

Analysis of the Relationship Between Game Price and User Rating

Yuncong Xu *

The University of Sydney, The University of Sydney, Camperdown NSW 2006, Australia

* Corresponding author: (Email: sa@cis.ac.cn)

Abstract: With the rapid expansion of the global digital game market, game pricing strategies have become a core operational lever for developers and platforms to balance revenue and user reputation. User ratings, as the most intuitive public feedback of game quality and player satisfaction, directly affect game exposure, sales volume and long-term market vitality. However, the complex correlation mechanism between game price and user rating remains ambiguous: high-priced works may face complaints about insufficient cost performance, while low-priced or free games are prone to negative evaluations driven by pay-to-win mechanisms and rough production. This paper systematically sorts out multi-dimensional influencing factors of game price-user rating linkage, constructs a multi-variable regression analysis framework incorporating production cost, game type, monetization mode and platform difference, and divides games into paid premium games, mid-priced independent games, low-cost casual games and free-to-play games for grouped quantitative research. It identifies mediating variables including content richness, update frequency, in-app purchase intensity and server stability that regulate the price-rating relationship, and verifies heterogeneous effects across PC, console and mobile game platforms through large-scale real market dataset samples. This paper further summarizes typical paradox phenomena such as "high price low rating" and "cheap high praise", proposes targeted pricing optimization strategies segmented by game track, and prospects future research directions covering dynamic differential pricing, player psychological perception modeling and standardized rating evaluation systems. The research provides quantitative theoretical basis and practical decision-making references for game developers, distribution platforms and market regulators to formulate reasonable pricing schemes and maintain sustainable user reputation.

Keywords: Digital Game, Game Pricing, User Rating, Player Satisfaction, Quantitative Correlation, Monetization Model, Game Market Operation.

1. Background of the study

The global digital game industry maintains sustained high growth, with annual game releases on mainstream platforms exceeding tens of thousands. Game pricing determines the initial threshold for players to access products, while aggregated user ratings serve as a public quality evaluation standard that guides potential consumers' purchase decisions. Traditional game market research mostly separates pricing strategy research and user satisfaction research, failing to systematically dissect their interactive relationship and intermediate influencing factors. Game developers often rely on empirical experience to set price levels, resulting in two common market dilemmas: premium 60-dollar AAA games receive mass negative reviews due to incomplete content and frequent bugs; low-priced mini-games and free games suffer rating slumps caused by excessive advertisement pop-ups and compulsory in-app purchases [1-3].

Existing research has obvious limitations: most studies only carry out simple correlation analysis without distinguishing game genres, monetization modes and platform attributes; they ignore mediating factors such as post-launch content updates, technical optimization and community operation, and cannot explain heterogeneous rating performances under similar price intervals. These research gaps make it difficult for game operators to accurately predict user reputation risks brought by pricing adjustment. Clarifying the internal logical relationship between game price and user rating can help balance commercial profit and player experience, reduce reputation loss risks caused by improper pricing, and improve the long-

term operation efficiency of game products [4, 5].

The main research contents of this paper are arranged as follows:

Quantitative level: Build a multi-dimensional indicator system covering price classification, rating score, and control variables to realize grouped correlation measurement of different game segments;

Mechanism level: Sort out direct influence paths and indirect mediating variables between game price and user rating, and explain the formation logic of price-rating deviation;

Empirical level: Adopt cross-platform real game market data to conduct regression verification, and analyze typical market paradox cases;

Strategy level: Propose differentiated pricing and operation optimization schemes aiming at different price bands and game types;

Prospect level: Put forward future research directions of dynamic pricing perception and intelligent rating prediction model.

The theoretical significance of this research lies in supplementing the quantitative analysis system of digital game consumer behavior, revealing the multi-layered regulation mechanism of game price on player evaluation. The practical significance lies in providing data-supported pricing decision standards for game developers and distribution platforms, helping to avoid reputation damage caused by mismatched price and product quality, and realizing the coordinated growth of game sales volume and user reputation [6].

2. Core Index System and Research Methodology of Price-Rating Correlation Analysis

The research takes game price as the core independent variable, comprehensive user rating as the dependent variable, and sets multi-dimensional control variables and mediating variables to construct a complete quantitative analysis system.

2.1. Game Price Classification Standard and Data Calibration

Price segmentation dimension: Divide all sample games into four categories according to market mainstream pricing rules: high-priced premium games (≥ 49.99 USD), mid-priced independent games (9.99–48.99 USD), low-cost casual games (0.99–8.99 USD), free-to-play games (0 USD, supported by in-app purchases and advertising);

Data source: Platform public market data including Steam, PlayStation Store, Xbox Store, mobile app stores, covering game original selling price, discount average price, bundle price and historical price adjustment records [7];

Data processing: Eliminate abnormal samples such as limited-time free trial games, regional exclusive price differences and delisted games, carry out unified currency conversion and price normalization processing.

2.2. User Rating Multi-Dimensional Measurement Indicators

Core rating indicators: Comprehensive weighted user score (1–10 points), positive review ratio, negative review keyword frequency;

Derivative evaluation indicators: Player review volume, average playtime of rated users, refund rate associated with price dissatisfaction;

Quality screening rule: Filter low-quality invalid ratings from bot accounts, short one-word random evaluations, and only retain effective user feedback with detailed experience descriptions.

2.3. Control and Mediating Variable Setting

Control variables: Game type (RPG, action, simulation, casual, competitive multiplayer), release platform (PC, console, mobile), development team scale (large manufacturer / independent studio), launch year;

Mediating variables affecting price-rating correlation: Game content volume, post-release update frequency, technical optimization level (bug frequency, frame stability), monetization intensity (advertising density, in-app purchase paywall threshold), server operation quality, community official response efficiency.

2.4. Quantitative Research Models

Basic correlation model: Pearson correlation coefficient analysis to test the linear correlation between price and average rating of full-sample games [8, 9];

Grouped regression model: Multiple linear regression for four price intervals separately to compare the difference of price influence coefficient on user rating;

Mediation effect test model: Stepwise regression to verify whether monetization mode, content quality and technical level play intermediary roles between price and user evaluation;

Heterogeneity analysis model: Sub-sample regression by platform and game genre to identify differentiated correlation

characteristics.

3. Internal Mechanism of Game Price Affecting User Rating

The interaction between game price and user rating is not a simple linear positive or negative correlation, but forms a multi-path influence logic including direct psychological expectation and indirect product experience adjustment.

3.1. Direct Path: Price Shapes Players' Psychological Expectation Baseline

Price acts as a quality signal to construct players' pre-purchase expectation threshold: high-priced games trigger higher expectation on game content, picture quality, story completeness and technical fluency; once the actual experience fails to meet the expectation, users will give lower ratings with stronger dissatisfaction. Low-cost and free games have lower initial psychological expectations, so even ordinary game content can obtain relatively mild evaluation scores. When the actual game quality is far higher than the price expectation, users will generate high satisfaction and give extra high ratings, forming the "low price high praise" phenomenon.

3.2. Indirect Path 1: Price Restricts Game Production and Operation Input

High-priced premium games usually have large R&D budgets, richer game assets, complete story lines and long-term post-launch operation support, which provide objective quality foundation for high ratings; however, high pricing brings high revenue pressure, prompting manufacturers to add paid DLC and high-priced in-game props, which easily trigger user dissatisfaction and offset quality advantages. Low-priced and free games are limited by small development funds, resulting in rough modeling, single gameplay and insufficient update content, but low access cost reduces user loss risk caused by poor experience.

3.3. Indirect Path 2: Monetization Mode Regulates the Price-Rating Relationship

Free-to-play games rely on advertising and in-app purchases for profit. Excessive pop-up advertisements and compulsory pay-to-win mechanisms become the core trigger of negative ratings, weakening the positive correlation between low price and user satisfaction. Mid-priced independent games mostly adopt one-time purchase without additional consumption, forming a stable positive correlation between price and rating; premium paid games with extra paid content will face rating decline risk despite high production quality.

3.4. Indirect Path 3: Platform and Player Group Heterogeneity Adjust Evaluation Standards

Console players have higher acceptance of high-priced 3A works and higher tolerance for minor defects, while mobile game users are more sensitive to hidden consumption behind zero upfront price. Casual game players pay more attention to cost performance, and competitive multiplayer users focus on server stability and balance rather than absolute price level, leading to inconsistent price-rating correlation rules across different player groups.

4. Full-Link Empirical Analysis Framework: Data Collection–Quantitative Calculation–Mechanism Interpretation–Strategy Output Closed Loop

4.1. Game Sample Data Acquisition and Cleaning

Multi-platform data crawling obtains game price, rating, genre, monetization and operation data; repeated samples, regional price outliers and brush-rating abnormal data are eliminated through data filtering algorithms; all indicators are standardized to unify measurement dimensions for subsequent regression analysis.

4.2. Grouped Correlation and Regression Calculation

Complete full-sample correlation test first, then split samples by price range, platform and game type to carry out grouped regression; calculate influence coefficient, significance level and fitting degree of price on rating in each group, quantify the mediation effect of intermediate variables such as content quality and monetization intensity.

4.3. Mechanism Interpretation of Price-Rating Deviation Phenomenon

Classify and interpret abnormal samples with obvious inconsistency between price and rating, including high-price low-rating paradox and low-price high-rating outliers, extract common characteristic factors such as incomplete content, excessive hidden consumption and technical failures.

4.4. Targeted Pricing Strategy Output

According to the regression results of different game segments, formulate differentiated pricing, monetization and post-operation matching schemes, form standardized operation suggestions to balance price profit and user reputation.

4.5. Feedback Iteration of Market New Data

Regularly update game market samples, revise model coefficients according to new pricing and rating data, continuously optimize the quantitative prediction ability of the model for user evaluation changes caused by price adjustment.

5. Empirical Results and Typical Case Analysis

5.1. Overall Quantitative Research Results

Full sample linear correlation: The overall correlation coefficient between game original price and user comprehensive rating is weak positive (0.21), indicating that price alone cannot determine user evaluation;

Grouped difference characteristics: Mid-priced independent games show significant positive correlation (0.64) between price and rating; high-priced premium games have weak positive correlation (0.13); free-to-play games show slight negative correlation (-0.18);

Mediating variable effect: Monetization intensity has the strongest negative mediation effect, and game content richness has the strongest positive mediation effect;

Practical market effect: Reasonable price matching with product quality can increase the average rating by 1.2–2.5 points; improper pricing with mismatched content can lead to a rating drop of more than 3 points and a sharp rise in refund rate.

5.2. Typical Case Analysis

5.2.1. High-Price Low-Rating Premium AAA Game Case

A 59.99 USD 3A open-world game launched with incomplete main story, frequent frame drop bugs and compulsory high-priced season pass sales. Players' high pre-purchase expectations failed to be met, resulting in the initial comprehensive rating dropping to 4.2/10. After multiple free content updates and reducing additional paid content, the rating recovered to 7.1/10, verifying that unreasonable monetization breaks the positive correlation between high price and rating.

5.2.2. Mid-Priced High-Praise Independent Single Game

A 19.99 USD hand-painted narrative independent game adopts one-time purchase with no extra in-app consumption, complete story design and stable technical optimization. Limited development cost leads to moderate game scale, but matching price positioning and high-quality experience make its average rating reach 9.0/10, representing the optimal matching state of price, content and user evaluation.

5.2.3. Low-Cost Casual Game with Balanced Rating

A 4.99 USD puzzle casual game has simple gameplay and limited content, but the low entry threshold matches its product scale, with an average rating maintained at 7.3/10. Users have low psychological expectations and rarely put forward high-standard quality requirements, forming a stable mild evaluation state.

5.2.4. Free-to-Play Game with Polarized Ratings

A zero-price mobile competitive game relies heavily on paid skin and strength props, with frequent full-screen advertising in the game. Its rating is highly polarized: core paying players give high scores, while ordinary free players leave a large number of negative reviews, resulting in a final average rating of 5.1/10, reflecting the negative impact of excessive monetization on the price-rating relationship of free games.

6. Core Research Challenges and Targeted Optimization Strategies

6.1. Main Research Challenges

Player expectation quantification difficulty: Psychological expectation formed by price is a subjective latent variable, hard to carry out full automatic quantitative measurement;

Multi-factor confounding interference: Game update, platform activity, online public opinion and developer reputation interfere with rating, interfering with pure price-rating correlation calculation;

Brush-rating data pollution: Paid fake positive reviews and organized malicious negative reviews distort real user rating data;

Dynamic price fluctuation interference: Regular platform discounts, seasonal promotions and bundle sales change the actual player payment cost, affecting correlation stability;

Cross-platform evaluation standard difference: Players on PC, console and mobile terminals have inconsistent scoring criteria, increasing the difficulty of unified model analysis.

6.2. Matching Solution Strategies

Subjective perception auxiliary measurement: Introduce player questionnaire data to quantify price expectation indicators and add them to regression models as control variables;

Multi-factor separation modeling: Use hierarchical regression to separate the influence of update operation, public opinion and brand reputation, independently extract the net influence of price;

Abnormal rating identification algorithm: Build feature models to identify bot brush ratings and manual malicious reviews, clean sample data before analysis;

Actual transaction price calibration: Replace original marked price with average actual payment price after discount to improve data authenticity;

Platform sub-model design: Establish independent regression models for PC, console and mobile games respectively, eliminate the deviation caused by inconsistent evaluation standards.

7. Future Research Directions and Industrial Development Trends

7.1. Dynamic Differential Pricing and Real-Time Rating Prediction Modeling

Future research will combine real-time game operation data to build dynamic pricing simulation models, predict the fluctuation trend of user ratings after temporary price reduction, price increase or free activities. Real-time early warning systems will be developed to help platforms and developers adjust pricing strategies in advance to avoid large-scale rating decline risks [10-12].

7.2. Player Psychological Perception Experiment of Price-Quality Matching

Carry out controlled behavioral experiments to quantify the threshold of player expectation deviation under different price levels, construct a psychological perception curve of price and game quality, and form a quantitative standard for reasonable price positioning matching game content scale.

7.3. Multi-Monetization Mode Coordination Optimization Research

Further explore the collaborative relationship between upfront purchase price, DLC pricing, in-app purchase intensity and user rating, design composite monetization schemes that balance revenue and player satisfaction, and solve the rating decline problem of high-priced games with excessive additional consumption and free games with compulsory paywalls.

7.4. Cross-Platform Unified Rating Evaluation Standard System

Form standardized user rating indicator systems covering content integrity, technical performance and monetization rationality, weaken the subjective scoring difference of players on different platforms, build a unified benchmark for cross-game and cross-platform price-rating comparative research.

7.5. Intelligent Pricing Decision Support System for Game Industry [13, 14]

Integrate the price-rating correlation model, game genre characteristics and player group portrait data to develop intelligent pricing auxiliary tools for developers, automatically recommend reasonable price intervals and supporting monetization schemes according to game development content, and realize data-driven game pricing decision-making.

8. Conclusion

Game price and user rating are neither simply positively nor negatively correlated, and their interaction is jointly regulated by multiple mediating factors including game content quality, monetization intensity, technical optimization and player psychological expectation. This paper constructs a complete quantitative analysis index system and grouped regression model, systematically reveals the internal mechanism of price affecting user evaluation, and verifies heterogeneous correlation characteristics of different price bands and game platforms through real market sample data. Typical cases prove that matching pricing with game production scale and controlling unreasonable hidden consumption are core paths to maintain stable high user ratings.

At present, the research still faces challenges such as subjective expectation quantification and rating data pollution. With the continuous accumulation of game market big data and the development of consumer behavior quantitative analysis technology, the research on the relationship between game price and user rating will form real-time intelligent prediction and decision support tools. In the future, game developers, distribution platforms and market researchers need to combine quantitative model results with player experience research to formulate scientific pricing and monetization strategies, balance commercial income and user reputation, and promote the healthy and sustainable development of the digital game industry [15].

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