables	Yes
Player FE	Yes
Weekly FE	Yes
Adjusted R^2	0.059
Observations	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Online Appendix K: Poisson Quasi-Maximum Likelihood Estimation

As indicated by Chen and Roth (2023), log transformations, commonly used in research, encounter challenges when the outcome of interest (Y) can be zero. Since $\log(Y)$ is undefined at zero, researchers often employ alternatives such as $\log(Y+1)$. A significant concern related to these log-like transformations is that the estimated average treatment effect (ATE) hinges on the units of Y, making interpretations as percentage effects unreliable, especially when the treatment shifts the outcome from zero to a non-zero value. Consistent with Chen and Roth (2023), we apply the Poisson quasi-maximum likelihood estimation (QMLE) to address this issue. Specifically, the number of games that a player joins in during a week ($GameNum_{it}$) and the number of games where a player teams up with her friends during a week ($GameNumFriend_{it}$) are nonnegative integers, and thus can serve as dependable variables in the Poisson QMLE specified in Equation (K.1).

$$y_{it} = \exp(\beta_0 + \beta_1 AIPlayer_{it} + X_{it} + \alpha_i + \delta_t + \varepsilon_{it}), \tag{K.1}$$

The results of Poisson QMLE are reported in Table K.1. To derive the estimated proportional treatment effect, we calculate $\exp(\beta_1) - 1$, which are 0.781 and 0.829, respectively. This indicates that introducing AI players increases the frequency of participating in the game and teaming up with friends by 78.1% and 82.9%, respectively. Hence, the findings from the Poisson QMLE align with our main results, underscoring the significant impact of AI players in enhancing player engagement and friend team-ups.

Table K.1. Impact of AI Players Using Poisson QMLE

Variables	(1) $GameNum$	(2) $GameNumFriend$
$AIPlayer_{it}$	0.577*** (0.020)	0.604*** (0.030)
Control Variables	Yes	Yes
Player FE	Yes	Yes
Weekly FE	Yes	Yes
Observations	136,728	135,648

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

In addition to the Poisson QMLE, we use Y as dependent variables (instead of the logarithmic value of Y) and estimate the specification in Equation (K.2) to alleviate potential biases from using log-like transformations. The estimations are shown in Table K.2. The significantly positive coefficients of $AIPlayer_{it}$ indicate that our results remain robust and consistent after addressing concerns about problematic log transformations with zero values.

$$y_{it} = \beta_0 + \beta_1 AIPlayer_{it} + X_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{K.2}$$

Table K.2. Impact of AI Players without Log Transformations

Variables	(1) $GameNum$	(2) $GameTime$	(3) $GameNumFriend$	(4) $GameTimeFriend$
$AIPlayer_{it}$	0.253^{***} (0.008)	2.540^{***} (0.127)	0.130^{***} (0.006)	1.450^{***} (0.095)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Observations	136,728	136,728	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Online Appendix L: Robustness Checks and Moderation Analysis for Two Ratio Outcomes

We present the robustness checks and moderation analysis for two ratio outcomes, i.e., $GameNumFriendRatio$ and $GameTimeFriendRatio$. Note that these two constructs are conceptually related and empirically correlated since they capture closely aligned dimensions of friend-based engagement: the share of matches played with friends and the share of time spent playing with friends. As these behaviors tend to move together, the estimated coefficients and R^2 values naturally appear similar.

Table L.1 displays the DID results after propensity score matching (PSM), which is consistent with our main findings.

Table L.2 shows the results from the relative time model, indicating that the parallel trends assumption is satisfied. While there are minor numerical differences in the estimated coefficients for $GameNumFriendRatio$ and $GameTimeFriendRatio$, these differences are minimal. For instance, the coefficients of $RelaWeek_{i,8}$ is 0.089 for $GameNumFriendRatio$ and 0.091 for $GameTimeFriendRatio$, reflecting a difference of only about 2%.

Table L.1. Impact of AI Players on Friend Team-ups after PSM (Using Ratio as DV)

Variables	(1) $GameNumFriendRatio$	(2) $GameTimeFriendRatio$
$AIPlayer_{it}$	0.132^{***} (0.005)	0.132^{***} (0.005)
Control Variables	Yes	Yes
Player FE	Yes	Yes
Weekly FE	Yes	Yes
Adjusted R^2	0.061	0.061
Observations	117,432	117,432

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Table L.2. Impact of AI Players on Friend Team-ups Over Time (Using Ratio as DV)

Variables	(1) $GameNumFriendRatio$	(2) $GameTimeFriendRatio$
$RelaWeek_{i-8}$	-0.010(0.010)	-0.010(0.010)
$RelaWeek_{i,-7}$	-0.004(0.010)	-0.004(0.010)
$RelaWeek_{i,-6}$	-0.005(0.010)	-0.006(0.010)
$RelaWeek_{i,-5}$	0.000(0.009)	0.001(0.009)
$RelaWeek_{i,-4}$	0.011(0.010)	0.011(0.010)
$RelaWeek_{i,-3}$	0.001(0.009)	0.002(0.009)
$RelaWeek_{i,-2}$	-0.010(0.009)	-0.009(0.009)
$RelaWeek_{i,0}$	0.335^{***}(0.012)	0.334^{***} (0.012)
$RelaWeek_{i,1}$	0.093^{***} (0.010)	0.093^{***}0.010)
$RelaWeek_{i,2}$	0.076^{***} (0.010)	0.076^{***}0.010)
$RelaWeek_{i,3}$	0.084^{***} (0.010)	0.085^{***}0.010)
$RelaWeek_{i,4}$	0.083^{***} (0.010)	0.086^{***}0.010)
$RelaWeek_{i,5}$	0.096^{***} (0.011)	0.096^{***}0.011)
$RelaWeek_{i,6}$	0.104^{***} (0.011)	0.103^{***}0.011)
$RelaWeek_{i,7}$	0.110^{***} (0.012)	0.109^{***}0.012)
$RelaWeek_{i,8}$	0.089^{***} (0.012)	0.091^{***}0.012)
Control Variables	Yes	Yes
Player FE	Yes	Yes
Weekly FE	Yes	Yes
Adjusted R^2	0.065	0.065
Observations	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Table L.3 reports the results from the Goodman-Bacon Decomposition, which reveal that our findings are robust after ruling out weights related to problematic comparisons in our DID estimation.

Table L.3. Goodman-Bacon Decomposition (Using Ratio as DV)

		$GameNumFriendRatio$	$GameTimeFriendRatio$
Comparison	Weight	Estimate	Estimate
Earlier treated vs. Later control	0.170	0.244	0.244
Later treated vs. Earlier control	0.043	0.307	0.307
Treated vs. Never treated	0.787	0.081	0.081
Overall DID		0.118	0.118
Unbiased DID		0.110	0.110

Table L.4 presents the results from the generalized synthetic control method (GSCM), alleviating concerns that our results are driven by unobservable time-varying confounders.

Table L.4. Impact of AI Players on Friend Team-ups Using GSCM (Using Ratio as DV)

Variables	(1) $GameNumFriendRatio$	(2) $GameTimeFriendRatio$
$AIPlayer_{it}$	0.105^{***} (0.004)	0.105^{***} (0.005)
Control Variables	Yes	Yes
Player FE	Yes	Yes
Weekly FE	Yes	Yes
Observations	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

We use the following regression specifications to estimate the results of moderating analysis with two ratios being dependent variables, i.e., $GameNumFriendRatio$ and $GameTimeFriendRatio$.

$$y_{it} = \beta_0 + \beta_1 AIPlayer_{it} + \beta_2 AIPlayer_{it} \times Novice_i + X_{it} + \alpha_i + \delta_t + \varepsilon_{it},$$

$$y_{it} = \beta_0 + \beta_1 AIPlayer_{it} + \beta_2 AIPlayer_{it} \times PreferRandTeam_i + X_{it} + \alpha_i + \delta_t + \varepsilon_{it}.$$

Tables L.5 and L.6 detail the results related to two moderators. The findings are consistent with those in the main paper. That is, the positive effect of introducing AI players on friend team-ups is stronger among novice players and those who initially favor random teammates.

Table L.5. Impact of AI Players: Moderating Role of Skill Levels (Using Ratio as DV)

Variables	(1) $GameNumFriendRatio$	(2) $GameTimeFriendRatio$
$AIPlayer_{it}$	0.100^{***} (0.006)	0.100^{***} (0.006)
$AIPlayer_{it} \times Novice_i$	0.028^{***} (0.007)	0.028^{***} (0.007)
Control Variables	Yes	Yes
Player FE	Yes	Yes
Weekly FE	Yes	Yes
Adjusted R^2	0.058	0.058
Observations	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Table L.6. Impact of AI Players: Moderating Role of Teammate Preferences (Using Ratio as DV)

Variables	(1) $GameNumFriendRatio$	(2) $GameTimeFriendRatio$
$AIPlayer_{it}$	0.096^{***} (0.006)	0.096^{***} (0.006)
$AIPlayer_{it} \times PreferRandTeam_i$	0.041^{***} (0.007)	0.041^{***} (0.007)
Player FE	Yes	Yes
Weekly FE	Yes	Yes
Adjusted R^2	0.058	0.058
Observations	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Online Appendix M: Robustness Check by Excluding the Top Players

To address the issue of the highly right-skewed distribution of some variables, we exclude players whose cumulative outcomes within our observation window, i.e., $\sum_{t=1}^{36} GameNum$, $\sum_{t=1}^{36} GameTime$, $\sum_{t=1}^{36} GameNumFriend$, or $\sum_{t=1}^{36} GameTimeFriend$, are in the top 1% (5%). In other words, we include only players whose values for all four variables lie within the 99th (95th) percentile. We re-estimate our main model. The results are reported in Tables M.1 and M.2, suggesting that our findings remain robust after excluding top players.

Table M.1. Impact of AI Players (Excluding Top 1% of Players)

Variables	(1) $\log(GameNum)$	(2) $\log(GameTime)$	(3) $\log(GameNumFriend)$	(4) $\log(GameTimeFriend)$
$AIPlayer_{it}$	0.168^{***} (0.005)	0.493^{***} (0.016)	0.088^{***} (0.004)	0.276^{***} (0.012)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.059	0.061	0.051	0.055
Observations	133,848	133,848	133,848	133,848

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Table M.2. Impact of AI Players (Excluding Top 5% of Players)

Variables	(1) $\log(GameNum)$	(2) $\log(GameTime)$	(3) $\log(GameNumFriend)$	(4) $\log(GameTimeFriend)$
$AIPlayer_{it}$	0.167^{***} (0.005)	0.483^{***} (0.016)	0.084^{***} (0.004)	0.260^{***} (0.012)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.047	0.050	0.039	0.042
Observations	123,516	123,516	123,516	123,516

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Online Appendix N: CEM+DID

We implement the coarsened exact matching (CEM) and subsequently re-estimate our regression model based on the matched sample. We apply a one-to-one matching strategy and improve the balance between treatment and control groups. To evaluate the quality of the matching, we conduct t-tests to compare the means of matching variables before and after the matching process. The detailed summary statistics are presented in Table N.1. The results indicate no significant differences between the treatment and control groups post-matching, suggesting effective correction of selection bias related to observable variables. Following this, we re-estimate our DID model with the matched sample. The results, presented in Table N.2, are consistent with our main findings as well as those obtained using DID+PSM.

Table N.1. Summary Statistics Before and After CEM

Variables	Before Matching Mean (Treated)	Mean (Control)	Difference	After Matching Mean (Treated)	Mean (Control)	Difference
$AvgTime$	3.127	2.340	0.787^{***}	1.403	1.379	0.024
$AvgTimeFriend$	1.289	0.997	0.292^{**}	0.536	0.497	0.039
$AvgGameWeekend$	0.085	0.072	0.013^{*}	0.048	0.048	0.000
$AvgGameWeekday$	0.178	0.138	0.040^{***}	0.096	0.096	0.000
$AvgWalkDist$	324.937	258.441	66.496^{**}	115.397	113.157	2.240
$AvgRideDist$	250.315	234.582	15.733	74.409	75.993	-1.584
$AvgWeaponNum$	0.035	0.035	0.000	0.005	0.005	0.000

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table N.2. Impact of AI Players on Human Player Engagement and Friend Team-ups after CEM

Variables	(1) $\log(GameNum)$	(2) $\log(GameTime)$	(3) $\log(GameNumFriend)$	(4) $\log(GameTimeFriend)$
$AIPlayer_{it}$	0.154^{***} (0.006)	0.450^{***} (0.019)	0.088^{***} (0.004)	0.275^{***} (0.015)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.066	0.070	0.059	0.063
Observations	92,448	92,448	92,448	92,448

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Online Appendix O: Rosenbaum Bounds Analysis

While PSM and CEM can mitigate bias from observable variables, hidden bias from unobservable factors might make our results not robust. If hidden bias exists, the matched players, one from the treatment group and the other from the control group, can have different probabilities of participating in AI matches due to unobservable variables, even though they share similar observable characteristics (Son et al. 2020). To evaluate the potential impact of such bias on our results, we conduct the Rosenbaum bounds sensitivity analysis (Rosenbaum 2002). Rosenbaum bounds analysis introduces a parameter $\Gamma \geq 1$ to measure the sensitivity of treatment effects. Γ indicates the degree of hidden bias as quantified by the odds ratio of differential treatment assignment owing to unobservable variables. This analysis primarily examines hypothetical p-values for treatment effects, Hodges-Lehmann point estimates, and confidence intervals for effect sizes at different levels of Γ.

Tables O.1-O.4 present the results of Rosenbaum bounds analysis for all four dependent variables, suggesting that our results remain statistically significant up to a relatively large Γ. In particular, the treatment effect with the dependent variable $\log(GameNum)$ is still significant even when $\Gamma = 2$. The treatment effect with the dependent variable $\log(GameNumFriend)$ is significant up to $\Gamma = 1.8$. The treatment effects with dependent variables $\log(GameTime)$ and $\log(GameTimeFriend)$ remain significant when $\Gamma \leq 1.7$. While there are no established rules for the range of Γ, the level of insensitivity to hidden bias in our study is comparable to (or exceeds) that reported in prior literature (Manchanda et al. 2015; Hock and Raithel 2020; Son et al. 2020; Zhang et al. 2022). Moreover, it is crucial to emphasize that the Rosenbaum bounds analysis represents a "worst-case" scenario. This analysis reveals how large the impact of unobservable factors should be to negate our findings, rather than finding the precise bounds of the effect of unobservable factors on the treatment effect. In summary, the results of the Rosenbaum bounds analysis confirm the robustness of our main findings, effectively ruling out the possibility that our results are driven by potential unobserved confounders.

Table O.1. Results for the Rosenbaum Bounds Analysis (DV: $\log(GameNum)$)

	p-value[a]		H-L Point Estimate		Confidence Interval[a]	
Gamma (Γ)	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
1.0	0.000	0.000	0.203	0.203	0.135	0.154
1.1	0.000	0.000	-0.097	0.303	0.115	0.175
1.2	0.000	0.000	-0.097	0.403	0.096	0.195
1.3	0.000	0.000	-0.097	0.403	0.080	0.214
1.4	0.000	0.000	-0.097	0.403	0.065	0.231
1.5	0.000	0.000	-0.097	0.403	0.052	0.247
1.6	0.000	0.000	-0.097	0.403	0.040	0.263
1.7	0.000	0.000	-0.097	0.403	0.029	0.277
1.8	0.000	0.000	-0.097	0.403	0.019	0.291
1.9	0.000	0.000	-0.097	0.403	0.010	0.304
2.0	0.000	0.011	-0.097	0.403	0.001	0.316

Note: H-L Point Estimate: Hodges-Lehmann point estimate.

[a] p-values and confidence intervals are at the 95% level.

Table O.2. Results for the Rosenbaum Bounds Analysis (DV: $\log(GameTime)$)

	p-value[a]		H-L Point Estimate		Confidence Interval[a]	
Gamma (Γ)	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
1.0	0.000	0.000	0.629	0.629	0.386	0.454
1.1	0.000	0.000	0.129	0.729	0.315	0.527
1.2	0.000	0.000	0.029	0.729	0.251	0.595
1.3	0.000	0.000	-0.071	0.729	0.194	0.659
1.4	0.000	0.000	-0.071	0.829	0.142	0.718
1.5	0.000	0.000	-0.071	0.929	0.094	0.774
1.6	0.000	0.000	-0.071	0.929	0.051	0.826
1.7	0.000	0.004	-0.071	1.029	0.011	0.876
1.8	0.000	0.347	-0.071	1.029	-0.031	0.922
1.9	0.000	0.959	-0.071	1.129	-0.073	0.966
2.0	0.000	1.000	-0.071	1.129	-0.114	1.008

Note: H-L Point Estimate: Hodges-Lehmann point estimate.

[a] *p*-values and confidence intervals are at the 95% level.

Table O.3. Results for the Rosenbaum Bounds Analysis (DV: $\log(GameNumFriend)$)

	p-value[a]		H-L Point Estimate		Confidence Interval[a]	
Gamma (Γ)	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
1.0	0.000	0.000	0.000	0.000	0.077	0.093
1.1	0.000	0.000	-0.100	0.100	0.063	0.108
1.2	0.000	0.000	-0.100	0.100	0.051	0.122
1.3	0.000	0.000	-0.100	0.100	0.041	0.136
1.4	0.000	0.000	-0.100	0.100	0.031	0.149
1.5	0.000	0.000	-0.100	0.100	0.023	0.162
1.6	0.000	0.000	-0.100	0.100	0.016	0.174
1.7	0.000	0.000	-0.100	0.100	0.009	0.186
1.8	0.000	0.002	-0.100	0.300	0.003	0.197
1.9	0.000	0.110	-0.100	0.400	-0.004	0.208
2.0	0.000	0.630	-0.100	0.400	-0.012	0.218

Note: H-L Point Estimate: Hodges-Lehmann point estimate.

[a] *p*-values and confidence intervals are at the 95% level.

Table O.4. Results for the Rosenbaum Bounds Analysis (DV: $\log(GameTimeFriend)$)

	p-value[a]		H-L Point Estimate		Confidence Interval[a]	
Gamma (Γ)	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
1.0	0.000	0.000	0.594	0.594	0.244	0.299
1.1	0.000	0.000	-0.006	0.694	0.195	0.352
1.2	0.000	0.000	-0.006	0.694	0.153	0.402
1.3	0.000	0.000	-0.006	0.694	0.116	0.449
1.4	0.000	0.000	-0.006	0.694	0.083	0.495
1.5	0.000	0.000	-0.006	0.694	0.054	0.539
1.6	0.000	0.000	-0.006	0.694	0.028	0.581
1.7	0.000	0.009	-0.006	0.694	0.005	0.621
1.8	0.000	0.280	-0.006	0.694	-0.024	0.660
1.9	0.000	0.861	-0.006	0.694	-0.054	0.697
2.0	0.000	0.996	-0.006	0.694	-0.083	0.732

Note: H-L Point Estimate: Hodges-Lehmann point estimate.
[a] *p*-values and confidence intervals are at the 95% level.

Online Appendix P: Whether and When to Join in the first AI match Is Plausibly Exogenous

We present suggestive empirical evidence and examine whether the engagement in AI matches (the treatment) can be considered plausibly exogenous. Building on the approach of Deshpande and Li (2019), we predict both the occurrence and timing of the treatment based on players' gaming experience. The underlying logic is that if engagement in the initial AI match cannot be systematically predicted by players' prior gaming experience, it suggests that the treatment can be considered plausibly exogenous.

To investigate whether player gaming experience predicts the likelihood of engaging in AI matches, we select players who have not engaged in any AI matches until a specific week and estimate the following equation:

$$\begin{aligned} Engagement_i = {} & \beta_0 + \beta_1 GameNum_i + \beta_2 GameTime_i + \beta_3 GameNumFriend_i \\ & + \beta_4 AvgTime_i + \beta_5 AvgTimeFriend_i + \beta_6 MatchDifficulty_i \\ & + \beta_7 AvgDistance_i + \beta_8 AvgAssist_i + \beta_9 AvgGameWeekend_i \\ & + \beta_{10} AvgGameWeekday_i + \beta_{11} AvgWalkDist_i + \beta_{12} AvgRideDist_i \\ & + \beta_{13} AvgWeaponNum_i + \varepsilon_i, \end{aligned} \tag{P.1}$$

where $Engagement_i$ is whether player i engages in AI matches during the current week; $GameNum_i$ is the number of games that player i joined in during the previous week; $GameTime_i$ is the time (in minutes) that player i spent on the game during the previous week; $GameNumFriend_i$ is the number of games in which player i teamed up with friends during the previous week; $AvgTime_i$ is player i's average weekly play time before the current week; $AvgTimeFriend_i$ is the average weekly time player i spent playing with friends before the current week; $MatchDifficulty_i$ is the average difficulty level of matches that player i joined in during the previous week; $AvgDistance_i$ is the average distance at which player i eliminated an opponent in the previous week; $AvgAssist_i$ is the average number of assists by player i in supporting teammates to eliminate opponents in a match during the previous week; $AvgGameWeekend_i$ ($AvgGameWeekday_i$) is player i's average number of games played on weekends (weekdays) before the current week; $AvgWalkDist_i$ is the average distance that player i walked in a match before the current week; $AvgRideDist_i$ is the average distance that player i traveled by vehicles in a match before the current week; and $AvgWeaponNum_i$ is the average number of weapon types that player i used to eliminate opponents in a match before the current week.

To examine whether player gaming experience can predict the timing of first engagement in an AI match, we use a sample of players who do not participate in any AI matches during a specific week but would later exclusively engage in AI matches. We estimate the following equation:

$$\begin{aligned} EngageWeek_i = {} & \beta_0 + \beta_1 GameNum_i + \beta_2 GameTime_i + \beta_3 GameNumFriend_i \\ & + \beta_4 AvgTime_i + \beta_5 AvgTimeFriend_i + \beta_6 MatchDifficulty_i \\ & + \beta_7 AvgDistance_i + \beta_8 AvgAssist_i + \beta_9 AvgGameWeekend_i \\ & + \beta_{10} AvgGameWeekday_i + \beta_{11} AvgWalkDist_i + \beta_{12} AvgRideDist_i \\ & + \beta_{13} AvgWeaponNum_i + \varepsilon_i, \end{aligned} \tag{P.2}$$

where $EngageWeek_i$ is the week in which player i begins to engage in the AI matches. The independent variables used in this analysis are consistent with those defined in Equation (P.1), which describes the player's past gaming experience.

We report the results obtained from Equations (P.1) and (P.2) in Table P.1. Columns (1) - (4)

present the results from Equation (P.1), while Columns (5) - (8) correspond to Equation (P.2). Specifically, Columns (1) - (4) examine how observable player gaming experience predicts the likelihood of engaging in AI matches among players who have not yet participated in AI matches during the specified week, as indicated in the column headings. Columns (5) - (8) estimate how observable player gaming experience predicts the timing of the initial engagement in an AI match. The analysis based on Equation (P.2) differs from that of Equation (P.1) by specifically focusing on players who have not engaged in any AI matches up to the week indicated in the column heading but will do so in subsequent periods. Our findings indicate that no observable characteristic consistently predicts the occurrence or timing of engagement in AI matches, suggesting that participation in AI matches is plausibly exogenous.

Table P.1. Factors that Predict Engagements in AI Matches and Their Timing

	Whether the player would engage				Timing of first engagement			
	(1) 5/25/20	(2) 6/8/20	(3) 6/22/20	(4) 7/6/20	(5) 5/25/20	(6) 6/8/20	(7) 6/22/20	(8) 7/6/20
$GameNum$	-0.008	0.038	0.479	-0.680	-0.492	-0.087	-1.599	0.506
	(0.097)	(0.163)	(0.432)	(0.504)	(0.573)	(0.746)	(1.396)	(1.103)
$GameTime$	0.003	-0.001	0.008	0.019	-0.021	-0.008	-0.040	-0.061
	(0.005)	(0.009)	(0.019)	(0.019)	(0.027)	(0.040)	(0.061)	(0.041)
$GameNumFriend$	0.073	-0.091	-0.116	0.132	0.025	0.952^{*}	-0.036	0.248
	(0.062)	(0.103)	(0.203)	(0.307)	(0.365)	(0.470)	(0.656)	(0.672)
$AvgTime$	-0.007	0.006	0.010	-0.010	-0.086	-0.041	0.039	0.060
	(0.010)	(0.014)	(0.024)	(0.038)	(0.061)	(0.064)	(0.077)	(0.083)
$AvgTimeFriend$	0.001	-0.007	0.000	0.047	-0.020	-0.064	-0.094	-0.132
	(0.009)	(0.013)	(0.020)	(0.032)	(0.052)	(0.058)	(0.065)	(0.071)
$MatchDifficulty$	-0.005	0.001	-0.014	0.007	0.036	0.027	0.062	-0.019
	(0.005)	(0.009)	(0.016)	(0.013)	(0.028)	(0.040)	(0.052)	(0.029)
$AvgDistance$	0.000	0.006	0.008	-0.004	-0.008	0.017	-0.041	0.009
	(0.001)	(0.010)	(0.015)	(0.004)	(0.005)	(0.044)	(0.047)	(0.009)
$AvgTeamwork$	-0.025	0.120	0.108	-0.517	0.219	-0.403	0.173	0.516
	(0.041)	(0.073)	(0.121)	(0.288)	(0.239)	(0.334)	(0.389)	(0.630)
$AvgGameWeekend$	-0.055	0.092	-0.561	-0.592	1.177	1.892	2.108	1.158
	(0.166)	(0.227)	(0.370)	(0.621)	(0.976)	(1.037)	(1.196)	(1.359)
$AvgGameWeekday$	0.113	0.067	-0.433	-0.066	1.282	0.877	0.236	-0.480
	(0.131)	(0.174)	(0.284)	(0.447)	(0.772)	(0.795)	(0.915)	(0.978)
$AvgWalkDist$	0.000	0.000	-0.001	0.000	0.000	0.000	0.002	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
$AvgRideDist$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
$AvgWeaponNum$	-0.017	-0.070	-0.045	-0.532	0.575	-0.005	0.756	1.279
	(0.124)	(0.155)	(0.250)	(0.419)	(0.731)	(0.706)	(0.807)	(0.916)

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Online Appendix Q: Considering Potential Switching Behavior

To account for potential switching behavior, where players may alternate between matches with and without AI players, we include three distinct groups for analysis as an additional robustness check: (a) players who only engage in AI matches post-intervention, (b) players who exclusively participate in non-AI matches post-intervention, and (c) players whose gameplay shifts from AI matches to exclusively human-only matches. Notably, group (b) functions as the control group in our primary analysis, while group (a) is slightly different from the defined treatment group. In the main analysis, the treatment group includes players who engage exclusively in AI matches after their first AI encounter, even if they participate in non-AI matches between the policy intervention and their subsequent AI matches. Group (a), however, is a subset of the treatment group in our main analysis, excluding those who participate in non-AI matches before their initial AI match. We conduct two sets of comparisons: group (a) versus group (b) and group (b) versus group (c) to assess the impact of introducing AI players. In these comparisons, group (b) consistently serves as the control group, while either group (a) or group (c) serves as the treatment group. We then re-estimate our main model and report the results in Tables Q.1 and Q.2. The results are substantially similar to our main results, which suggest that switching between AI and non-AI matches does not distort our main findings.

Table Q.1. Impact of AI Players: Group (a) vs. Group (b)

Variables	(1) $\log(GameNum)$	(2) $\log(GameTime)$	(3) $\log(GameNumFriend)$	(4) $\log(GameTimeFriend)$
$AIPlayer_{it}$	0.162^{***} (0.005)	0.482^{***} (0.017)	0.083^{***} (0.004)	0.263^{***} (0.013)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.064	0.067	0.058	0.063
Observations	120,960	120,960	120,960	120,960

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Table Q.2. Impact of AI Players: Group (b) vs. Group (c)

Variables	(1) $\log(GameNum)$	(2) $\log(GameTime)$	(3) $\log(GameNumFriend)$	(4) $\log(GameTimeFriend)$
$AIPlayer_{it}$	0.127^{***} (0.005)	0.360^{***} (0.018)	0.020^{***} (0.003)	0.032^{**} (0.011)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.065	0.066	0.048	0.050
Observations	100,656	100,656	100,656	100,656

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Online Appendix R: Two-Way Fixed Effects Weights

To address concerns regarding treatment heterogeneity and potential biases in DID estimation due to staggered adoption (Goodman-Bacon 2021), we utilize the heterogeneous treatment effect estimation method proposed by De Chaisemartin and d'Haultfoeuille (2020) to assess the robustness of our findings. Goodman-Bacon (2021) cautions that two-way fixed effects estimators can be biased when applying the multiperiod DID approach in contexts of staggered adoption. By employing the De Chaisemartin and d'Haultfoeuille method, we aim to mitigate these biases, thereby enhancing the validity of our analysis. In our research context, players began to engage in AI matches at various times, leading to treatment heterogeneity in terms of time. Essentially, our analysis focuses on the expected coefficients ($E[\hat{\beta}_{fe}]$), where $\hat{\beta}_{fe}$ represents the treatment effect in group g at time t (De Chaisemartin and d'Haultfoeuille 2023). With the parallel trends assumption, $E[\hat{\beta}_{fe}]$) is the weighted average of treatment effects among all (g,t) cells:

$$E[\hat{\beta}_{fe}] = E\left[\sum_{(g,t):D_{g,t}=1} W_{g,t}\Delta_{g,t}\right],$$

where $\Delta_{g,t}$ denotes the average treatment effect for player g in week t. $D_{g,t}$ serves as the treatment indicator, which is a dummy variable indicating if player g began to engage in AI matches in week t, and $W_{g,t}$ specifies the weight for each (g,t) cell, with the summation of one.

De Chaisemartin and d'Haultfoeuille (2023) indicate that $W_{g,t}$ can be negative, which implies that $\hat{\beta}_{fe}$ might not satisfy the "no-sign reversal property:" $E[\hat{\beta}_{fe}]$ can be positive even if the treatment effects for each player in every time period are consistently negative. To mitigate this issue, we utilize the software package developed by De Chaisemartin and d'Haultfoeuille (2020). Our findings reveal a very small proportion of negative weights, and the total negative weight is almost zero (-0.023). Therefore, we effectively eliminate the possibility that the variations in treatment effects among players might distort our coefficient estimation.

Online Appendix S: Moderating Role of Skill Levels

We use additional proxies for player skill levels to conduct moderation analysis.

Using the average number of opponents a player eliminates as another measure of skill: We calculate the average number of opponents a player eliminates per match before the policy. Players who eliminate opponents fewer than the median among all players are labeled as novices, while those who eliminate more are categorized as masters. These classified skill levels are then used as a moderating variable in our regression model estimations in Equation (10). Table S.1 presents the results, which are consistent with the findings from our moderation analysis in Section 5.4.1.

Table S.1. Impact of AI Players: Moderating Role of Skill Levels (Using Opponents Eliminated)

Variables	(1) $\log(GameNum)$	(2) $\log(GameTime)$	(3) $\log(GameNumFriend)$	(4) $\log(GameTimeFriend)$
$AIPlayer_{it}$	0.152^{***} (0.006)	0.424^{***} (0.020)	0.079^{***} (0.005)	0.241^{***} (0.016)
$AIPlayer_{it} \times Novice_i$	0.029^{***} (0.007)	0.130^{***} (0.022)	0.016^{**} (0.005)	0.069^{***} (0.018)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.066	0.067	0.059	0.062
Observations	136,728	136,728	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Using the match difficulty level as another measure of skill: Note that in PUBG, players are matched with other players with similar skill levels to ensure balanced gameplay (Chen et al. 2021). Thus, a higher level of match difficulty suggests that the players in the match generally possess higher skill levels. We obtain the average difficulty levels of all matches that a player participated in before the policy. Players who engage in matches with difficulty levels below the median among all players are labeled as novices, while those who participate in matches with difficulty levels above the median are categorized as masters. We re-estimate the regression specification and obtain consistent results, as shown in Table S.2.

Table S.2. Impact of AI Players: Moderating Role of Skill Levels (Using Match Difficulty)

Variables	(1) $\log(GameNum)$	(2) $\log(GameTime)$	(3) $\log(GameNumFriend)$	(4) $\log(GameTimeFriend)$
$AIPlayer_{it}$	0.149^{***} (0.006)	0.439^{***} (0.020)	0.079^{***} (0.005)	0.251^{***} (0.016)
$AIPlayer_{it} \times Novice_i$	0.035^{***} (0.007)	0.104^{***} (0.022)	0.016^{**} (0.005)	0.051^{**} (0.018)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.066	0.067	0.058	0.062
Observations	136,728	136,728	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Using a continuous form of the average number of opponents eliminated per match: We conduct further analysis using a continuous measure of the average number of opponents eliminated per match. Specifically, we calculate the average number of opponents eliminated per match before the policy (Avg_Kills) and employ the specification in Equation (S.1). Notably, a higher value of Avg_Kills indicates a higher skill level of the player. The estimated results in Table S.3 show significantly negative coefficients for the interaction term, implying that the beneficial effects of AI players are weaker among players with advanced skill levels and stronger among those with lower skill levels. These results are consistent with the findings from our moderation analysis.

$$\log(y_{it}) = \beta_0 + \beta_1 AIPlayer_{it} + \beta_2 AIPlayer_{it} \times Avg\_Kills_i + X_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \qquad \text{(S.1)}$$

Table S.3. Impact of AI Players: Moderating Role of Skill Levels (Using Continuous Avg_Kills)

Variables	(1) $\log(GameNum)$	(2) $\log(GameTime)$	(3) $\log(GameNumFriend)$	(4) $\log(GameTimeFriend)$
$AIPlayer_{it}$	0.200^{***} (0.007)	0.629^{***} (0.024)	0.107^{***} (0.006)	0.356^{***} (0.020)
$AIPlayer_{it}$ $\times Avg\_Kills_i$	-0.033^{***} (0.005)	-0.139^{***} (0.019)	-0.020^{***} (0.004)	-0.080^{***} (0.016)
Control Variables	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.066	0.067	0.059	0.062
Observations	136,728	136,728	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Online Appendix T: Changes in Players' Eliminations Before and After the Policy

We use the average number of opponents a player eliminates per match in a week ($AvgElimination_{it}$) as another proxy for player performance and empirically examine the impact of introducing AI players on player eliminations. Specifically, we apply the regression model specified in Equation (T.1), using $\log(AvgElimination_{it})$ as the dependent variable.

$$\log(AvgElimination_{it}) = \beta_0 + \beta_1 AIPlayer_{it} + X_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{T.1}$$

The results are presented in Table T.1, indicating that the introduction of AI players leads to an increase in player eliminations. This increase suggests an improvement in players' performance and self-efficacy.

Table T.1. Impact of AI Players on Player Eliminations

Variables	(1) $\log(AvgElimination)$
$AIPlayer_{it}$	0.245^{***} (0.012)
Control Variables	Yes
Player FE	Yes
Weekly FE	Yes
Adjusted R^2	0.082
Observations	50,353

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

Online Appendix U: Another Metric to Assess Team Interaction

We investigate how the introduction of AI players affects the interaction among team members by using the frequency at which a player is knocked down and subsequently revived by team members as an additional measure of team interactions. In PUBG, players who are knocked down by opponents are not immediately eliminated from the game. Instead, they are given a chance to be revived by teammates before succumbing to their injuries (Higham 2017). For example, when a player is seriously injured due to enemy fire, they enter a "knocked down" state where they cannot use weapons but can crawl slowly for cover or to facilitate rescue by a teammate. Teammates are notified when a player is knocked down and can locate the downed player on their map. Reviving the downed player requires a teammate to physically reach the player, stay nearby, and perform the revival process for a few seconds without interruption. If the revival process is successfully completed before the downed player's health bar depletes fully, the downed player is restored to a minimal health state, allowing them to heal and return to the game battle.

Table U.1. Impact of AI Players on the Team Interactions

Variables	(1) $\log(AvgTeammateAssist)$
$AIPlayer_{it}$	0.124^{***} (0.011)
Control Variables	Yes
Player FE	Yes
Weekly FE	Yes
Adjusted R^2	0.081
Observations	42,323

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

This aspect of the game provides us with a unique metric for assessing team interactions: the frequency at which a player is knocked down but not fully eliminated. This metric reflects the frequency with which a player receives help from her teammates. We estimate the model in Equation (1), where y_{it} represents the average number of times that player i is knocked down and revived by team members during a specific week t ($AvgTeammateAssist_{it}$). A higher value of this measurement indicates more team interactions and support. We report the results in Table U.1. The significantly positive coefficient of

$AIPlayer_{it}$ reveals that introducing AI players boosts team interactions, aligning with the findings discussed in Section 5.3.

Online Appendix V: Mediation Analysis with Churn Rate as the Dependent Variable

Following the conceptual framework in Section 5.3, we perform a further mediation analysis using churn probability ($ChurnProb_{it}$) as the dependent variable. The results, presented in Table V.1, suggest that the mediation effects of player skill levels and team contribution on churn probability are statistically significant. These mediation analyses provide further support for the underlying mechanisms driving the observed effects of AI players.

Table V.1. Mediation Analysis of Churn Probability

Variables	(1) $\log(AvgEliminateDistance_{it})$	(2) $\log(AvgTeamwort_{it})$	(3) $\log(ChurnProb_{it})$
$AIPlayer_{it}$	0.324^{***} (0.009)	0.034^{***} (0.002)	-0.119^{***} (0.005)
$\log(AvgEliminateDistance_{it})$			-0.268^{***} (0.002)
$\log(AvgTeamwort_{it})$			-0.494^{***} (0.005)
Control Variables	Yes	Yes	Yes
Player FE	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes
Adjusted R^2	0.087	0.194	0.327
Observations	136,728	136,728	136,728

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Robust standard errors clustered by each player are in parentheses.

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