IMPROVING GAME RATINGS FOR ENHANCED USER SATISFACTION AND GAME ACQUISITION

BUSINESS REPORT **2024**

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BUSINESS CONSULTING REPORT

Prepared For:
Play Quest Conquer (PQC)

A business consulting report with comprehensive analysis of factors influencing game ratings to guide strategic improvements for enhanced user satisfaction and game acquisition at Play Quest Conquer (PQC)

Executive Summary

This consulting report provides a strategic analysis for Play Quest Conquer (PQC) aimed at enhancing game ratings and driving business profitability. Our objective was to identify critical factors influencing game ratings and to develop actionable strategies that align with PQC's business goals.

Our comprehensive analysis revealed that game type and complexity are significant drivers of ratings. Games with higher complexity tend to receive better ratings; however, excessive complexity can lead to diminishing returns. The interplay between game type and complexity demonstrates a compounded impact on ratings, underscoring the importance of carefully balancing these elements. Additionally, while extended play times show a slight negative effect on ratings, the level of interest and engagement a game generates positively correlates with higher ratings. Notably, games with higher stickiness, as indicated by sustained user engagement, tend to achieve superior ratings, highlighting the critical role of maintaining player interest.

We recommend PQC optimize game complexity and type to balance ratings and player retention. Expanding player capacity and adding features to boost interest will improve engagement. Future efforts should refine the predictive model to capture complex interactions, integrate additional variables, and address current limitations like minimal variable impact and potential overfitting.

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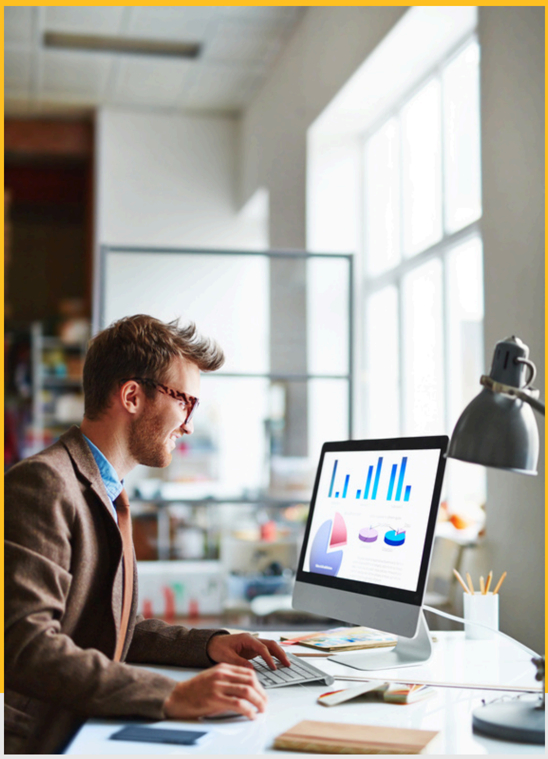
Introduction

Background

Play Quest Conquer (PQC)

Play Quest Conquer (PQC) is a Sydney-based online gaming platform that offers a wide variety of engaging and interactive games.



Game Configuration

The dataset comprises a variety of games categorized by type, release year, age suitability, and player configuration. The games are classified into different types, such as BaseGame and PremiumGame, indicating the diversity in game offerings. The release years span across multiple periods, reflecting both newer and older games within the collection.

Regarding player configuration, the games differ in the minimum and maximum number of players required or allowed. Some games are designed for smaller groups, requiring only a few participants, while others accommodate larger groups, offering a more inclusive gaming experience. This variation in player numbers caters to different gaming scenarios, from intimate sessions to large gatherings.

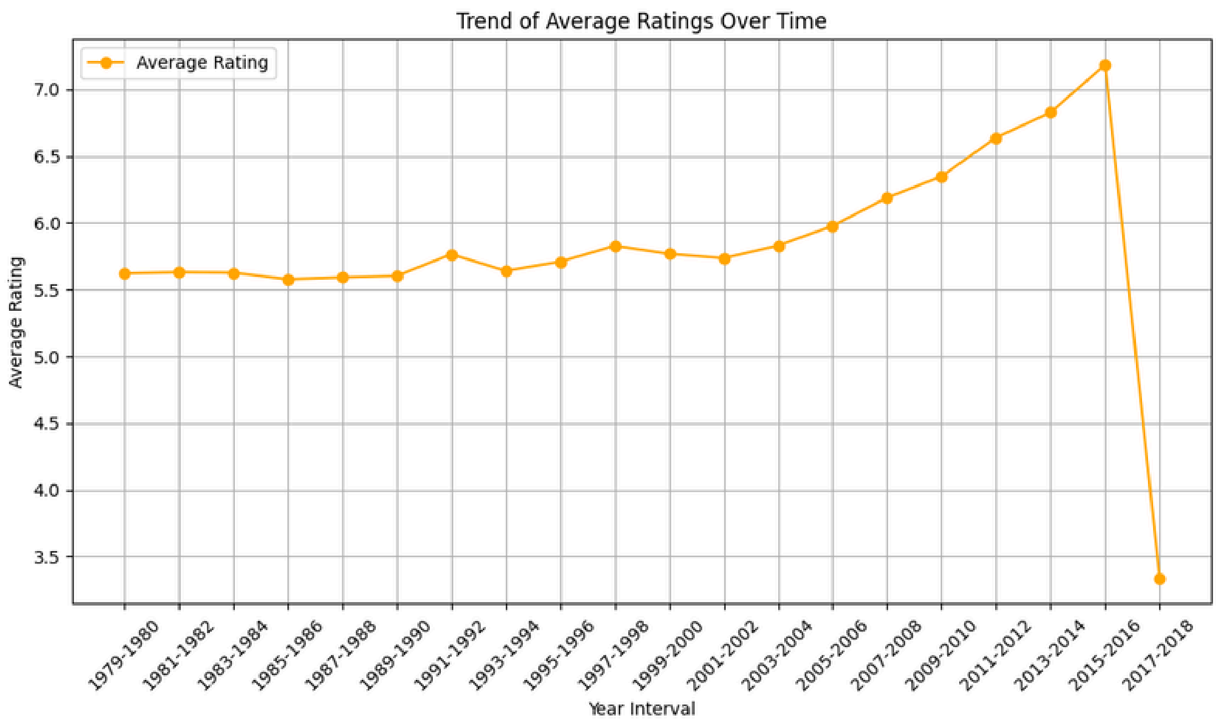
Introduction

Business Analysis using BACCM model

Business Need

Play Quest Conquer (PQC) struggles with declining game ratings and profitability, which dropped suddenly after a steady increase until 2015.

In a rapidly expanding global gaming market, where the Australian gaming network is forecasted to reach $53.49 million in revenue by 2024 and 2.4 million users by 2027 ((Gaming Networks – Australia | Statista Market Forecast, n.d.), PQC needs to improve game quality and ratings to stay competitive and profitable.



Introduction

Business Analysis using BACCM model

Solutions

Based on the model's insights, several key solutions are recommended

Balance Complexity Levels

While higher complexity generally benefits ratings ((Lee et al., 2018), avoid excessive complexity due to diminishing returns. Aim for an optimal level of complexity that enhances gameplay without negatively impacting user experience.

Optimize Feature Interactions

Consider the interactions between game types and complexity to refine game design. Avoid combinations that result in lower effectiveness according to the interaction terms in the model.

Focus on Game Type

Invest in developing and promoting games that align with high-performing game types and feature increased complexity. These elements are shown to significantly improve ratings, as evidenced by their positive coefficients in the model.

Monitor Play Time

Carefully control average play time to mitigate its minor negative effect on ratings. Ensure games are engaging and immersive but not overly lengthy to maintain high user satisfaction.

Enhance Game Stickiness

Focus on increasing user retention by enhancing features that boost long-term engagement. This includes improving gameplay mechanics and user interface to keep players invested.

Introduction

Business Analysis using BACCM model

Context

According to the Unity Gaming Report 2024, there's a growing demand for innovative gameplay and engaging content. The gaming industry is evolving quickly, with rising competition and changing preferences. PQC risks losing market share if it doesn't innovate and improve game ratings and engagement.

Value

PQC

Gaining detailed insights from consultants will help refine strategies to improve game ratings, enhance market position, and boost profitability.

Gamers

Improved game quality and features will lead to a more enjoyable experience, increasing engagement and satisfaction.

Consulatant

Delivering actionable recommendations will showcase their expertise, strengthening their reputation and potentially leading to further opportunities.

Introduction

Business Analysis using BACCM model

01 Changes

PQC aims to boost average ratings to drive profits and market positioning by using data insights to refine game features and marketing strategies.

02 Stakeholders

Key stakeholders include market research managers for strategic decisions, the executive team for growth and profitability, development and marketing teams for game improvements and promotions, users for feedback, and investors for company performance and growth.

Data Understanding

Overview

The dataset includes 24,813 games with average features from around 1997. Most support 2-6 players and have low complexity (mean = 1.99). Ratings average 6.21 with moderate variation and include outliers, such as games with up to 99 players and extremely high ratings. Some games have significant community engagement with up to 53,680 ratings and 11,798 comments.

Predictors and Target

The dataset features 17 attributes, including categorical data on game type and age category, numerical data on gameplay requirements and complexity, player engagement metrics, and the target variable, Average_Rating, which indicates the game's overall rating.

7

Missing Values

The Game_Name column has 7 missing values. No other columns have missing values.

-99

Released Year Error

The value -99 in the Released_Year column likely represents missing or unknown data.

2015

Data Accuracy

The sharp drop in ratings post-2015 can be observed which might be due to data insufficiency or declining game quality, changes in market dynamics, or potential rating system adjustments.

Data Preparation

Missing Values

The 7 missing values in the Game_Name field don't affect Average_Rating or the analysis, so they can be ignored without impacting the findings' reliability.

Outliers

-99

Since -99 in the Released_Year does not appear to be random, it will be excluded from the analysis without imputation

Data Encoding

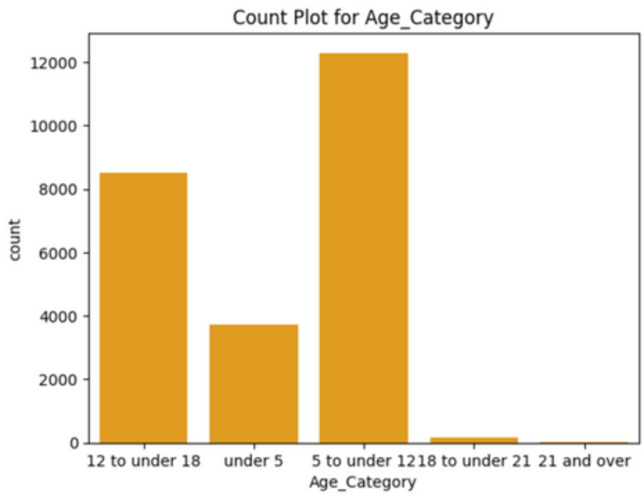
Categorical variables such as Game_Type and Age_Category have been encoded into numerical formats. This encoding transforms non-numeric categories into a format that can be utilized by machine learning algorithms, allowing for more effective analysis and model training.

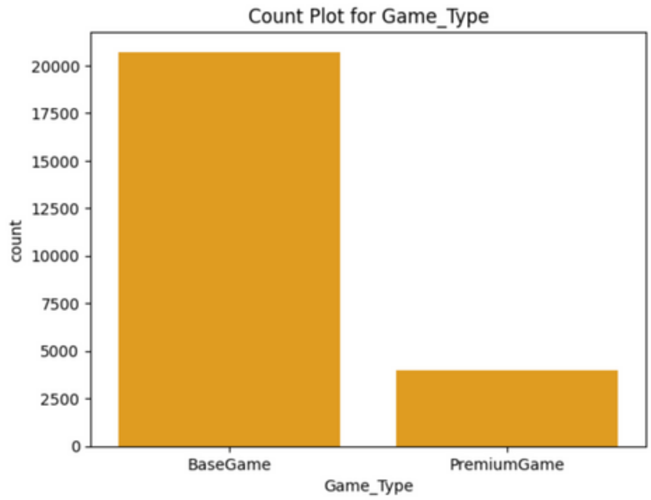
Data Scaling

Numerical features were scaled before training the model to enhancing model performance and convergence by balancing the influence of features with different magnitudes.

Exploratory Data Analysis

Univariate Analysis



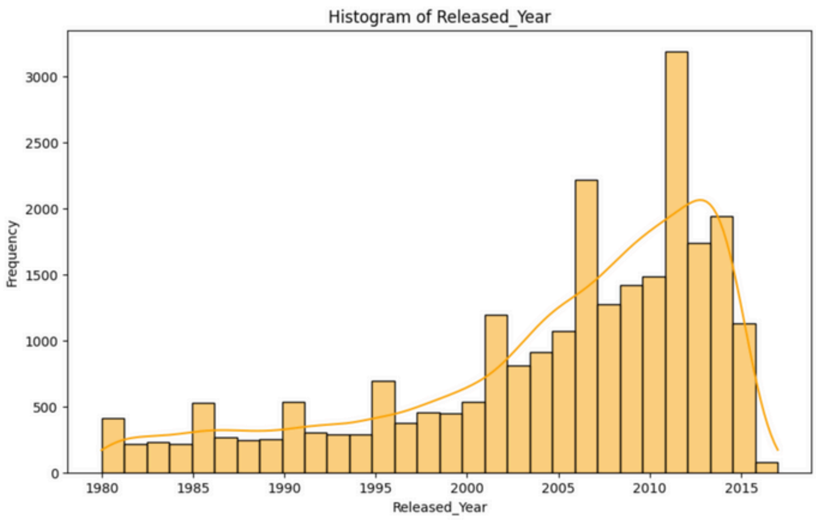


01 Age_Category

The Age_Category variable reveals that the highest frequency of players is observed in the "5 to under 12" age group, followed by 12 to under 18 and then under 5.

02 Game_Type

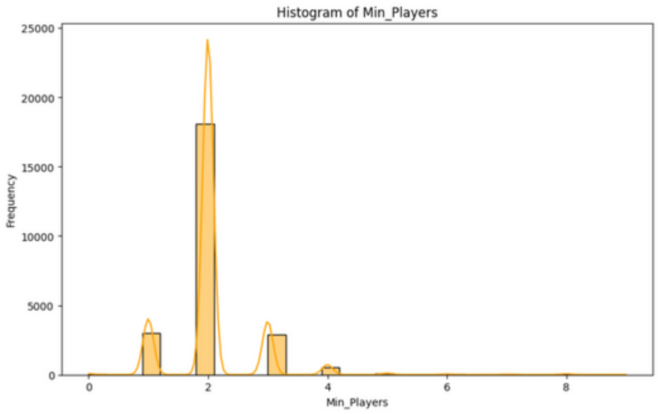
Base Games are significantly more popular than Premium Games.

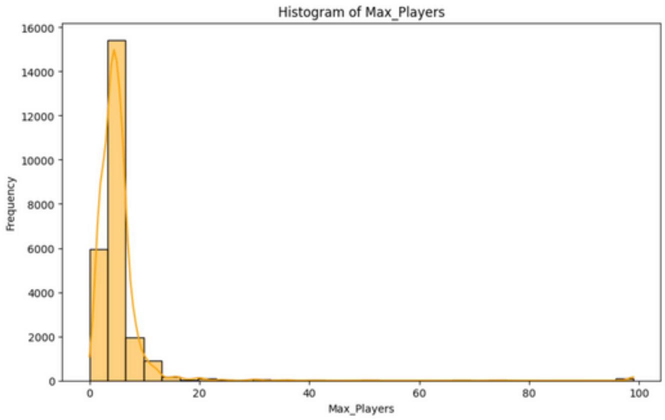


03 Released_Year

The year of release varies from an unusual outlier of -99 to 2017, with a mean year of 1997. Game released have significantly dropped after 2015 and show consistent release until 2000 with steady growth until 2015. The distribution is skewed.

Univariate Analysis



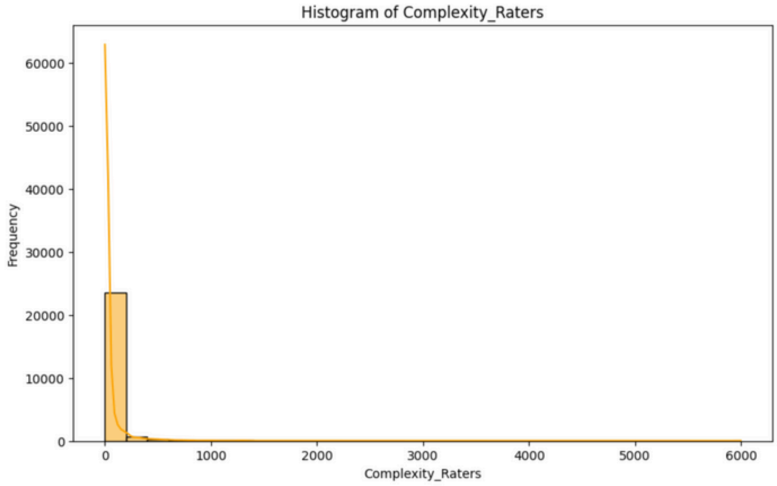


01 Min_Players

Most games have a minimum of 2 players.

02 Max_Players

The average maximum is 5.32 players, catering mostly to smaller groups.

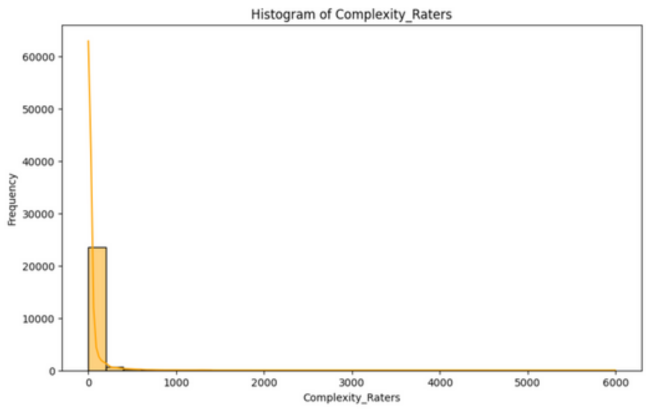


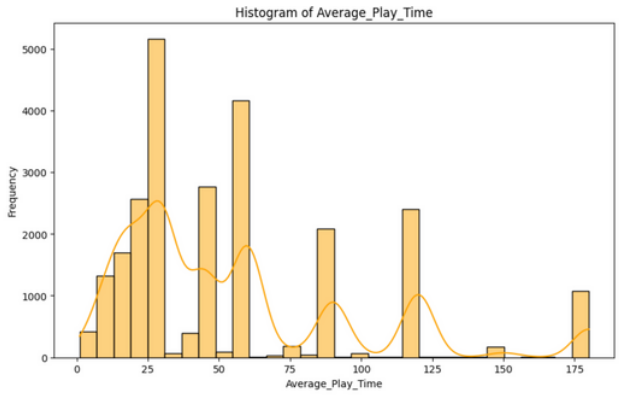
03 Average_Complexity

Games have an average complexity rating ranging from 1.00 to 5.00, with a mean of 1.99. The low average complexity suggests that most games are relatively simple, which could impact their appeal to different types of players.

Exploratory Data Analysis

Univariate Analysis



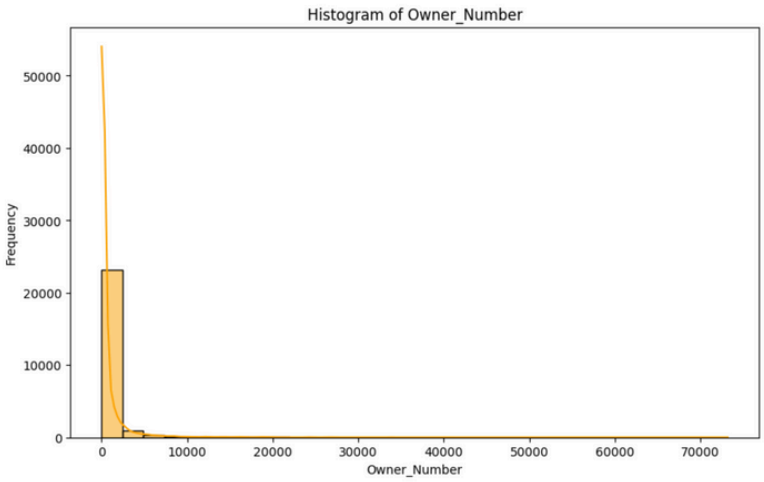


01 Complexity_Raters

The number of people rating game complexity ranges from 1 to 5,996, with a mean of 42.55. This variation indicates differing levels of feedback on game complexity across the dataset.

02 Average_Play_Time

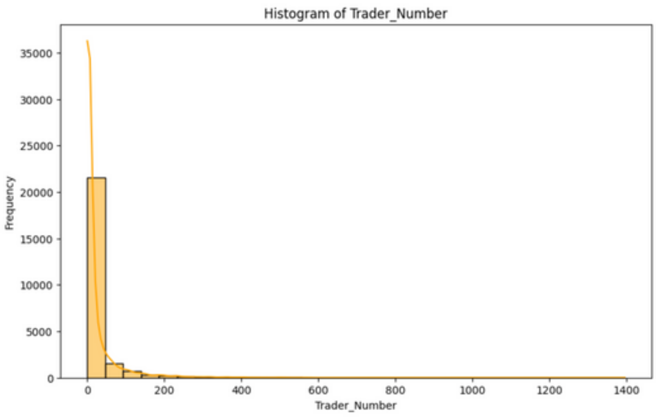
The average playtime for games varies from 1 to 180 minutes, with a mean of 55.21 minutes. This range reflects a mix of short and long-duration games available on the platform.

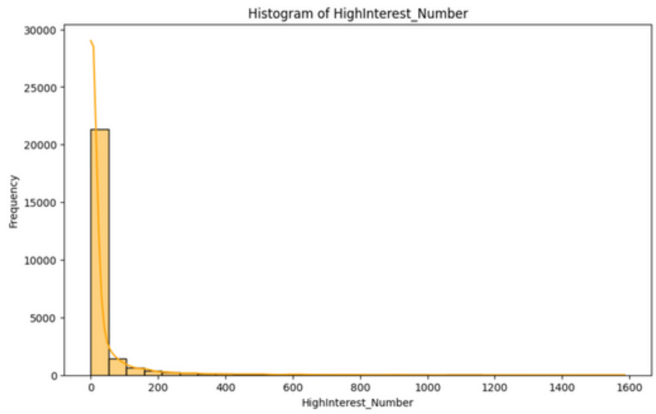


03 Owner_Number

The number of owners for games ranges from 0 to 73,188, with a mean of 674.20. This wide range highlights the varying popularity and ownership levels of the games.

Exploratory Data Analysis
Univariate Analysis



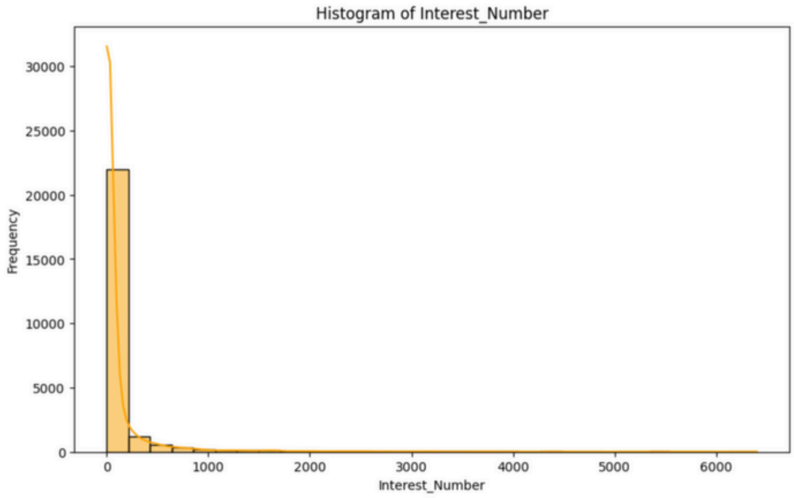


01 Trader_Number

The number of traders for games ranges from 0 to 1,395, with a mean of 23.19. This suggests that while some games see significant trading activity, most have relatively low trading engagement.

02 High_Interest_Number

The number of people indicating high interest in games ranges from 0 to 1,586, with a mean of 32.46. This reflects a range of strong interest levels among users for different games.

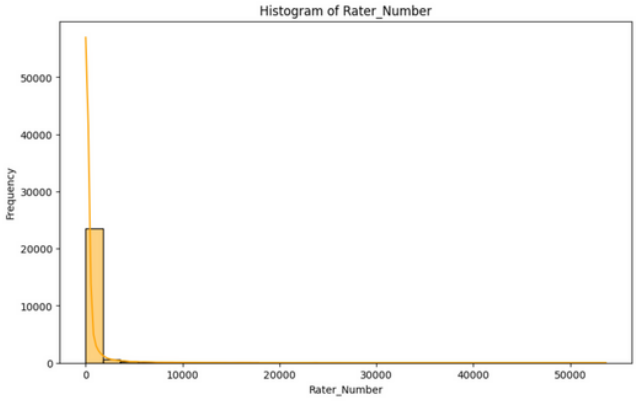


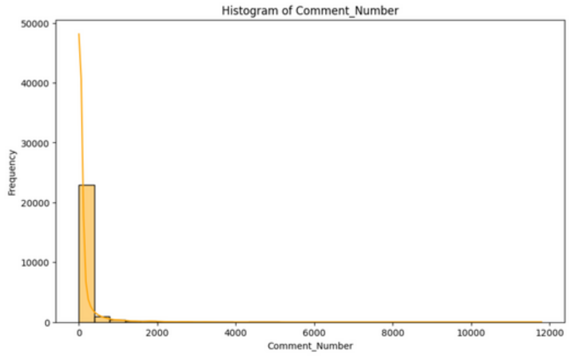
03 Interest_Number

The general interest number spans from 0 to 1,586, with a mean of 111.18. This suggests substantial overall interest in the games across the platform.

Exploratory Data Analysis

Univariate Analysis



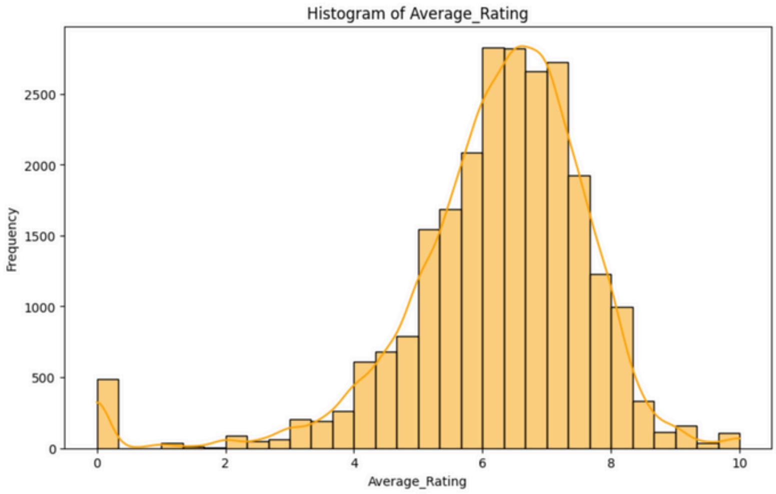


01 Rater_Number

The number of raters for games ranges from 0 to 6,402, with a mean of 125.99. This indicates varying levels of user engagement in rating the games.

02 Comment_Number

The number of comments per game ranges from 0 to 11,798, with a mean of 426.81. This highlights significant levels of user feedback for many games, reflecting diverse opinions and engagement.

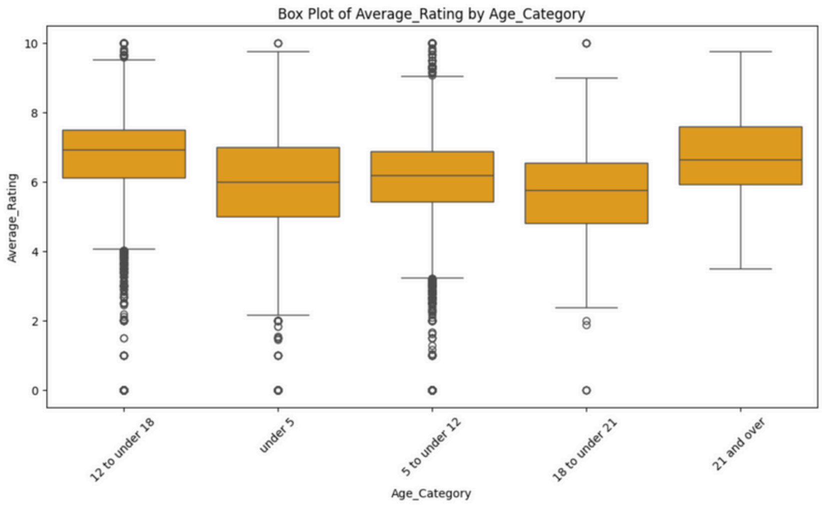


03 Average_Rating

The average rating of games ranges from 0 to 10, with a mean of 6.21. This suggests that, overall, games on the platform receive relatively favorable reviews from players.

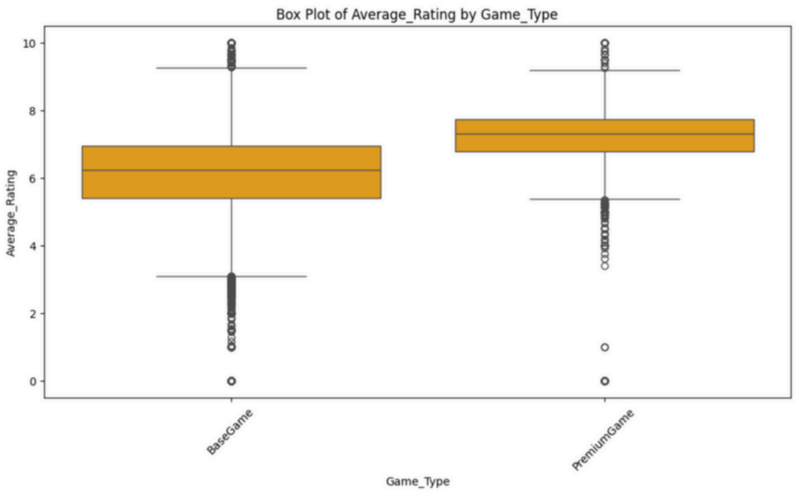
Exploratory Data Analysis

Bivariate Analysis



01 Age_Category+ Average_Rating

The box plot shows consistent median ratings across age groups, with younger groups, especially "under 5" and "12 to under 18," having more variability and outliers, indicating diverse opinions, while older groups show more consistent ratings.

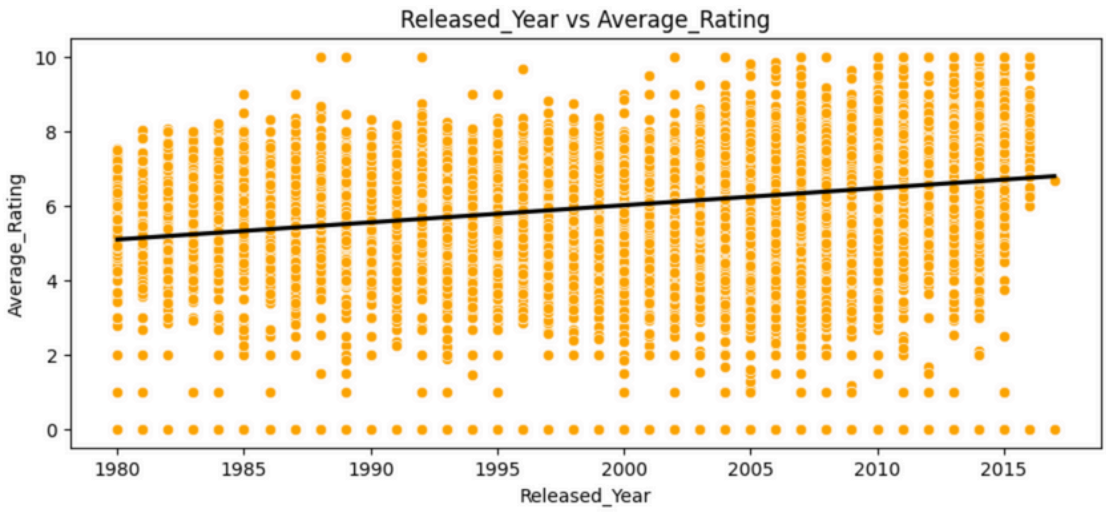


02 Game_Type+ Average_Rating

"BaseGame" and "PremiumGame" have similar average ratings and IQRs, but "BaseGame" shows more extreme low outliers, indicating higher variability in user satisfaction.

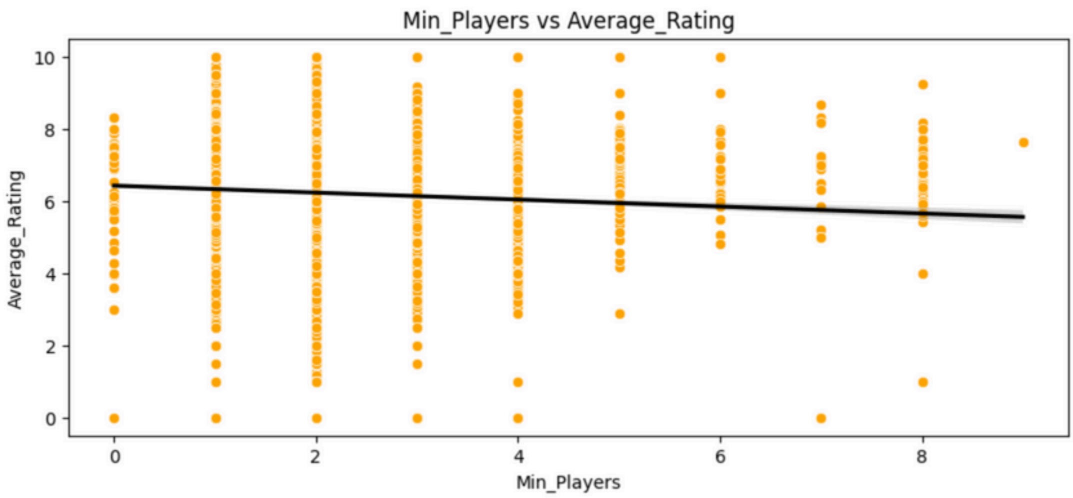
Exploratory Data Analysis

Bivariate Analysis



03 Released_Year+ Average_Rating

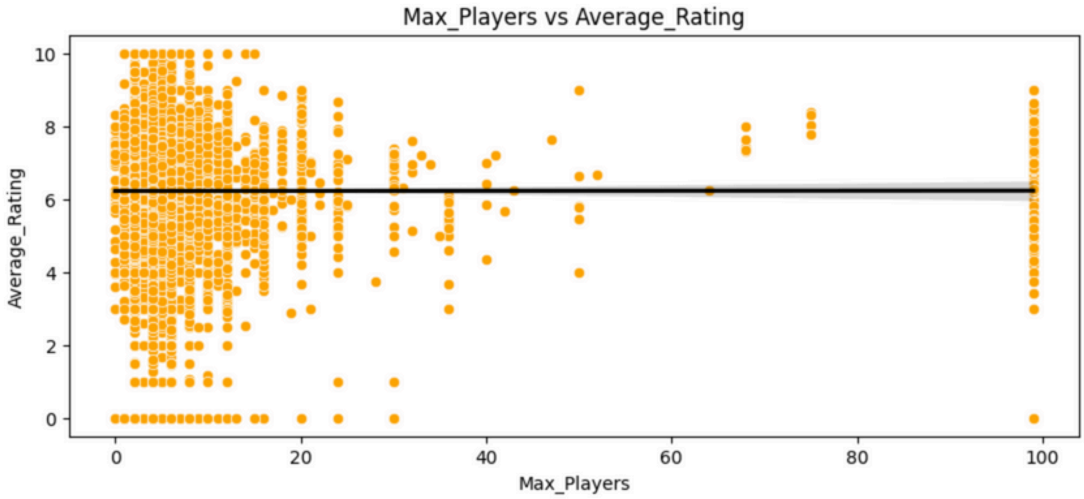
TThe scatter plot with a trendline shows that newer releases slightly trend toward higher ratings, but the wide spread indicates that release year is not a strong determinant of ratings.



04 Min_Player+ Average_Rating

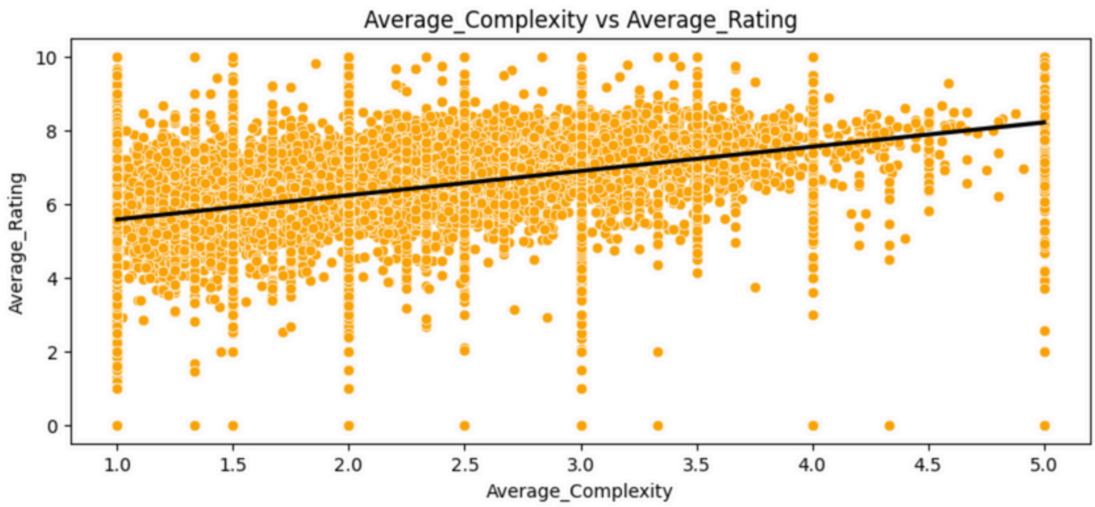
The scatter plot shows a downward trend, indicating that games with fewer minimum players tend to have higher ratings, though variability suggests it's not a strong predictor.

Bivariate Analysis



05 Max_Players+ Average_Rating

Most games support fewer players (median 4), with ratings widely spread, indicating that larger player counts do not consistently lead to higher ratings.

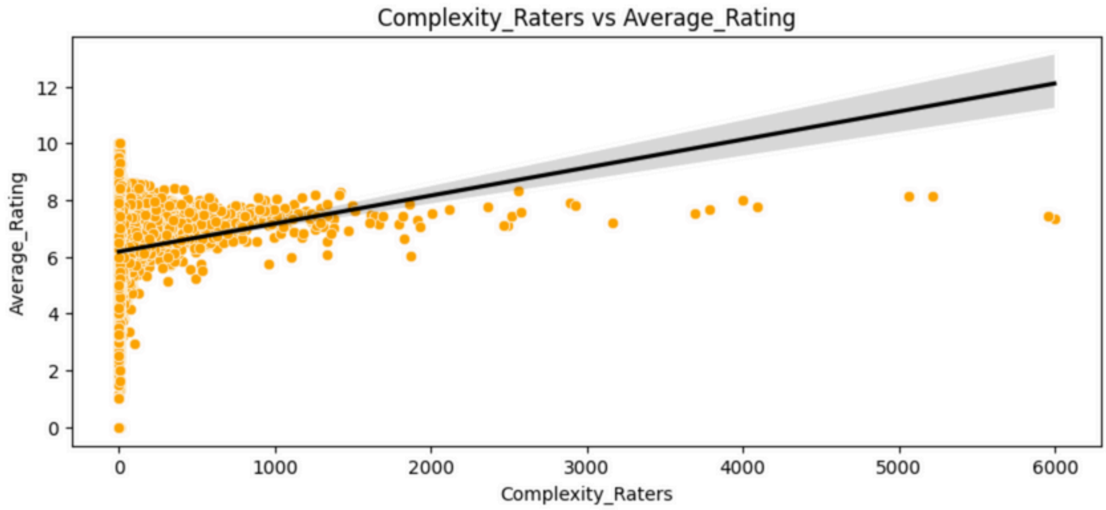


06 Average_Complexity+ Average_Rating

TA weak positive correlation exists, with more complex games slightly tending toward higher ratings, but the wide spread suggests complexity alone doesn't determine success.

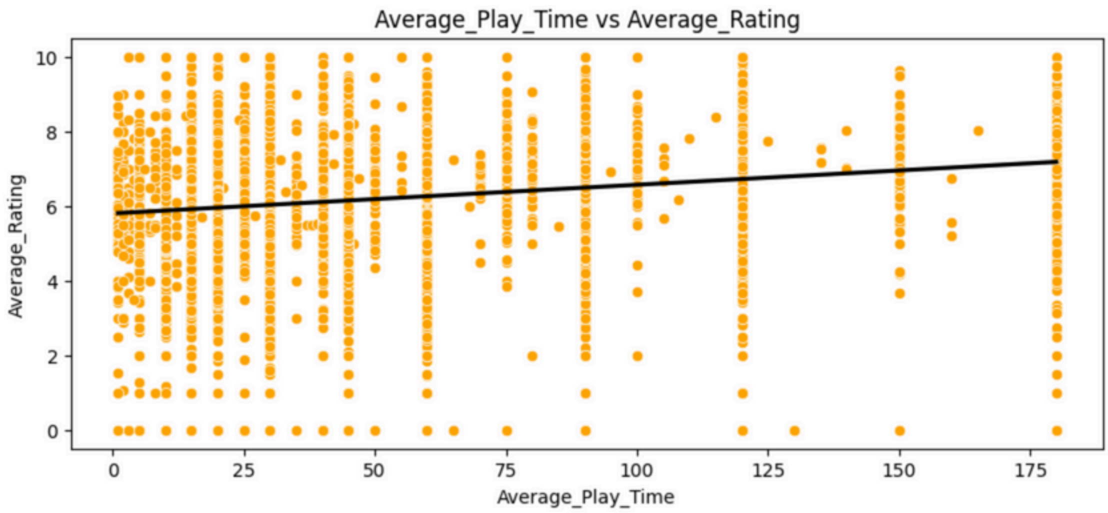
Exploratory Data Analysis

Bivariate Analysis



07 Complexity_Raters+ Average_Rating

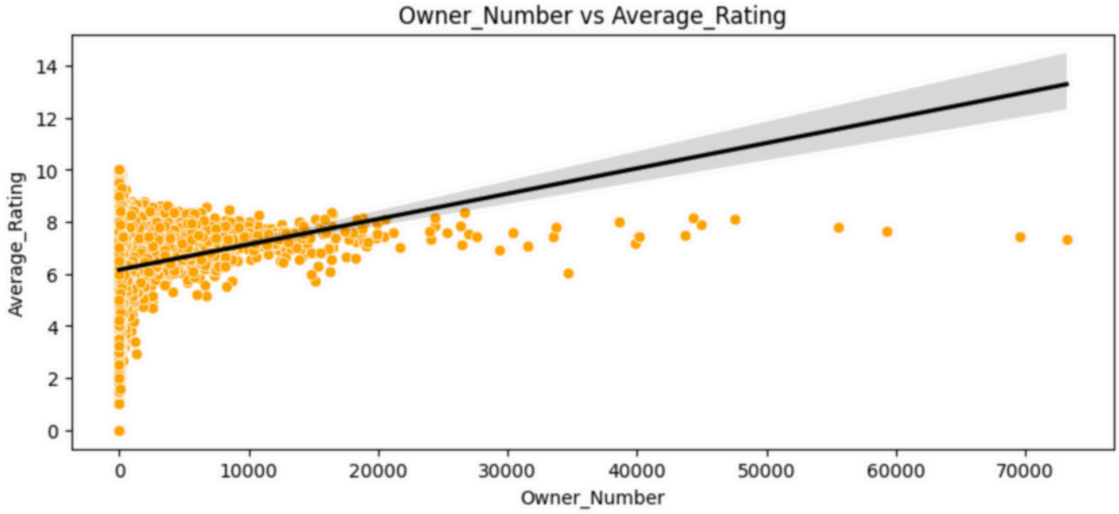
Games with more raters tend to have higher average ratings, though variability indicates that fewer raters can still lead to diverse quality perceptions.



08 Average_Play_Time+ Average_Rating

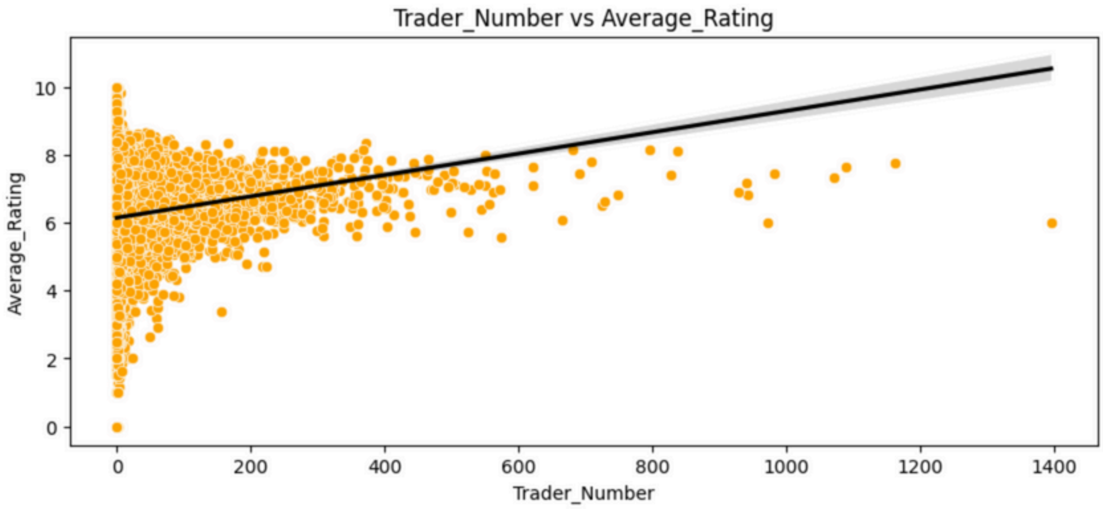
There's a weak positive correlation, showing games with longer play times slightly tend toward higher ratings, but significant variability suggests other factors influence ratings.

Bivariate Analysis



09 Owner_Number+ Average_Rating

Games with more owners show slightly higher ratings, though the weak correlation and variability suggest other factors are more influential.

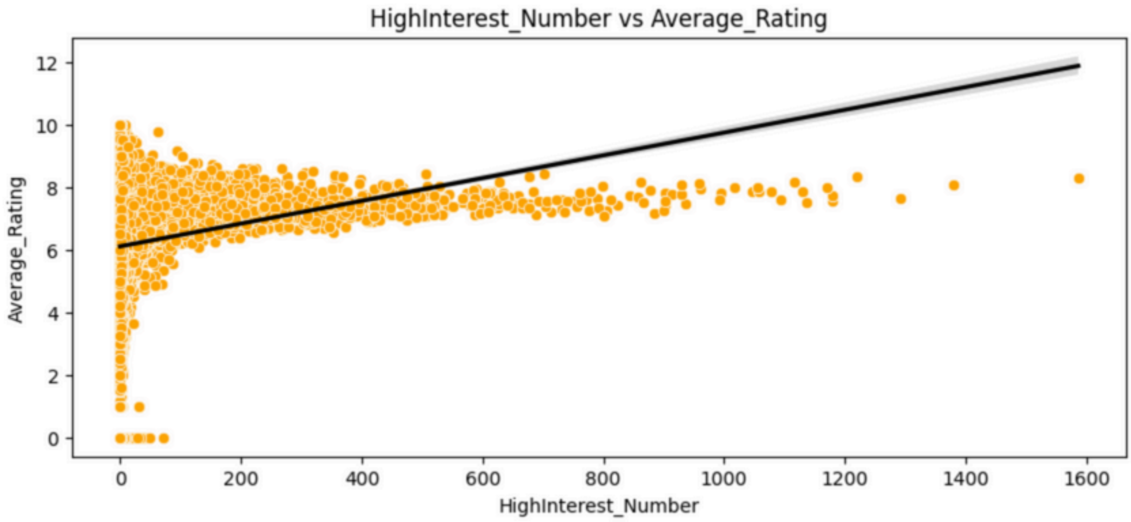


10 Trader_Number+ Average_Rating

Games with more traders tend to have slightly higher ratings, but the weak correlation and variability indicate that other factors also significantly affect ratings.

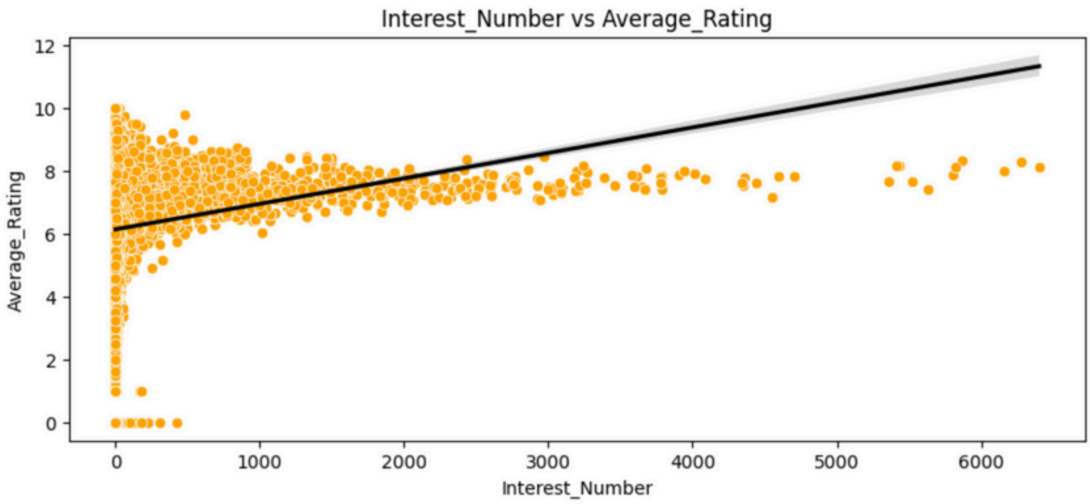
Exploratory Data Analysis

Bivariate Analysis



11 Hight_Interest_Number+ Average_Rating

A weak positive correlation suggests that games with higher high-interest counts tend to have slightly better ratings, though variability implies other factors also play a role.

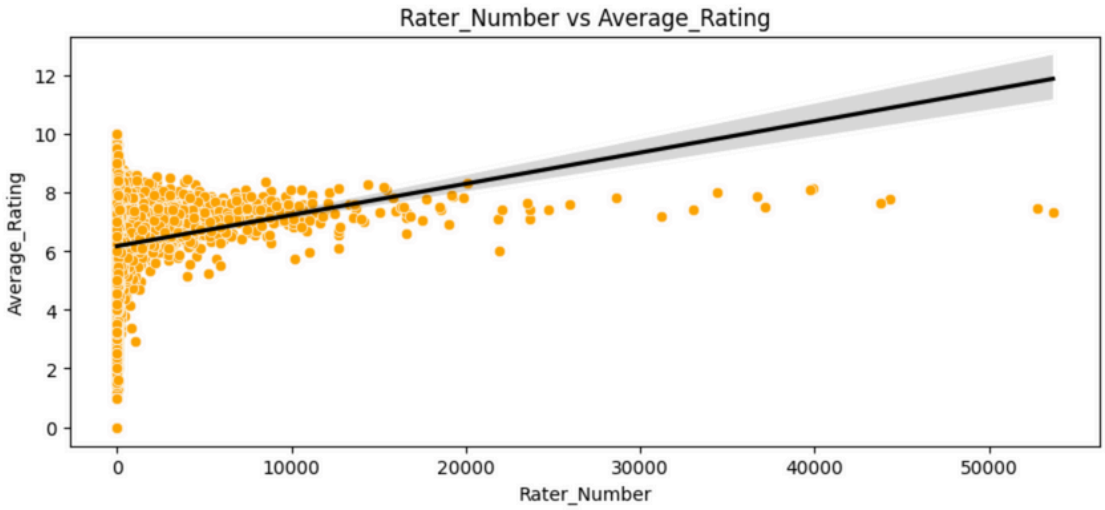


12 Interest_Number+ Average_Rating

Games with higher interest numbers slightly trend toward better ratings, but the weak correlation and variability suggest other factors are at play.

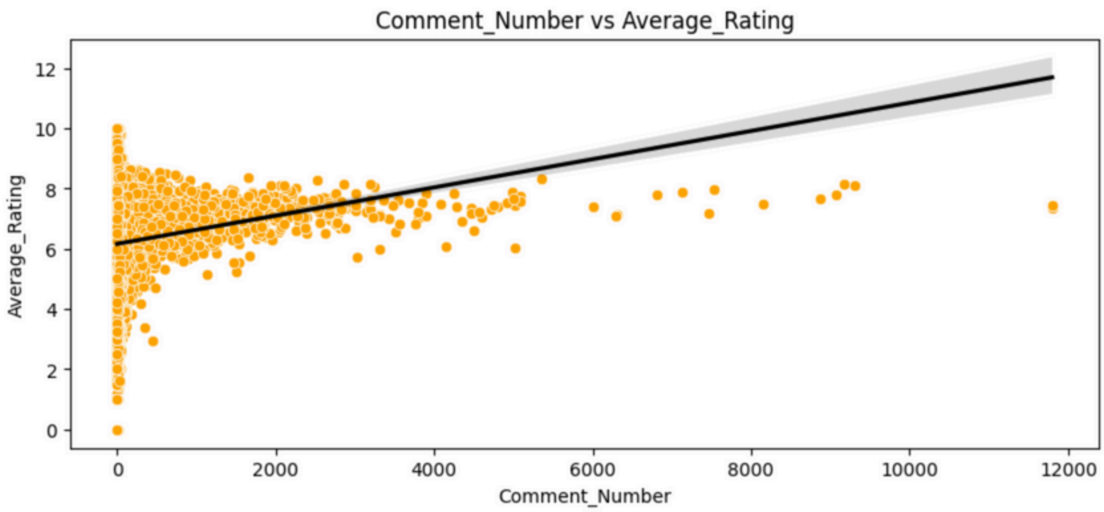
Exploratory Data Analysis

Bivariate Analysis



13 Rater_Number+ Average_Rating

Games with more raters generally have slightly higher ratings, but the weak correlation and wide spread indicate many factors influence a game's rating.

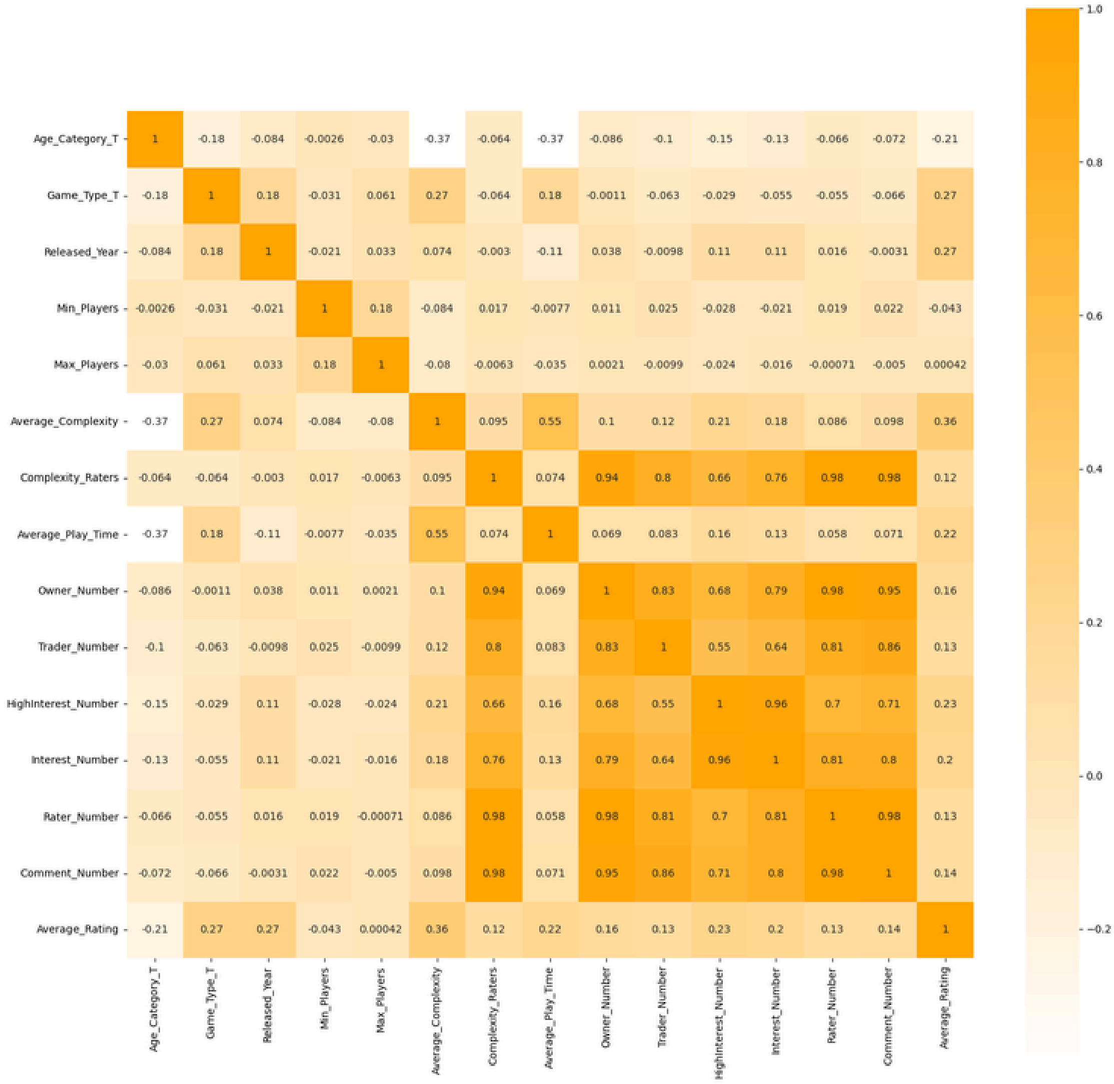


14 Comment_Number+ Average_Rating

Games with more comments tend to have higher ratings, though the variability in comment counts suggests that popularity or rating alone doesn't fully explain the volume of comments.

Exploratory Data Analysis

Multivariate Analysis



A heatmap, used after encoding categorical variables, revealed positive correlations between certain features and the target, as well as relationships among predictor variables themselves.

Machine Learning Model

Feature Selection & Data Split

Feature Selection

We selected features with a correlation of 0.2 or higher with the target and addressed multicollinearity by retaining only one feature per group with correlations above 0.9, ensuring model efficiency.

Data Split

We split the dataset 80:20 for training and testing, leveraging the large dataset size for robust model training while preserving a portion for accurate performance evaluation.

Train Data

80% of dataset was splitted for training

Test Data

20% of remaining dataset was used for testing

Model Selection

Model Selection

We selected a supervised machine learning model for our analysis due to the nature of our labeled dataset, where the expected output is continuous numeric data.

We specifically chose multiple linear regression, to predict continuous numeric data, accounting for the influence of multiple features on the target variable simultaneously.

Model Training

Polynomial Equation: y = 0.6480 * Game_Type_T + 1.2706 * Average_Complexity + -0.0057 * Average_Play_Time + 0.0016 * Interest_Number + 0.6480 * Game_Type_T^2 + -0.1474 * Game_Type_T Average_Complexity + -0.0015 * Game_Type_T Average_Play_Time + 0.0003 * Game_Type_T Interest_Number + -0.1818 * Average_Complexity^2 + 0.0012 * Average_Complexity Average_Play_Time + -0.0001 * Average_Complexity Interest_Number + 0.0000 * Average_Play_Time^2 + -0.0000 * Average_Play_Time Interest_Number + -0.0000 * Interest_Number^2 + 4.3482 * Intercept

The equation shows game type and complexity impact ratings, with complexity being more significant. Play time and interest have less effect, and interactions indicate complex relationships. High complexity may reduce returns, and some game types with high complexity might underperform.

Pros and cons of the Model Selected

the selected maching learning model come with its own sets of advantages and disadvantages.

Pros

Multiple linear regression is simple and interpretable, showing how each predictor affects a continuous outcome. It provides clear coefficients, aiding in feature selection and understanding variable influence.

Cons

It assumes linearity, normality, and homoscedasticity, which may not hold true. It can struggle with collinear predictors and complex, non-linear relationships, and is sensitive to outliers, which can skew results.

Model Evaluation

Model Evaluation

Overall, while the model demonstrates some predictive capability, the metrics suggest that there is significant potential for enhancement in capturing the relationship between features and the target variable.

R-squared (R^2)

Our model has an R-squared value of 0.21. This indicates that the model explains 21% of the variability in the target variable. This suggests that while the model captures some relationship between the features and the target variable, a substantial amount of the variance remains unexplained.

Mean Absolute Error (MAE)

The model's average prediction error is 1 unit, translating to 90% accuracy. This suggests room for improvement in predictive accuracy.

Root Mean Squared Error (RMSE)

The RMSE is 1 unit, reflecting a moderate level of accuracy. It indicates predictions are reasonably close but could be improved.

Further Improvement

To improve the model, enhance feature engineering, optimize hyperparameters with Grid Search, and experiment with algorithms like Gradient Boosting or neural networks. Increase and clean the data, apply regularization to avoid overfitting, use cross-validation for performance evaluation, and consider ensemble methods for better accuracy.

Recommendations

1. **Invest in Game Development and Innovation:** “With the development of network and streaming media technology, the online video industry has made great progress during the last ten years”,(Rong et al., 2019). Allocate resources to develop and innovate game features that cater to player preferences and enhance complexity. Regular updates and new content can keep players engaged and improve game ratings.

2. **Monitor and Adjust Game Metrics Regularly:** Track average playtime, player capacity, and feedback to guide game adjustments and feature improvements.

3. **Foster Community:** Engage players to gather insights and boost ratings through positive reviews and word-of-mouth.

4. **Implement A/B Testing:** Use A/B testing to evaluate the impact of different game features and adjustments on player ratings. This approach can help identify which changes lead to improved ratings and player satisfaction. Since online stickiness, satisfaction, and trust have a significant positive impact on repurchase intention, these factrs can also be taken into account while testing(Xu and Liu (2010)).

5. **Focus on Competitive Benchmarking:** Compare game performance with competitors to guide strategy and maintain a competitive edge.

6. **Enhance Customer Support:** Improve player satisfaction and ratings by addressing issues promptly and effectively.

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