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A Study on the Impact of Data Science-Based Opponent Strategy Analysis on Competitive Performance Among Esports Players in Airoli and Belapur, Navi Mumbai

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Abstract - This study examines how data science-based opponent strategy analysis is perceived to relate to competitive performance among esports players in Airoli and Belapur, Navi Mumbai. A quantitative, cross-sectional questionnaire exported from Google Forms contained 99 responses covering age group, location, primary game, competitive experience, awareness and use of analytics tools, match-review and opponent-study habits, perceived benefits, challenges, and future interest. Responses were summarised using frequencies and percentages, and three exploratory Spearman rank correlations were calculated. Most respondents were at least somewhat familiar with analytics tools (62 (62.6%)), and 51 (51.5%) said they often or always study opponents' previous matches. 56 (56.6%) agreed or strongly agreed that analysing an opponent's gameplay helps them understand that opponent's strategy, and 53 (53.5%) agreed or strongly agreed that it improves their chances of winning. Strategic planning (48 (48.5%)) was the area most often reported as improving. The most common specific barrier was lack of access to performance-tracking tools (20 (20.2%)), and 69 (69.7%) were probably or definitely interested in using data science-based tools in future. None of the three exploratory correlations reached the .05 significance level. The findings reflect self-reported perceptions from a convenience sample and do not establish that opponent analysis causes better match results.

Key Words: Data science, Esports, Opponent strategy analysis, Competitive performance, Gameplay analytics, Navi Mumbai

INTRODUCTION

Esports has grown into an organised competitive activity in which players and teams compete in ranked matches and tournaments. Games such as BGMI, Valorant, Counter-Strike 2, and other multiplayer titles demand technical ability, communication, teamwork, and good judgement. A player may be skilled individually, but understanding the way an opponent approaches a match can also make a difference.

Opponent strategy analysis means reviewing available information about another player or team before or after a match. This may include movement patterns, preferred positions, weapon or character choices, attacking and defensive habits, and common mistakes. Data science gives players a more organised way to examine such information. Match statistics, replay reviews, simple dashboards, and, where suitable data are available, machine-learning models can help identify patterns that may be difficult to notice during live play.

Airoli and Belapur provide a local setting in which to explore how competitive players use these methods. Players may differ in their gaming experience, access to tools, and familiarity with analytics. This study therefore focuses not only on whether players use data, but also on how useful they believe it is and what prevents them from using it. It treats data analysis as a support for skill and experience, not as a guaranteed route to winning. The paper reports the responses of 99 players who completed the survey.

Objectives

1) To understand esports players' awareness and use of data science and performance-analysis tools.
2) To examine how players study opponents' previous matches and gameplay patterns.
3) To explore the perceived relationship between opponent analysis, decision-making, and competitive performance.

LITERATURE REVIEW

Bahrololloomi et al. (2023) developed performance metrics for League of Legends using information from previous matches and machine-learning methods [1]. Their work illustrates how player-level statistics can be organised to assess performance and support match-outcome prediction. It is relevant here because it shows how past match data may inform preparation, although the model was developed for a particular game.

Do et al. (2021) examined whether player experience with selected champions could help predict outcomes in League of Legends [2]. Their work highlights that familiarity and experience with in-game choices can be useful pre-match information, supporting the broader idea that past performance records may help players and teams prepare.

Viggiato and Bezemer (2020) analysed professional Dota 2 matches to investigate factors associated with decisive wins [3]. Their study used historical match information and machine-learning approaches, showing how match data can be examined to understand patterns related to outcomes.

Bapela, Ranchod, and Ingram (2025) studied real-time prediction of Dota 2 match outcomes using in-game chat logs and game events [4]. Their research shows that communication data, combined with gameplay events, can provide information for predicting outcomes, and points to the potential value of analysing team communication alongside individual statistics.

Hojaji et al. (2025) explored deep-learning techniques for identifying key performance indicators in League of Legends, including win prediction, map navigation, and vision control [5]. Their work reinforces the importance of selecting game-relevant indicators rather than relying on one general measure of player skill.

Minami et al. (2024) investigated the prediction of esports competition outcomes using EEG data from expert players [6], illustrating that outcome prediction research extends beyond in-game statistics to physiological signals.

Overall, previous research demonstrates that esports match data can be used to study player performance and predict aspects of competition. However, professional datasets and machine-learning models may not reflect how everyday ranked or local tournament players use analysis. The present study addresses this practical perspective by asking players in Airoli and Belapur about their own analysis habits and perceived benefits.

RESEARCH METHODOLOGY

Research Design

The study follows a quantitative, cross-sectional, descriptive survey design, with exploratory association analysis for selected ordinal variables. Information was collected at one point in time through a structured questionnaire. The responses describe players' habits and perceptions; they do not, on their own, prove that opponent analysis causes better results.

Primary and Secondary Data

Primary data were collected through a Google Forms questionnaire of 18 questions covering age group, current location, primary game, competitive experience, participation frequency, awareness and use of analytics tools, methods used to evaluate gameplay, match-review and opponent-study habits, perceived usefulness of match statistics, strategy changes, perceived effect on winning and decisions, areas of improvement, challenges, and willingness to use data science-based tools in future. The response export also contained respondents' names; these were not used in the analysis and are not reproduced. Secondary data were drawn from six published studies on esports performance metrics, match prediction, and gameplay analytics [1]–[6].

Study Area, Population, and Sample

The study area is Airoli and Belapur, Navi Mumbai. The target population includes players who participate in ranked or competitive gaming, online competitions, or esports tournaments. The export contains 99 responses (N = 99). By reported location, 42 (42.4%) were from Airoli, 39 (39.4%) from Belapur, and 18 (18.2%) from other nearby areas of Navi Mumbai. The last group is retained in all overall results because it was part of the collected data, but it is not part of the Airoli–Belapur target area.

Sampling Method

Convenience sampling is used because a complete list of esports players in the two locations is not readily available. The response export does not document the recruitment procedure or the number of people invited, so the sample is treated as a non-probability convenience sample and a response rate cannot be calculated. This should be confirmed against the actual fieldwork.

Data Analysis and Ethical Considerations

Responses were summarised using frequencies and percentages. Percentages use N = 99 unless stated otherwise. Question 16 allowed more than one answer, so its percentages are shares of respondents and add to more than 100%. Three exploratory Spearman rank correlations were calculated for ordered response variables at a two-sided significance level of $\alpha = .05$. Response categories were mapped to ordinal scores, which assumes an order but not equal distances between categories. Correlation is not treated as proof of causation. Names were excluded from the analysis. The export does not include the survey introduction or documentation of consent and ethics review, so these should be confirmed with the supervisor; this applies particularly to the respondents who reported being below 18 years of age.

Objectives and hypotheses

The following hypotheses were tested exploratively using two-sided Spearman rank correlations at α = .05. Because the response categories are ordinal and the sample is a non-probability convenience sample, no multiple-testing correction was applied.

Table -1: Objectives and hypotheses

No.	Objective	Null Hypothesis (H_0)	Alternative Hypothesis (H_1)
1	To understand esports players' awareness and use of data science and performance -analysis tools.	$H0_1$: There is no significant association between data science awareness and performance-analysis tool usage (ρ = 0).	$H1_1$: There is a significant association between data science awareness and performance-analysis tool usage (ρ ≠ 0).
2	To examine how players study opponents' previous matches and gameplay patterns.	$H0_2$: There is no significant association between opponent match analysis and understanding gameplay patterns (ρ = 0).	$H1_2$: There is a significant association between opponent match analysis and understanding gameplay patterns (ρ ≠ 0).
3	To explore the perceived relationship between opponent analysis, decision-making, and competitive performance.	$H0_3$: There is no significant association between opponent analysis, decision-making, and competitive performance (ρ = 0).	$H1_3$: There is a significant association between opponent analysis, decision-making, and competitive performance (ρ ≠ 0).

Note: ρ represents Spearman's rank correlation coefficient.

Data analysis and interpretation

Each graph below shows the frequency of responses to one questionnaire item (N = 99). The graphs are bar charts of response counts; they describe what respondents reported and do not show causal effects. The questionnaire wording is given above each graph, followed by its interpretation.

5.1 Respondent Profile

Q1. What is your age group?

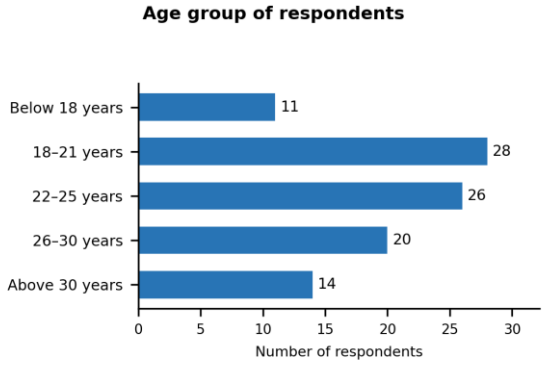


Fig -1: Age distribution of respondents (N = 99).

The largest age group was 18–21 years (28 (28.3%)), followed by 22–25 years (26 (26.3%)) and 26–30 years (20 (20.2%)). A further 14 (14.1%) were above 30 years and 11 (11.1%) were below 18. The sample is therefore mainly young adults, but it spans a wide age range, so results should not be read as describing one age group only.

Q2. Where are you currently located*?*

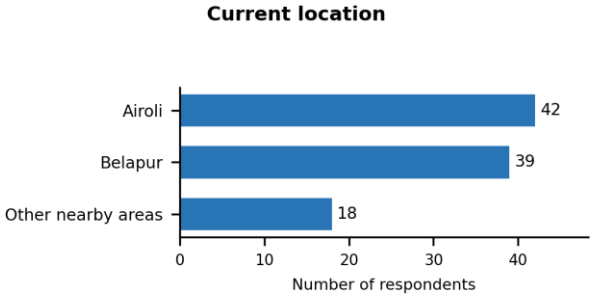


Fig -2: Current location of respondents (N = 99).

Airoli accounted for 42 (42.4%) of responses and Belapur for 39 (39.4%), so the two target locations are represented in a broadly similar proportion. A further 18 (18.2%) came from other nearby areas of Navi Mumbai. Because overall results combine all three groups, they describe the whole sample rather than Airoli and Belapur alone.

Q3. Which esports game do you primarily play?

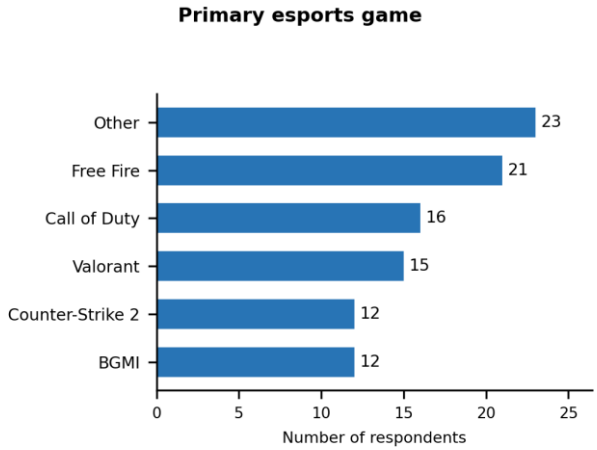


Fig -3: Primary esports game played (N = 99).

Players reported a variety of titles. "Other" was the most common answer (23 (23.2%)), followed by Free Fire (21 (21.2%)), Call of Duty (16 (16.2%)), and Valorant (15 (15.2%)). Counter-Strike 2 and BGMI each had 12 respondents (12.1%). Because the titles differ in rules and available statistics, comparisons across games should be made cautiously, and the specific games within "Other" are not identified.

Q4. How long have you been playing competitive or ranked games?

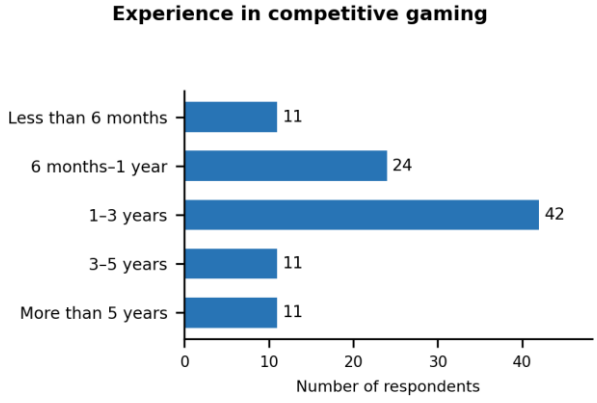


Fig -4: Experience in competitive or ranked gaming (N = 99).

Most respondents had some competitive experience: 42 (42.4%) had played for 1–3 years, the largest group, and 24 (24.2%) for 6 months to 1 year. Smaller groups had played for less than 6 months (11), 3–5 years (11), or more than 5 years (11). The sample is therefore weighted towards players with between six months and three years of experience.

Q5. How frequently do you participate in competitive gaming?

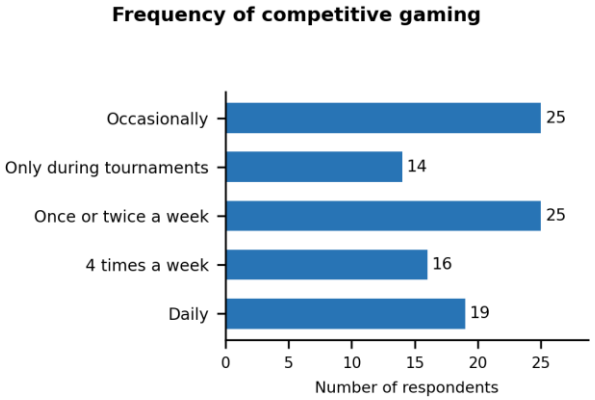


Fig -5: Frequency of participation in competitive gaming (N = 99).

Participation was spread across several patterns: 25 (25.3%) played occasionally and 25 (25.3%) once or twice a week, while 19 (19.2%) played daily and 16 (16.2%) four times a week. 14 (14.1%) played only during tournaments. Roughly 35.4% played at least four times a week, so the sample contains both regular and occasional competitors.

5.2 Awareness and Use of Analytics

Q6. Are you aware of data analytics or performance-tracking tools used in esports?

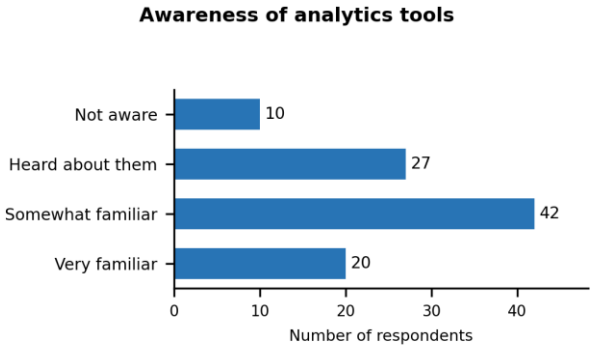


Fig -6: Awareness of data analytics and performance-tracking tools (N = 99).

A majority knew something about analytics tools: 42 (42.4%) were somewhat familiar and 20 (20.2%) very familiar, together 62 (62.6%). A further 27 (27.3%) had only heard about such tools and 10 (10.1%) were not aware of them. Awareness is therefore fairly widespread, but a sizeable minority has little or no familiarity, which is relevant to objective 1.

Q7. Do you use any tools or platforms to analyse your gameplay performance?

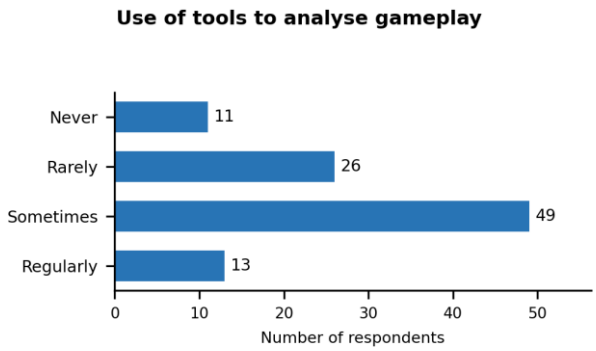


Fig -7: Use of tools or platforms to analyse gameplay (N = 99).

Actual use was more moderate than awareness: 49 (49.5%) used tools to analyse their gameplay sometimes and 13 (13.1%) did so regularly, while 26 (26.3%) did so rarely and 11 (11.1%) never. Regular use was relatively uncommon (13.1%), which suggests that knowing about analytics does not always lead to routine use.

Q8. Which of the following methods do you use to evaluate your gameplay?

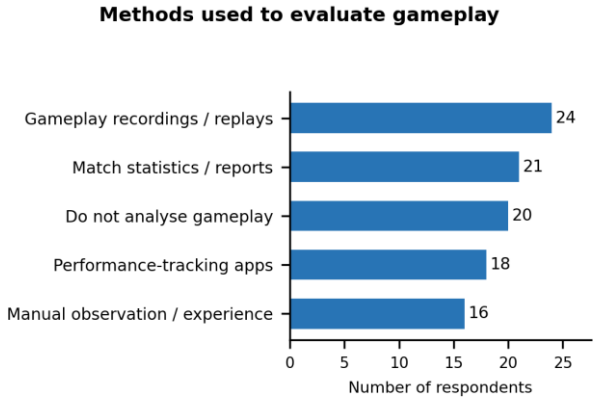


Fig -8: Methods used to evaluate gameplay (N = 99).

Gameplay recordings and replays were the most common method (24 (24.2%)), followed by match statistics and game reports (21 (21.2%)), performance-tracking applications (18 (18.2%)), and manual observation and personal experience (16 (16.2%)). A further 20 (20.2%) said they do not analyse their gameplay. Replay review and statistics-based methods together account for most answers, but note that only a minority used dedicated tracking applications.

5.3 Match Review and Opponent Analysis

Q9. How often do you analyse your previous matches to improve your performance?

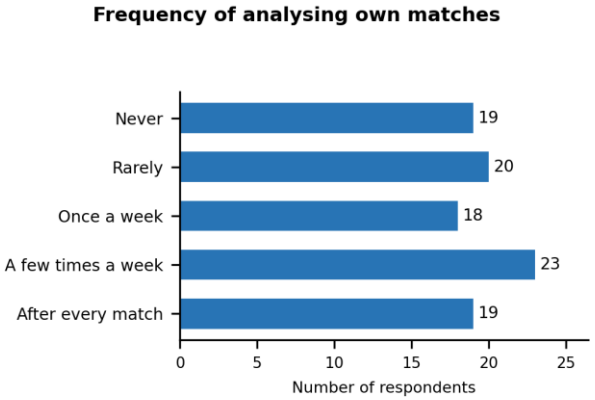


Fig -9: Frequency of analysing previous matches (N = 99).

Habits of reviewing one's own previous matches varied widely: 23 (23.2%) reviewed matches a few times a week, 19 (19.2%) after every match, and 18 (18.2%) once a week, while 20 (20.2%) did so rarely and 19 (19.2%) never. The spread is nearly even across categories, so there is no single typical review routine in this sample.

Q10. Do you study your opponents' previous matches or gameplay patterns before competing against them?

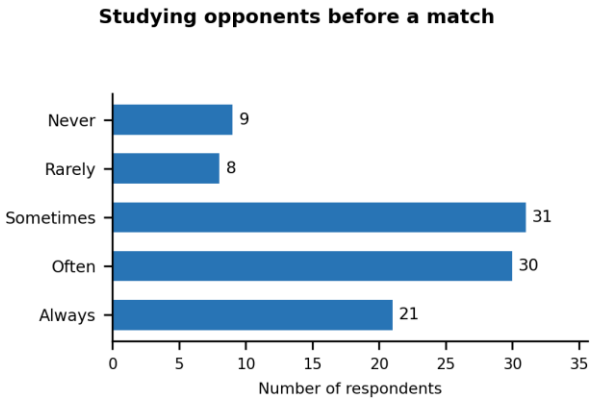


Fig -10: Studying opponents' previous matches before competing (N = 99).

Studying opponents before a match was common: 31 (31.3%) did so sometimes, 30 (30.3%) often, and 21 (21.2%) always, so 51 (51.5%) did so often or always. Only 17 (17.2%) did so rarely or never. Opponent study is therefore a regular part of preparation for a majority of respondents, which addresses objective 2.

Q11. Do you think analysing an opponent's previous gameplay helps you understand their strategy?

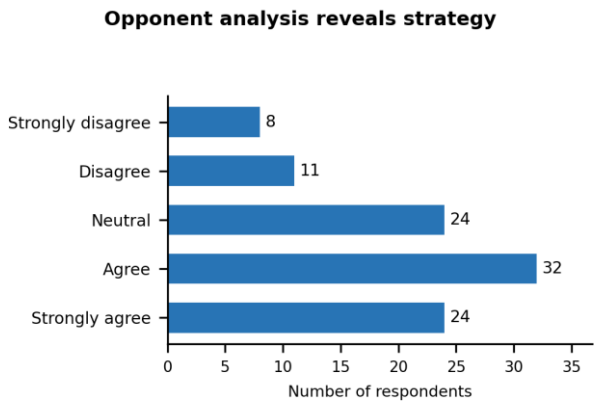


Fig -11: Belief that opponent analysis helps understand strategy (N = 99).

Overall, 56 (56.6%) agreed or strongly agreed that analysing an opponent's previous gameplay helps them understand the opponent's strategy (32 agreed and 24 strongly agreed). A further 24 (24.2%) were neutral, while 19 (19.2%) disagreed or strongly disagreed. The belief that analysis reveals strategy is held by a majority but is not universal.

Q12. How useful do you find match statistics in identifying an opponent's strengths and weaknesses?

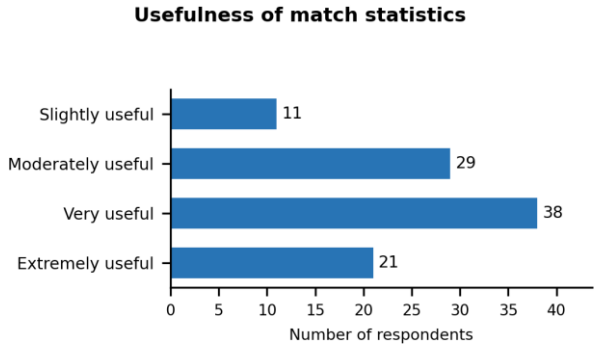


Fig -12: Perceived usefulness of match statistics (N = 99).

No respondent chose "not useful"; 38 (38.4%) found match statistics very useful and 21 (21.2%) extremely useful, together 59 (59.6%). 29 (29.3%) rated them moderately useful and 11 (11.1%) slightly useful. Match statistics were therefore generally seen as helpful for identifying an opponent's strengths and weaknesses.

Q13. Have you ever changed your gaming strategy after analysing an opponent's gameplay?

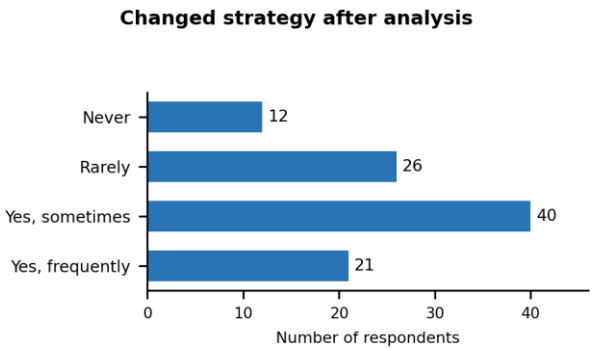


Fig -13: Changing strategy after analysing an opponent (N = 99).

Overall, 61 (61.6%) had changed their strategy after analysing an opponent, of whom 21 did so frequently and 40 sometimes. 26 (26.3%) said rarely and 12 (12.1%) never. Opponent analysis therefore translates into actual strategic adjustment for a clear majority, although a sizeable minority rarely or never adjust.

5.4 Perceived Competitive Performance

Q14. Do you believe analysing opponents helps improve your chances of winning competitive matches?

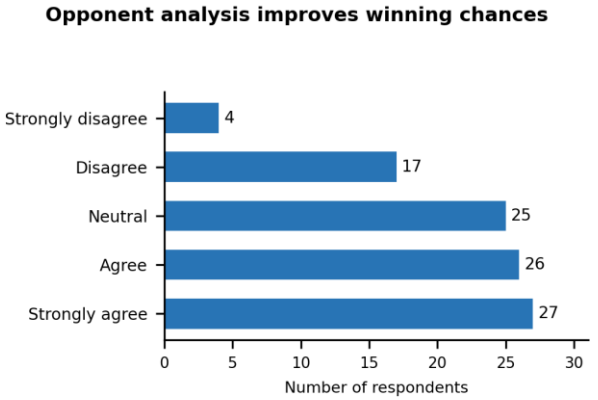


Fig -14: Belief that opponent analysis improves chances of winning (N = 99).

Overall, 53 (53.5%) agreed or strongly agreed that analysing opponents improves their chances of winning (27 strongly agreed). A further 25 (25.3%) were neutral and 21 (21.2%) disagreed or strongly disagreed. A small majority therefore perceives a benefit for winning, but this is a belief and not a measured change in win rate.

Q15. Has analysing gameplay data helped you make better decisions during matches?

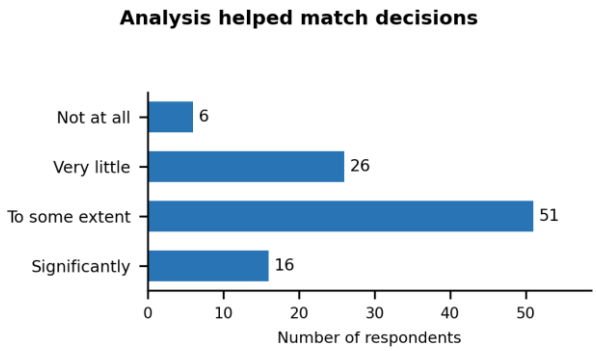


Fig -15: Whether gameplay analysis helped decisions during matches (N = 99).

Most respondents felt that analysing gameplay data helped their decisions at least to some extent: 51 (51.5%) said "to some extent" and 16 (16.2%) "significantly", together 67 (67.7%). A further 26 (26.3%) said "very little" and 6 (6.1%) "not at all". The modal answer was a moderate rather than a strong effect, which is a cautious but positive picture.

Q16. In your experience, what area of competitive gaming improves the most through opponent analysis?

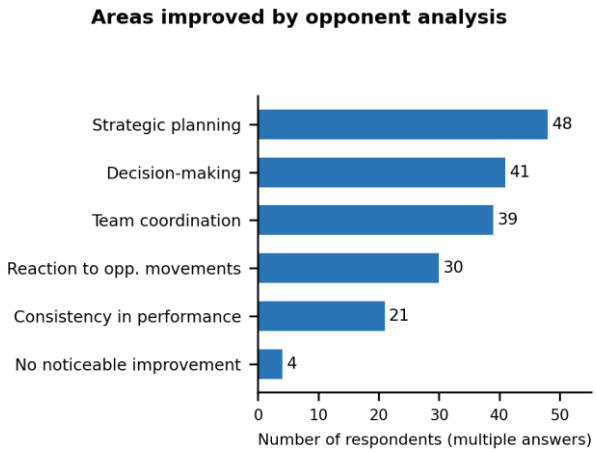


Fig -16: Areas that improve most through opponent analysis (N = 99; multiple answers).

Note. Question 16 allowed multiple answers; counts add to more than 99 and percentages are shares of the 99 respondents.

Respondents could name more than one area. Strategic planning was named most often (48 (48.5%)), followed by decision-making (41 (41.4%)) and team coordination (39 (39.4%)). Reaction to opponent movements (30 (30.3%)) and consistency in performance (21 (21.2%)) were named less often, and only 4 (4.0%) reported no noticeable improvement. Opponent analysis is thus mainly associated with planning and decision-making.

5.5 Challenges and Future Interest

Q17. What is the biggest challenge you face when using data analytics for gaming?

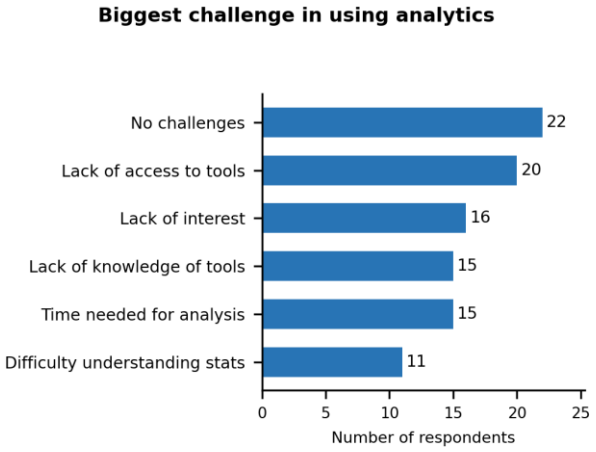


Fig -17: Biggest challenge in using data analytics (N = 99).

The most frequent specific barrier was lack of access to performance-tracking tools (20 (20.2%)), followed by lack of interest (16 (16.2%)), lack of knowledge about analytical tools (15 (15.2%)), and the time required for analysing matches (15 (15.2%)). 11 (11.1%) had difficulty understanding gameplay statistics, and 22 (22.2%), the largest single group, reported no challenges. Taken together, 46 respondents (46.5%) named access, knowledge, or understanding barriers.

Q18. Would you be interested in using data science-based tools to analyse opponents and improve your competitive gaming performance in the future?

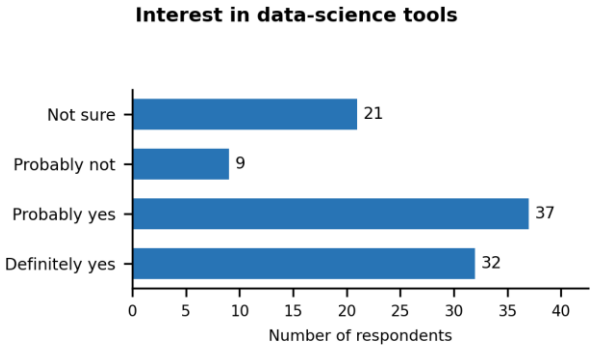


Fig -18: Interest in using data science-based tools in future (N = 99).

Interest in future use was high: 32 (32.3%) said "definitely yes" and 37 (37.4%) "probably yes", together 69 (69.7%). A further 21 (21.2%) were not sure and only 9 (9.1%) said "probably not". Willingness to adopt data science-based tools appears strong even though current regular use is limited.

Exploratory Correlation Analysis

None of the three correlations reached the .05 significance threshold. The association between how often players study opponents and their belief that analysis improves winning chances was positive but very small ($\rho = 0.103$, $p = 0.311$). The association between tool use and perceived help in match decisions was essentially zero ($\rho = -0.007$, $p = 0.948$), and the association between reviewing one's own matches and the belief that opponent analysis reveals strategy was small and negative ($\rho = -0.111$, $p = 0.276$). These results do not show that analysis has no effect; they indicate only that these survey measures did not establish statistically significant monotonic relationships in this sample.

Findings

1) Awareness of analytics tools was fairly high (62 (62.6%) at least somewhat familiar), but regular use was lower (13 (13.1%)).

2) Studying opponents before matches was common: 51 (51.5%) did so often or always.

3) 56 (56.6%) agreed that opponent analysis helps them understand strategy, and 59 (59.6%) rated match statistics very or extremely useful.

4) Overall, 61 (61.6%) had changed their strategy after analysing an opponent.

5) 53 (53.5%) believed opponent analysis improves their chances of winning, and 67 (67.7%) said gameplay data helped their decisions to some extent or significantly.

6) Strategic planning (48 (48.5%)) was named most often as the area improved by opponent analysis, followed by decision-making (41 (41.4%)) and team coordination (39 (39.4%)).

7) The most common specific barrier was lack of access to performance-tracking tools (20 (20.2%)); 69 (69.7%) were probably or definitely interested in using data science-based tools in future.

8) None of the three exploratory Spearman correlations was statistically significant at the .05 level.

LIMITATIONS

1) The study is limited to players reached in Airoli and Belapur, and 18 (18.2%) responses came from other nearby areas of Navi Mumbai, so it may not represent the wider esports community in Navi Mumbai.

2) Convenience sampling may produce a sample that differs from the overall player population, and the recruitment procedure is not documented.

3) Questionnaire responses are self-reported and may not match players' actual match statistics or performance.

8. CONCLUSIONS

Data science offers esports players practical ways to review match statistics, recognise opponent habits, and prepare strategies. In this sample of 99 players from Airoli, Belapur, and nearby areas, awareness of analytics tools was fairly common, studying opponents was a regular habit for many, and a majority believed that opponent analysis helps them understand strategy, adjust their approach, and improve their chances of winning. Strategic planning and decision-making were the areas most often reported as improving. Interest in using data science-based tools in future was high (69.7%), although access to tools, knowledge, and understanding of statistics remain barriers for many players.

These findings should be read as descriptive evidence of players' perceptions, not as proof that opponent analysis causes better results. None of the exploratory correlations was statistically significant, data cannot replace practice, communication, teamwork, or the ability to adapt, and the value of analysis is likely to depend on how well players interpret and apply it. Future research could record locality and recruitment more precisely, use non-overlapping response options, and compare players' actual match records before and after a period of structured opponent review.

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