Using Generative AI to Uncover What Drives Player Enjoyment in PC and VR Games

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Abstract. As video games continue to evolve, understanding what drives player enjoyment remains a key challenge. Player reviews provide valuable insights, but their unstructured nature makes large-scale analysis difficult. This study applies generative AI and machine learning, leveraging Microsoft Phi-4 LLM and XGBoost, to quantify and analyze game reviews from Steam and Meta Quest stores. The approach converts qualitative feedback into structured data, enabling comprehensive evaluation of key game design elements, monetization models, and platform-specific trends. The findings reveal distinct patterns in player preferences across PC and VR games, highlighting factors that contribute to higher player satisfaction. By integrating Google Cloud for large-scale data storage and processing, this study establishes a scalable framework for game review analysis. The study's insights offer actionable guidance for game developers, helping optimize game mechanics, pricing strategies, and player engagement.

Keywords: Generative AI; Textual Data Quantification; Phi-4 LLM; Game Review Analysis

1 Introduction

The global video game market size is projected to grow from USD 248.52 billion in 2023 to USD 664.96 billion by 2033, according to GlobeNewswire, registering a CAGR of 10.32% [1]. This indicates that the video game industry is not only expanding rapidly but also has a substantial impact on the global economy.

As the video game industry continues its rapid expansion, game reviews become essential as they assess the enjoyment factor in games, which is the core element that keeps players engaged. Reviews help identify both the strengths and weaknesses of a game, providing valuable feedback for developers and players alike. They also play a crucial role in determining a game's success or failure, influencing players' decisions on whether to invest their time and money in a particular title. Additionally, reviews serve as a tool for understanding what makes a game enjoyable while highlighting areas for potential improvement [2], [3]. However, gamers can be a difficult group to satisfy, with many holding high expectations regarding game quality[4].

Existing research primarily focused on analyzing player feedback through textmining and natural language processing (NLP) techniques only[5], [6], [7]. For example, techniques such as Latent Dirichlet Allocation (LDA), a topic modeling method, and TextBlob, an NLP library, were used to extract valuable insights from player reviews regarding their preferences, challenges, and experiences across various video games[8], [9]. While these techniques are powerful tools for large-scale analysis, they often struggle to capture the more nuanced aspects of player feedback, such as emotional complexity, sarcasm, or cultural context, thereby limiting the depth of the insights generated. As a result, they may fail to accurately interpret emotions of enjoyment toward a particular game or contextual descriptions related to specific game design elements [10], [11].

This study aims to lay the foundation for a deeper understanding of the factors that contribute to player enjoyment in video games across both PC and VR platforms, as well as various genres. By leveraging generative AI techniques—such as automated text summarization, sentiment analysis, and topic modeling—an empirical analysis will be conducted of player reviews from Steam and Meta stores. This approach enables the identification of key elements like gameplay mechanics, story and characters, level design, and monetization strategies that correlate with positive player experiences. The insights gained from this study can inform game developers and designers about what aspects resonate most with players, guiding the creation of more engaging and enjoyable games.

Additionally, it provides a data-driven basis for future research in game design, player psychology, and user experience, ultimately contributing to advancements in the gaming industry and academic studies related to interactive media. Based on the analyzed literature, the research questions are:

- RQ1: What are the key game design features that contribute most significantly to player enjoyment in PC versus VR games?
- RQ2: In what ways do monetization strategies affect player satisfaction in free-to-play versus non-free-to-play games?
- RQ3: What differences exist in player enjoyment between PC and VR game genres?
- RQ4: How can generative AI techniques be employed to identify the primary factors influencing positive player reviews across different game genres and platforms?

Given the rapidly evolving nature of the gaming industry, this study focuses on games released between 2020 and 2024, a period marked by significant shifts in player behavior following the COVID-19 pandemic. While this temporal scope allows us to capture emerging trends, it may not fully represent longer-term patterns in gaming preferences. Moreover, user-generated reviews, while rich in insights, introduce challenges such as review bombing, where mass negative reviews may distort sentiment analysis and misrepresent player satisfaction [7]. Finally, while generative AI techniques facilitate large-scale text analysis, they may struggle with linguistic nuances like sarcasm and humor, potentially impacting sentiment classification accuracy [12].

In the following sections, we begin with the Literature Review, which explores

the application of generative AI and machine learning techniques in video game review analysis, as well as studies on player satisfaction and monetization strategies. Next, the Methodology section details the data collection process, including scraping player reviews from the Steam and Meta Quest stores, and utilizing generative AI for text analysis and feature extraction. This section outlines the step-by-step approach for transforming player reviews into numerical data suitable for machine learning models.

The Analysis section examines the dataset through statistical aggregation, feature engineering, and machine learning, identifying key patterns and relationships influencing player satisfaction. Finally, the Discussions and Conclusions section interprets these findings, evaluates their significance and implications, and acknowledges limitations. It also outlines potential areas for further research and discusses how these insights can inform game developers and contribute to advancements in game design and player experience.

2 Literature Review

2.1 Popular Video Games Platforms

Valve is a major player, primarily through its Steam platform, which is the largest digital distribution platform for PC games. Steam supports a wide variety of video games, and its compatibility with multiple HMDs makes it a significant player in the PCVR space[8].

It is important to note that, unlike Meta's store, Steam does not use a numerical rating system for game reviews. Instead, players can rate a game as either "Recommended" (positive review) or "Not Recommended" (negative review). In contrast, Meta employs a numerical rating system ranging from 0 to 5, where 0 indicates not recommended at all, while 5 signifies highly recommended. These reviews also include a textual component where players share their personal experiences. While anyone can read these reviews, Valve Corporation provides an application programming interface (API) that enables the scraping of review data. This scraped data can then be analyzed using various methods to understand player experiences (Kang et al., 2017) or to evaluate the helpfulness of reviews.

The Meta Store serves as the official virtual reality app store for Meta's head-mounted displays (HMDs). It can be accessed both within VR and in 2D on PCs and mobile devices. The platform comprises four subcategories: Quest, Rift, Go, and GearVR. As of July 2022, the store offers a total of 3,547 VR games. Meta boasts a significant user base of over 1,490,000, supported by three primary types of HMDs: phone-powered VR (e.g., GearVR), PC VR (e.g., Rift, Rift S), and all-in-one standalone devices (e.g., Quest, Quest 2, Quest 3, Quest 3s). Notably, the Meta Store is exclusive to Meta series HMDs and is not compatible with devices from other

manufacturers.[13]

Meta dominates the market with around 60% of VR headset distribution (Oculus Rift S, Meta Quest 2, Meta Quest 3) (Fig. 1). Thus, the Meta Quest Store is a reliable data source due to its exclusive focus on VR content. Unlike platforms such as Steam VR or PlayStation VR, which support both PC and VR games, the Meta Quest Store offers only VR-specific experiences[9].

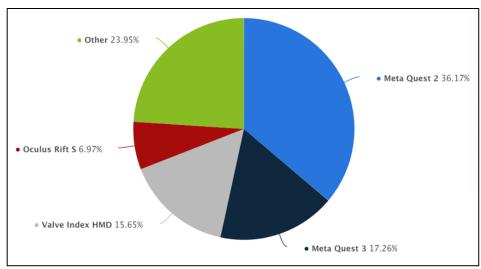


Fig. 1. Steam user's share of VR headsets by device[14].

2.2 Limitations of Existing Research

Several studies have analyzed reviews from different digital video game distribution platforms. Pagano and Maalej found that most reviews are submitted shortly after an application's release, with the frequency declining rapidly over time. They also noted that reviews often cover multiple topics such as feature requests, user experience, and bug reports [15]. Guzsvinecz focused on PC video game reviews using textual data from Steam. Lin and colleagues analyzed reviews of early access titles and specific top-level genres (TLGs) and genres[6], while Guzsvinecz examined the effects of playtime and game mechanics on reviews within the Souls-like subgenre[5].

While Viggiato and Bezemer in [16] leveraged large language models like OPT-175B and Yang Yu et al. in [17] employed Bidirectional Encoder Representations from Transformers (BERT) for sentiment analysis of game reviews, they overlooked several crucial elements that influence player satisfaction, such as gameplay mechanics, story development, level design, and the immersive qualities unique to VR games.

Another limitation is the genre-specific focus of some studies. For instance,

Guzsvinecz's focus on "Souls-like" games provided valuable insights into that particular genre like correlations between positive reviews, playtime, and game design features such as graphics and style but limited the applicability of the findings to other types of games[5].

Although monetization strategies are central to the gaming industry's economic model and heavily influence user satisfaction, only Dayi Lin et al. [6] addressed monetization strategies in their analysis of Steam game reviews. Their study merely noted that free-to-play video games tend to receive shorter reviews compared to non-free-to-play games in terms of text length. However, it did not explore the correlation between monetization and player enjoyment.

The focus on analyzing English-language reviews in several studies, including [4], [6], [10], and [17], limits the generalizability of findings by excluding non-English-speaking players and diverse cultural perspectives. This introduces bias by focusing on Western markets, neglecting significant gaming regions such as Asia. Additionally, the linguistic nuances and sentiment expressions unique to non-English reviews are missed, potentially affecting the accuracy of sentiment analysis. As a result, these studies do not fully capture the global gaming community's feedback, limiting the breadth of insights into player experiences.

2.3 Summary

Table 1. Similar works comparison table

Journals	Uses Steam Reviews	Uses Meta Reviews	Uses Generative	Correlatio en with genres	Correlate with design elements	Correlate with monetization	al analysis	games	fNumber of reviews analyzed
JA1	Yes	No	No	Yes	No	No	No	NA	35,983,481
JA2	Yes	No	No	No	Yes	Yes	No	6,224	12,338,364
JA3	Yes	No	No	No	Yes	No	No	21	993,932
JA4	Yes	Yes	No	No	No	No	No	7,413	176,428
JA5	Yes	No	No	No	Yes	No	No	1	99,993
JA6	Yes	Yes	No	No	No	No	No	9	105,757
JA7	Yes	No	No	No	No	No	No	750	17,635
JA8	No	Yes	No	Yes	Yes	No	No	157	115,531
JA9	Yes	No	No	No	No	No	No	NA	614,403
JA10	Yes	No	Yes	No	No	No	Yes	6,224	12,383,364
JA11	Yes	No	Yes	Yes	Yes	No	No	4	1,600,00
Our	Yes	Yes	Yes	Yes	Yes	Yes	1-11	4,856	517,600
Study									

The comparative analysis in Table 1 further reinforces the gaps identified in previous research and underscores how our study advances the field. The references to the journals corresponding to Table 1 are: JA1:[4], JA2:[6], JA3:[5], JA4:[8], JA5:[10],

JA6:[18], JA7:[7], JA8:[9], JA9: [16], JA10:[11], JA11:[17]. All these studies were published between 2019-2024.

While multiple studies have analyzed Steam game reviews, few have combined this dataset with Meta game reviews, which offer a different perspective on player sentiment. Our study is among the few that integrate both sources, allowing for a more comprehensive analysis that bridges platform-specific biases.

Moreover, while prior studies have explored correlations between reviews and game genres, game mechanics, or monetization strategies, these aspects have largely been examined in isolation. The figure highlights that most existing research tends to focus on only one or two of these factors rather than considering them holistically. Our study addresses this limitation by simultaneously examining correlations with game genres, gameplay elements—including story, mechanics, and artistic aspects—and monetization models. This multifaceted approach provides a richer understanding of how various design and economic factors shape player sentiment.

Another important distinction is our study's adoption of generative AI, which remains largely unexplored in existing research. By leveraging generative AI, our study is able to conduct a more nuanced analysis of player feedback, moving beyond sentiment classification to uncover underlying trends and emergent themes in game reviews.

Additionally, Table 1underscores the significant variation in the number of games and reviews analyzed across studies. While some studies focus on only a handful of titles, others examine tens of thousands of reviews without necessarily offering detailed insights into game design factors. Our study strikes a balance by analyzing a substantial dataset of 4,856 games and 517,600 reviews, ensuring both depth and breadth in our findings.

Finally, the inclusion of multilingual reviews in our study marks a notable departure from prior research, which has predominantly focused on English-language data. As illustrated in Fig. 2, only a few studies have considered reviews in multiple languages. By addressing this gap, our study provides a more globally representative perspective on player experiences, capturing diverse linguistic and cultural contexts that are often overlooked.

In sum, the comparative findings from the literature review substantiate the need for a more integrative and expansive approach to game review analysis. By leveraging a diverse dataset, incorporating generative AI, and examining multiple interrelated factors, our study offers a more comprehensive and methodologically advanced contribution to the field.

3 Methodology

To answer the RQs, reviews of all video games on the Steam and Meta Quest stores from 2020-2024 were scrapped and analyzed. This section is divided into two parts: Subsection 3.1 outlines the scrapping process, Subsection 3.2 details the data processing. All analyses were conducted using Google Cloud[19]. Scrapping code and functions used in the analysis were sourced from Github[20], [21] and PyPi[22].

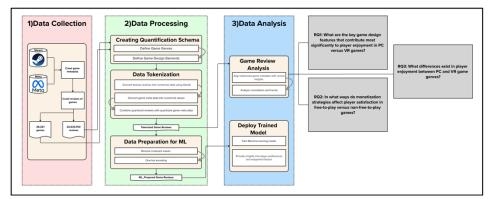


Fig. 2. The workflow of the study

3.1 Data Scraping

For Steam games, the process starts by loading previous datasets to avoid redundant requests. The script then retrieves a list of all games from Steam's API, using unique game IDs (AppIDs) as references. For each game, it checks if the game has already been processed or if it remains unreleased, in which case it is skipped. If a game is new and relevant, a request to the Steam API retrieves details shown in Fig. 3 like the game's name, release date, genres, and price.

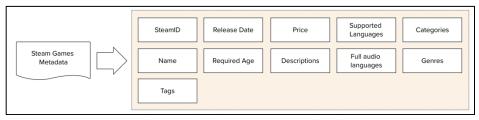


Fig. 3. The source (raw) Steam games metadata dataset

Similarly, for VR games from the Meta store, the process starts by accessing

every game's unique url from VRDB, a comprehensive database for Meta Quest VR games on the Meta store[23]. The script makes HTTP requests to VRDB's website to retrieve pages of game listings, utilizing pagination to scrape multiple pages efficiently. Once fetched, the HTML content is parsed using BeautifulSoup to locate embedded JavaScript data containing game details. Using regular expressions, key attributes such as game ID, name, and genres are extracted, while additional details like release date, ratings, and price are captured, as can be seen in Fig. 4 below.

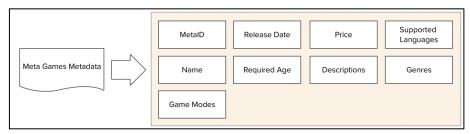


Fig. 4. The source (raw) Meta games metadata dataset

To ensure accuracy, the script filters out games with release dates of 2019 or earlier, gathering only data for games that meet the specified date criteria. The extracted information is then saved to a json file, with regular autosaves to prevent data loss. Unreleased games or those with insufficient data are logged separately to streamline future runs.

By focusing on games with release dates starting from 2020, the scraper maintains a targeted dataset, storing only high-priority information and minimizing unnecessary API calls. The script's systematic approach ensures efficient, relevant data collection while maintaining data integrity and completeness.

Once all games are scraped, the review scraping script is executed to collect reviews for each game. The process begins by loading each game's ID and details from the raw games metadata file. It then verifies whether each game has a minimum of 25 reviews to process, ensuring that games with a low number of reviews are excluded to avoid potential biases. If the criterion is met, the script retrieves reviews in all available languages. This approach ensures the creation of a culturally diverse and generalized dataset, mitigating biases towards any specific culture or demographic. For each game with sufficient reviews, a CSV file is generated. These files are named according to the game ID and the total number of reviews scraped, enabling the incremental storage of all collected reviews. Reviews are written in order of rating, with the highest-rated review appearing in the first row. The Python process stops collecting reviews for a game once all reviews are gathered or the specified total review count is reached. This batch-oriented design facilitates efficient and organized data collection across multiple games and languages.

Table 2. Descriptive summary of Steam games reviews dataset

```
*Total number of Steam games: 23,107
*Total sum of game reviews: 31,832,390
*Top 10 Games with the Highest Reviews:
          Reviews
Game ID
553850
              336,460
              313,125
990080
              293,388
 261550
              253,629
 1468810
              224,207
              201,079
 526870
              194.630
              186,800
 427520
              180,898
```

Table 3. Descriptive summary of Meta games reviews dataset

```
-----*Total number of Steam games: 3,210
*Total sum of game reviews: 701,360
*Top 10 Games with the Highest Reviews:
| Game ID
                     Reviews
7190422614401072
                       9,731 |
 4416817901687071
                       9,705
 3947713001963656
                       9,692 |
 7276525889052788
                       9,650
3661420607275144
                       9,646
 2370815932930055
                       9,470
                       9,465
 4979055762136823
                       9,188
 4215734068529064
 2031826350263349
                       9,115
```

Table 2 and Table 3 present the output of a custom Python script that processed individual CSV files to generate a descriptive summary. Of 65,686 Steam games, reviews were collected for 23,107 that met the minimum criterion of at least 25 reviews, totaling 31,832,390 reviews. Similarly, of 9,336 VR games on Meta, reviews were collected for 3,210, totaling 701,360 reviews. The resulting dataset is openly accessible at Mendeley Data (https://doi.org/10.17632/jxy85cr3th.2) [24].

3.2 Data Processing

3.2.1. Data Quantification Schema

The tokenization schema created for processing game and review data ensures systematic analysis by leveraging industry standards and insights from reputable sources. Age ranges are classified using the PEGI (Pan-European Game Information) rating system [25], while price ranges are based on VGinsights Steam Analytics [26], as shown in Fig. 5. These price ranges are divided into five categories:

- 0.01-4.99 (below the ± 5 range for indie games).
- \$5–\$14.99 (within the \pm \$5 range for indie games).
- \$15-\$24.99 (within the $\pm 5 range for AA games).
- \$25-\$39.99 (within the \pm \$5 range for AAA games).
- \$40+ (above the \pm \$5 range for Premium AAA games).

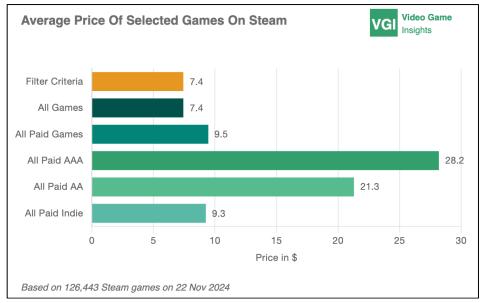


Fig. 5. Average price of selected games on Steam [26]

Also, game genres are classified based on [4], [27], [28], and include Action, Adventure, Casual, Puzzle, RPG, Racing, Simulation, Sports, Strategy, Fighting, Horror, Battle Royale, Shooter, Survival, Music, Education, Entertainment, Meditation, and Exercise. As shown in Table 4, these genres ensure comprehensive coverage of both PC and VR games. The 'Value' column in Table 4 represents the presence of a given genre in a game, where 0 indicates its absence and 1 signifies its inclusion. This classification allows for a structured analysis of game genres by the

Generative AI model.

Table 4. Game genres tokenization schema

Game Genre	Value	Description
Action	0-1	Fast-paced gameplay focused on combat and movement.
Adventure	0-1	Exploration and storytelling with player-driven narratives.
Casual	0-1	Simple, easy-to-learn gameplay often for short sessions.
Puzzle	0-1	Problem-solving challenges requiring logic and strategy.
Role-Playing	0-1	Character progression through quests and narrative-driven gameplay.
Racing	0-1	Competitive gameplay involving speed and vehicles.
Simulation	0-1	Realistic emulation of real-world activities or systems.
Sports	0-1	Competitive games based on physical sports.
Strategy	0-1	Planning and tactical decision-making gameplay.
Fighting	0-1	One-on-one or group combat with specific skill sets or techniques.
Horror	0-1	Games designed to evoke fear and suspense.
Battle Royale	0-1	Multiplayer survival games with a shrinking play area.
Shooter	0-1	Gameplay focused on firearms or ranged combat mechanics.
Survival	0-1	Resource management and survival in challenging environments.
Music	0-1	Games focused on rhythm and music interaction.
Education	0-1	Games designed to teach or reinforce learning objectives.
Entertainment	0-1	Games designed primarily for relaxation and fun without specific goals.

Furthermore, the schema incorporates critical game design elements derived from [29], [30], [31], covering gameplay, graphics, difficulty, story, audio, avatar customization, controls, monetization models, replayability, community, multiplayer features, and spatial presence.

Table 5. Game Design elements tokenization schema

Design Element	Value	Description
Gameplay	1-5	Score of how good the core mechanics and interactive experience of the game are?
Graphics	1-5	How good is the visual presentation and design quality?
Difficulty	1-5	Score of how good the balance and challenge is offered to players?
Story	1-5	Score of how good the narrative depth and engagement is?
Audio	1-5	Score of how good the sound effects, music, and overall auditory design are?
Avatar	1-5	Score of how good the representation and customization of the player's character is?
Controls	1-5	Score of how good the usability and responsiveness of input methods is?
Monetization Model	1-5	Score of how good the strategies are used for game revenue, such as in-app purchases?
Replayability	1-5	Score of how good the potential for repeated play sessions is?
Community	1-5	Score of how good the interaction and engagement with other players is?
Multiplayer	1-5	Score of how good the features are supporting cooperative or competitive play?

1-5

As shown in Table 5, these design elements are essential in assessing the overall quality of a game, as they influence player engagement, immersion, and satisfaction. Each game review is scored on a 1-5 scale against these design elements, allowing for a structured evaluation of gameplay mechanics, difficulty, graphics, audio, and spatial presence, which contribute to the overall experience. Storytelling enhances emotional investment, while customization options enable greater player expression. Additionally, monetization models, multiplayer features, and community engagement shape long-term retention and player perception. By evaluating these aspects, the schema provides a comprehensive framework for understanding how good or bad a game is.

Building on the framework established by Lin D et al. [6], we further identified distinct categories to classify each review effectively, as shown in Table 6. These attributes allow for a structured analysis of review content, capturing aspects such as helpfulness, sentiment, suggestions, and technical issues. Additionally, we introduced the Recommended and Review Language attributes to enhance the classification schema. The Recommended attribute provides insight into the overall sentiment of the reviewer, indicating whether they endorse the game. Meanwhile, Review Language was added to account for linguistic diversity in user feedback, ensuring a more comprehensive understanding of reviews across different regions and player demographics.

The 'Value' column in Table 6 represents whether a specific review characteristic is present, with 0 indicating its absence and 1 signifying its inclusion. For Review Language, values range from 1 to 11, denoting different languages to facilitate multilingual analysis. By incorporating these elements, the schema enables a more nuanced evaluation of player reviews, supporting deeper insights into user experiences and preferences.

The language categories were determined based on the top 10 most spoken languages on Steam, as identified in Steam's October 2024 Monthly Survey Fig. 6. These include Simplified Chinese, English, Russian, Spanish, Portuguese, German, Japanese, French, Polish, and Turkish. Additionally, a separate category, "Other," was included to account for reviews written in languages outside of this list, ensuring comprehensive language classification within the schema.

Table 6. Review attributes tokenization schema

Field Name	Value	Description
Recommended	0-1	Whether the reviewer recommends the game (1) or not (0)
Is_Helpful	0-1	Whether the content of the review is helpful to the developer (1) or not (0)
Is_Pro	0-1	Whether the review highlights a positive aspect of the game (1) or not (0)
Is_Con	0-1	Whether the review identifies a negative aspect of the game (1) or not (0)
Is_Video	0-1	Whether the review includes a URL to a video review (1) or not (0)
Is_Suggestion	0-1	Whether the review includes a suggestion on improving the game (1) or not (0)
Is_Bug	0-1	Whether the review describes a bug that occurs in the game (1) or not (0)
Review_Language	1-11	1 = Chinese, 2 = English, 3 = Russian, 4 = Spanish, 5 = Portuguese, 6 =
		German, 7 = Japanese, 8 = French, 9 = Polish, 10 = Turkish, 11= Others

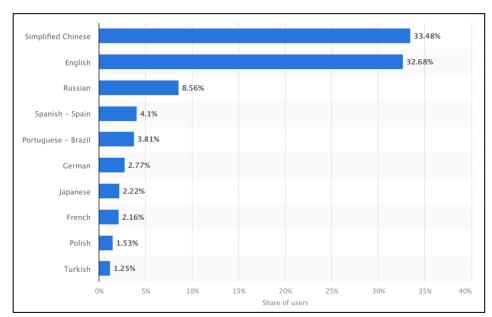


Fig. 6. Steam's most common languages[32]

3.2.2. Quantifying Game Metadata

This process involves converting raw game metadata into structured categorical and numerical features. The goal is to create a uniform dataset where each game is represented by a set of predefined attributes.

For both Meta and Steam stores, the same schema is applied for feature extraction and tokenization. This ensures that game data from different platforms is processed in a unified manner, facilitating cross-platform analysis.

As shown in Table 7 and Table 8, categorical mapping is applied to games using a set of predefined categories, each associated with relevant keywords. These keywords

are extracted directly from the raw scraped games files, where they appear under the respective key names listed in the 'Derived From' column. For example, on Steam the Action category includes terms like Action RPG, Action Roguelike, Beat 'em up, and Hack and Slash, which are found in the 'Genre' or 'Tag Mapping' fields in the games file[33].

 Table 7. Categorical mapping for Steam games

Category	Key words	Derived From
Action	Action, Action RPG, Action Roguelike, Action-Adventure, Beat 'em up, Character Action Game, Combat, FPS, Fighting, Hack and Slash, Shooter, Swordplay, Twin Stick Shooter	
Adventure	Action-Adventure, Adventure, Atmospheric, Exploration, Fantasy, Open World, Puzzle, Story Rich, Visual Novel	Genre, Tag Mapping
Battle_Royale	Battle Royale, FPS, Multiplayer, PvP, Shooter, Survival	Genre, Tag Mapping
Casual	2D, Casual, Cute, Family Friendly, Free to Play, Indie, Puzzle, Relaxing, Simulation	Genre, Tag Mapping
Education	Education, Game Development, Programming, Software Training, Trivia, Web Publishing	Genre, Tag Mapping
Entertainment	Entertainment, Feature Film, Movie, Streaming, TV, Video Production	onGenre, Tag Mapping
Fighting	2D Fighter, 3D Fighter, Beat 'em up, Boxing, Competitive, Fighting, Martial Arts, Wrestling	Genre, Tag Mapping
Free_To_Play	Free to Play	Category Flag, Tag Mapping
Horror	Dark, Gore, Gothic, Horror, Lovecraftian, Psychological Horror, Survival Horror, Thriller, Vampires, Zombies	Genre, Tag Mapping
Is_3D	3D	Tag Mapping
Is_Coop	Co-op, Online Co-op	Category Flag
Is_Early_Access	Early Access	Category Flag
Is_Indie	Indie	Category Flag
Is_Multiplayer	MMO, Multi-player, Multiplayer, Online PvP, PvP	Category Flag
Is_Singleplayer	Single-player	Category Flag
Is_Steam	Steam Achievements	Category Flag
Is_VR	VR Only, VR Support, VR Supported	Category Flag
Music	8-bit Music, Electronic Music, Instrumental Music, Music, Music- Based Procedural Generation, Rhythm, Rock Music, Soundtrack	Genre, Tag Mapping
Puzzle	Card Game, Hidden Object, Logic, Match 3, Puzzle, Puzzle Platformer, Sokoban, Sudoku, Time Manipulation, Word Game	Genre, Tag Mapping
Racing	ATV, BMX, Combat Racing, Cycling, Driving, Motorbike, Offroad, Racing, Vehicular Combat	Genre, Tag Mapping
Role_Playing_Gar	m Action RPG, CRPG, Dungeon Crawler, JRPG, Party-Based RPG, RPG, Roguelike, Roguelite, Strategy RPG, Turn-Based RPG	Genre, Tag Mapping
Shooter	Arena Shooter, FPS, Gun Customization, Hero Shooter, Looter Shooter, On-Rails Shooter, Shooter, Tactical Shooter, Third-Person	Genre, Tag Mapping

	Shooter, Twin Stick Shooter
Simulation	City Builder, Colony Sim, Farming Sim, Immersive Sim, Genre, Tag Mapping
	Management, Medical Sim, Simulation, Space Sim, Trading, Train
	Sim, Transportation
Sports	Baseball, Basketball, Boxing, Football (American), Football (Soccer), Genre, Tag Mapping
	Golf, Hockey, Motocross, Pool, Racing, Rugby, Skateboarding,
	Sports, Tennis, Volleyball
Strategy	4X, Card Battler, Chess, Deckbuilding, Grand Strategy, RTS, Real Genre, Tag Mapping
	Time Tactics, Strategy, Strategy RPG, Tactical RPG, Tower Defense,
	Turn-Based Strategy, Turn-Based Tactics
Survival	Base Building, Crafting, Open World Survival Craft, Resource Genre, Tag Mapping
	Management, Roguelike, Roguelite, Survival, Survival Horror

 Table 8. Categorical mapping for Meta games

Category	Key words	Derived From
Action Adventure Battle_Royale	Action, Arcade, Fighting, Party Game, Platformer, Shooter Adventure, Narrative, Sandbox, World Creation NA	Genre Genre NA
Casual	Hangout, Party Game, Platformer, Puzzle, Tabletop	Genre
Education	Learning	Genre
Entertainment	NA	NA
Fighting	Fighting	Genre
Free_To_Play	NA	Price
Horror	Survival	Genre
Is_3D	NA	NA
Is_Coop	Co-op	Game Mode
Is_Early_Access	NA	NA
Is_Indie	NA	NA
Is_Multiplayer	Multiplayer	Game Mode
Is_Singleplayer	Einzelspieler, Single User	Game Mode
Is_Steam	NA	NA
Is_VR	NA	NA
Music	Rhythm	Genre
Puzzle	Puzzle, Tabletop	Genre
Racing	Racing	Genre
Role_Playing_Gare	mRole Playing	Genre
Shooter	Shooter	Genre
Simulation	Sandbox, Simulation, World Creation	Genre

Sports	Sports	Genre
Strategy	Strategy, Tabletop	Genre
Survival	Sandbox, Survival, World Creation	Genre

As noted in Table 8, some categories are not explicitly defined. This is because Meta does not provide specific labels for these categories. However, despite the absence of direct categorization, certain attributes can still be inferred from the raw game metadata.

For example, the 'Free_to_Play' category is determined based on the price value found in the raw game file. If the price is 0, the 'Free_to_Play' value is set to 1; otherwise, it is assigned 0. Similarly, since these games are sourced from the Meta store, the 'Is_Steam' attribute is set to 0 by default, as they are not from Steam's store. On the other hand, the 'Is_VR' attribute is automatically set to 1, as all VR games are inherently 3D.

The final output of this process is a CSV file in which each row represents a single quantified game.

3.2.3. Quantifying Game Reviews

The quantification approach of game reviews converts unstructured text reviews into standardized, machine-readable formats for analyzing user-generated content. Using the Microsoft Phi-4 Large Language Model (LLM), it tokenizes qualitative data into interpretable metrics based on defined schemas for review attributes (e.g., "Language") and Game Design elements (e.g., "Gameplay"). Text-to-numerical conversion employs structured prompts and Python tools like Pydantic for validation. Preprocessing ensures data integrity, discarding invalid reviews while storing outputs in CSV format.

This scalable method supports real-time and multimodal data integration. A case study on the Steam game 'HELLDIVERS 2' demonstrates its effectiveness in extracting insights into review metrics and game design elements. To demonstrate and evaluate the proposed approach, we applied it to quantify a dataset of computer game reviews sourced from the Steam platform [33].

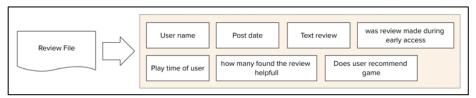


Fig. 7. The source (raw) game review dataset

Fig. 7, shows all the columns of the review dataset. Each review of a game is stored as a separate row.

To analyze the review data and apply statistical or machine learning techniques, it must first be quantified - converting text, numbers, into numerical formats. However, before implementing the proposed approach, it is essential to understand the target (quantified) dataset.



Fig. 8. Structure of the target quantified review dataset

Only the reviews datasets were quantified, as the main file containing all games did not require Generative AI quantification. Comparing the category columns in Fig. 7 and Fig. 8 reveals significant differences in rows, columns, and data values, adding complexity to the transformation process. The quantification approach employs Generative AI for transformation, while column extraction was done manually based on literature. Although Generative AI can suggest columns, adopting standard categories is generally preferable for comparability with other analyses.

The comprehensive schemas in Table 5 and Table 6 are processed using Microsoft's Phi-4 Large Language Model 14B params LLM [34] hosted locally to tokenize data systematically, providing a robust foundation for advanced machine learning analysis.

The LLM quantifies the fields outlined in these schemas, converting textual reviews into standardized, machine-readable numerical representations, assigning 0 to fields where insufficient data to evaluate. For instance, when the LLM processes a review such as "This game is amazing," it generates a structured JSON output as can be seen below (Table 9).

Table 9. Structured JSON output from Phi-4 LLM

```
"Is_Helpful": 0,
                         "Recommended": 1,
                                                       "Controls": 0,
"Is_Pro": 1,
                         "Gameplay": 0,
                                                       "Monetization_Model": 0,
"Is_Con": 0,
                         "Graphics": 0,
                                                       "Replayablity": 0,
"Is_Video": 0,
                         "Difficulty": 0,
                                                       "Community": 0,
"Is_Suggestion": 0,
                         "Story": 0,
                                                       "Multiplayer": 0,
"Is_Bug": 0,
                         "Audio": 0,
                                                       "Spatial_Presence": 0
"Language": 2,
                         "Avatar_Customization": 0,
```

To achieve this, we've created a custom Python script that leverages a well-structured data extraction pipeline to transform the raw, text-based Steam and Meta game reviews into a standardized numerical format. The script begins by defining both schemas highlighted in Table 5 and Table 6 through a Pydantic model[35], which ensures consistent encoding of each text review's attributes and game design elements.

Table 10. Gameplay and Graphics schema in a Pydantic model

Table 10 shows how fields like 'Gameplay' and 'Graphics' are represented in a Pydantic model. This data processing model imposes strict type and range constraints, preventing incomplete or misleading values from entering the dataset.

Next, the script employs the LLM-based prompt-and-response mechanism, using the locally hosted Microsoft Phi-4 Large Language Model, to convert each textual review into a JSON object conforming to the Pydantic schema.

Table 11. Prompt used to convert text reviews into numerical values in JSON format

```
Use the below schemas to convert any game text review into numerical values as per the schemas provided.
Do not output multiple JSON blocks or repeated keys.
No comments, no trailing commas, no extra text.
Adhere to the following rules strictly:
1-If a review contains only symbols (e.g., "****) or non-alphanumeric characters you should set all fields to 0 except for `Language`, which
should be set to 11 (Other).
2-Do not infer positivity, negativity, or other attributes from special characters or emojis. Treat such reviews as uninformative unless
meaningful words are present.
3-Ensure 'Recommended' is strictly 0 or 1.
4-All rating fields ('Gameplay', 'Graphics', etc.) must be integers between 0 and 5, in case you cant find sufficient data in the review that
satisfies a specific field you should set that field to 0. Never give a 1 to 5 rating for any field if you cant find sufficient data in the review that
supports it. NEVER MAKE UP DATA.
5-For binary fields (e.g., `Is_Helpful`, `Is_Pro`), ensure values are strictly 0 or 1.
6-If a game review includes numerical ratings (e.g., "gameplay is 7/10"), you should normalize these ratings to the required range of 1-5
where 0 represents insufficient data. Never use the ratings in the review directly without ensuring they abide to the schema. For example, a
review that states "story is 7/10" would equate to setting the value for the 'Story' field to 4/5.
  For example if text review is: "This game is amazing" your output would look like this:
"Is_Helpful": 0,"Is_Pro": 1,"Is_Con": 0,"Is_Video": 0,"Is_Suggestion": 0,"Is_Bug": 0,"Language": 2,"Recommended": 1,"Gameplay": 0,"Graphics":
0, "Difficulty": 0, "Story": 0, "Audio": 0, "Avatar\_Customization": 0, "Controls": 0, "Monetization\_Model": 0, "Replayablity": 0, "Community": 0, "Community": 0, "Controls": 0, "Monetization\_Model": 0, "Replayablity": 0, "Community": 0, "Controls": 0, "Controls": 0, "Monetization\_Model": 0, "Replayablity": 0, "Community": 0, "Controls": 0, "Contro
O."Multiplayer": O."Spatial Presence": 0
Actual review to be tokenized is: "(review)"
```

Table 11 highlights the prompt that outlines the rules for transforming natural language text into a strictly formatted JSON structure with integer fields only. LangChain converts the Pydantic schema we created earlier into instructions for the LLM to follow, ensuring the output can be parsed as JSON. These instructions are embedded into the prompt using a variable called {format_Instructions}. The script uses the {review} variable to append the prompt with each raw text review, creating a combined input that provides the model with both context and instruction. This combined input is then sent to the LangChain pipeline, where the LLM processes it and generates a structured JSON response.

The large language model (LLM) assigns scores to defined fields like gameplay, graphics, and difficulty by parsing each sentence or rating in the text reviews. It also classifies reviews by attributes such as language and recommendation status. The data-processing script sanitizes text by removing invalid characters or empty content, discarding unprocessable reviews into a separate "Discarded" CSV file for transparency. Valid reviews are submitted to the LLM, which generates structured JSON outputs aligned with predefined schemas. Successfully parsed reviews are stored with original IDs and numeric tokens in a new CSV file. The script logs discarded reviews and marks completed games to avoid redundancy. This workflow ensures the creation of a transparent, machine-readable dataset that preserves data integrity and captures qualitative insights from player reviews.

We quantified the 100 most-rated reviews from a total of 4,856 PC and VR games. Specifically, we analyzed the top 3,860 games with the highest number of ratings from the Steam store and 996 from the Meta store. By focusing on the most-rated reviews from games with the highest number of ratings, we aimed to ensure a representative analysis of player sentiment while minimizing biases that may arise

from less-reviewed or niche titles.

3.2.4. Evaluation

In order to evaluate the proposed approach, we analyzed the top-rated 1,000 text reviews from the game HELLDIVERS 2, which had the highest number of reviews among all the games scraped. The tokenization process highlighted earlier in the report transformed these reviews into structured numerical data. This tokenized dataset, stored in a .csv file, was uploaded to Google Looker Studio[36] to generate visualizations.

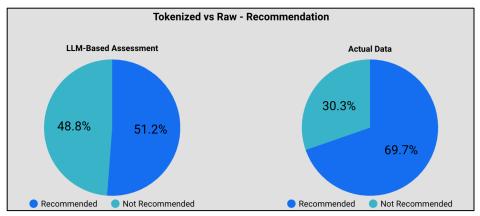


Fig. 9. Recommendation column in tokenized vs raw files for HELLDIVERS 2

Fig. 9 illustrates the proportion of recommended versus non-recommended reviews, as well as the alignment between the LLM-based tokenization assessments and the actual raw data. The discrepancy between the LLM-based assessment and the actual recommendation data from Steam can be attributed to the fact that LLM-based assessment determines whether a review is positive or negative based on text sentiment analysis, which involves evaluating word choice, tone, and context. However, on Steam, users explicitly click "Recommended" or "Not Recommended", which may not always align with the sentiment expressed in the text.

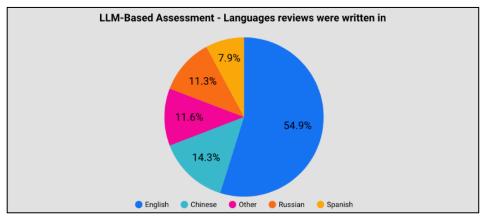


Fig. 10. Language distribution of HELLDIVERS 2 text reviews

Fig. 10. illustrates the Phi-4 model's attempt to label the languages of the top 1,000 highest-rated reviews. The results align with Gamalytic's statistics[37], which indicate that 40.2% of the player base originates from English-speaking countries, such as the United States and the United Kingdom, while 8.4% are from China.

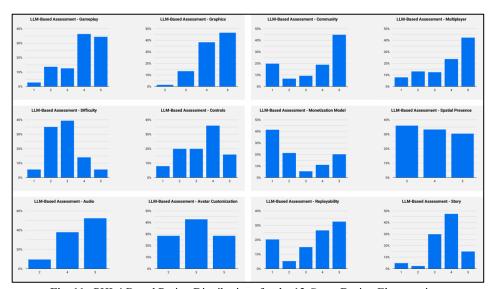


Fig. 11. PHI-4 Based Rating Distributions for the 12 Game Design Elements in HELLDIVERS 2

To evaluate the effectiveness and state of mind of PHI-4 in quantifying qualitative player feedback, we applied it to the dataset of 1,000 textual reviews from HELLDIVERS 2. As seen in the bar charts in Fig. 11, PHI-4 successfully scored and quantified the reviews based on the 12 key game design elements shown in Table 5,

demonstrating its ability to extract meaningful insights from unstructured text. The structured rating distributions suggest that the model is highly effective in translating subjective player experiences into a numerical assessment, offering a valuable tool for analyzing game design components.

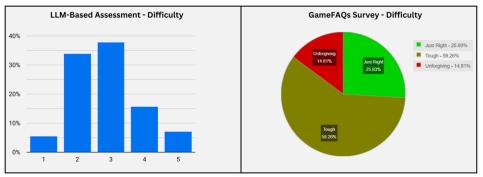


Fig. 12. Distribution of "Difficulty" Ratings in LLM-Based Assessment vs. GameFAQs Survey

For the "Difficulty" element in HELLDIVERS 2, the bar chart on the left in Fig. 12 reveals that most ratings are concentrated around scores 2 and 3. This indicates that players generally perceive the difficulty as mostly fixed and unfair, as outlined in the schema (Table 5).

Interestingly, this assessment corresponds closely with data from the GameFAQs survey[38] which surveyed 46 players in total when it comes to the difficulty of HELLDIVERS 2 and the result can be seen in the pie chart on the right in Fig. 12. Both the LLM's assessment and the statistic from GameFAQs underscore the game's challenging nature. The GameFAQs data highlights subjective player sentiments such as "Tough" or "Unforgiving," whereas PHI-4 focuses on structured evaluations of the difficulty design, including fairness and pacing. These perspectives are complementary, converging on the notion that the game is demanding and overly difficult. This underscores the validity of the model's evaluation, highlighting its alignment with player-reported perceptions of the game's difficulty.

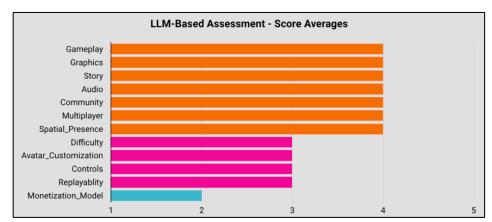


Fig. 13. Averages of tokenized scores across game design elements for HELLDIVERS 2

From Fig. 13, it's evident that core elements such as "Gameplay," "Graphics," and "Story" earn high ratings, while mid-range aspects like "Difficulty" and "Replayability" suggest room for improvement. "Monetization Model" ranks lowest, indicating that players are least satisfied with the current approach and view it as an area in need of enhancement. To provide an overall assessment of HELLDIVERS 2, an aggregate score of 3.5/5 was calculated by averaging the individual design element ratings shown in Fig. 13, aligning well with published ratings. Notably, this LLM-derived score does not conflict with the 6.6/10 overall user rating on Metacritic[39], highlighting a general consistency with user perceptions.

3.3 Data Preparation

Before conducting the analyses, we first prepared our quantified data. We began by combining the 4,856 individual quantified review files, each representing reviews for a single game, into a single dataset. The objective was to calculate the average rating for each game design element and store it as a single row per game in a CSV file named 'Tokenized_Reviews_Averages.csv'. Each review dataset contained 1-5 ratings for 12 game design elements:

- Gameplay
- Difficulty
- Graphics
- Story
- Audio
- Avatar Customization
- Controls
- Monetization Model
- Replayability

- Community
- Multiplayer
- Spatial Presence

The Python script iterated through all review CSVs, calculated average scores per game, and merged them into a single dataset. This dataset was later uploaded to BigQuery for further analysis.

Finally, all game data was structured and stored in Google Cloud Storage, a cloud-based data warehouse designed for efficient large-scale storage [40]. This step was necessary to ensure that the dataset could be processed seamlessly, allowing for structured exploration and comparative analysis across different game platforms. The data uploaded to Google Cloud Storage consisted of two key datasets: 'Tokenized Game Metadata.csv' and 'Tokenized Reviews Data.csv', both of which served as the foundation for all subsequent analytical steps.

The next step was to use Google BigQuery, a platform that allows large-scale data analysis and management [19], to write queries on our data and derive insights and visualizations. The first action taken was to merge both datasets into a single table in BigQuery, with the price attribute being transformed from a numerical value into a categorical attribute, as outlined in the Data Quantification Schema section (3.2.1). This transformation enabled more efficient querying and allowed for a unified analysis, facilitating the extraction of insights that consider both game metadata and review data in tandem.

3.4 Creating visuals in Google Looker

Once we had our dataset in Google BigQuery, we began running queries to visualize the data differently.

3.4.1. Correlation Between Positive Ratings and Game Design Elements

We created a query that calculates the correlation between price category and high rating percentages across different game design elements for both PC and VR games using the CORR() function in BigQuery.

First, the query converts Price_Category into numerical values (0 to 5), where 0 represents free-to-play games and 5 represents premium AAA games, enabling statistical correlation analysis. It then computes the percentage of high ratings (4+) across 12 game design elements (such as graphics, audio, gameplay, and replayability) and averages them to obtain a total high rating percentage for each game.

Using the CORR() function, the query determines the Pearson correlation coefficient between the encoded price category and the total high rating percentage, separately for VR games (Is VR = 1) and PC (non-VR) games (Is VR = 0). This

analysis provides insights into whether pricing influences overall game ratings differently in VR and PC gaming environments.

3.4.2. Comparing Player Satisfaction Across VR and PC Games

A BigQuery query was written to calculate the percentage of PC and VR games that receive high ratings (4+ on a 1-5 scale) across 12 game design elements, such as gameplay, graphics, audio, and multiplayer experience.

It first groups the dataset by Is_VR (where 1 represents VR games and 0 represents PC games) to analyze the difference in rating distributions between these two categories. For each design element, it computes the percentage of games with high ratings by dividing the count of games rated 4 or higher by the total number of games in that category. Additionally, the query calculates a total high rating percentage by averaging the high ratings across all 12 design elements, providing an overall metric for game quality in VR vs. PC games. This helps in identifying whether VR games tend to receive higher or lower ratings compared to non-VR games across different aspects of game design.

3.4.3. Highest rated Game Design Elements per Game genre

A BigQuery query was developed to analyze how different game genres influence player ratings across various game design elements. The games metadata dataset originally stored game genres as separate binary columns (Table 4), with a value of 1 indicating that a game belongs to that genre. To facilitate more flexible analysis, the query first unpivots the genre columns, transforming them into a long-format structure where each row represents a single game-genre combination. This ensures that each game can be analyzed under multiple genres if applicable while keeping essential metadata such as VR support, 3D capabilities, and multiplayer mode.

The second stage of the query further unpivots game design elements (e.g., Gameplay, Graphics, Audio, Monetization Model) to create a structured dataset where each row represents a specific rating for a game within a given genre. This allows for detailed comparisons of how different game genres affect ratings for various design aspects, enabling insights into whether certain genres tend to excel in specific areas. The final output provides a structured view of how game genre, platform type (VR vs. PC), and gameplay features interact, offering valuable insights for game developers and researchers studying the relationship between genre and player satisfaction.

3.2 Applying Machine Learning using XGBoost

To extend the analysis beyond descriptive statistics and explore predictive modeling, a machine learning approach was implemented using XGBoost, a high-performance gradient boosting algorithm[41]. XGBoost was selected for this study due to its ability to handle non-linear interactions, categorical variables, and missing data more effectively than traditional regression models[42]. A boosted tree model predicts the output $y^{\hat{}}$ if or an input x_i as the sum of multiple decision trees:

$$\hat{y}_i = F_M(x_i) = \sum_{m=1}^M f_m(x_i)$$
 (1)

Where M is the total number of trees, $F_m(x_i)$ is the prediction from the m-th decision tree [42].

Game ratings are influenced by intricate dependencies between features, such as the interplay between price, genre, and multiplayer functionality. For instance, while VR games might receive high ratings for spatial presence, they do not necessarily score higher on community engagement. Similarly, higher-priced games may exhibit strong graphics quality but lower multiplayer engagement. These types of non-linear relationships are naturally handled by XGBoost's decision tree-based structure.

Another advantage of XGBoost is its ability to manage categorical and binary variables without requiring manual encoding. Traditional regression models require feature transformations, such as converting price categories into numerical values, which can lead to loss of interpretability. XGBoost, however, can process these variables directly, preserving their original meaning while optimizing predictions[42].

Additionally, XGBoost provides robustness against outliers[42], a common challenge in game rating analysis. Some free-to-play games, for example, receive extreme ratings—either overwhelmingly positive or negative—based on factors unrelated to gameplay quality, such as microtransactions. Linear Regression is highly sensitive to such extreme values, whereas XGBoost assigns less influence to outliers, improving prediction stability.

Lastly, XGBoost scales efficiently to large datasets, making it particularly well-suited for analyzing thousands of games and millions of player reviews. The dataset used in this study contained a diverse set of features with complex interdependencies, making XGBoost's ability to handle correlated features a critical advantage.

The objective is to predict overall game ratings based on game metadata, player reviews, and pricing categories. By leveraging XGBoost, we aim to uncover complex relationships between game attributes and player satisfaction, allowing for data-driven insights into what factors contribute to highly rated games. To ensure accurate

predictions, we performed one-hot encoding for the Price Category attribute and created a new table without irrelevant attributes such as ID, Is Steam, Required Age, and Is Early Access. Table 12 presents the BigQuery query used to prepare the dataset for machine learning.

Table 12. BigQuery query used to prepare dataset for machine learning

```
CREATE OR REPLACE VIEW `game_reviews.game_ml_dataset` AS

SELECT

- One-hot encode `Price_Category`

CASE WHEN Price_Category = 'Free' THEN 1 ELSE 0 END AS Price_Free,

CASE WHEN Price_Category = 'Low-Priced Indie' THEN 1 ELSE 0 END AS Price_Low_Priced_Indie,

CASE WHEN Price_Category = 'Mid-Priced Indie' THEN 1 ELSE 0 END AS Price_Mid_Priced_Indie,

CASE WHEN Price_Category = 'AA Games' THEN 1 ELSE 0 END AS Price_AA_Games,

CASE WHEN Price_Category = 'AAA Games' THEN 1 ELSE 0 END AS Price_AAA_Games,

CASE WHEN Price_Category = 'Premium AAA Games' THEN 1 ELSE 0 END AS Price_Premium_AAA_Games,

- User inputed features

Is_VR, Is_3D, Is_Indie, Free_To_Play, Is_Coop, Is_Singleplayer, Is_Multiplayer,

Action, Adventure, Casual, Puzzle, Role_Playing_Game, Racing,

Simulation, Sports, Strategy, Fighting, Horror, Battle_Royale,

Shooter, Survival, Music, Education, Entertainment

FROM `game_reviews.prediction_inputs`
```

Following this, we initiated the training of XGBoost by executing the query shown in Table 13 on the newly prepared dataset.

Table 13. BigQuery query to run XGBoost regression

4 Analysis

4.1 Overview Of Quantized Data

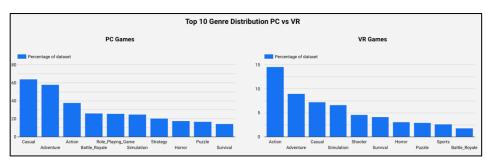


Fig. 14. Genre Distribution of PC vs. VR Games

Fig. 14 presents the top 10 genre distribution for PC vs. VR games, showcasing the percentage of the quantized dataset of games metadata occupied by each genre across the two platforms. The left side of the figure illustrates PC games, while the right side highlights VR games. The distributions are based on the total dataset of 4,856 games, capturing the most commonly occurring genres in each platform.

In PC games, the most prevalent genre is Casual, which makes up the largest portion of the dataset, followed closely by Adventure. Action games hold the third-highest share, while genres such as Battle Royale, Role-Playing Games, and Simulation have a moderate presence. The remaining genres—Strategy, Horror, Puzzle, and Survival—appear less frequently but are still among the most common.

In VR games, Action emerges as the most dominant genre, significantly surpassing other categories. Adventure and Casual games also hold substantial shares but trail behind Action. Simulation follows closely, while Shooter, Survival, and Horror genres show moderate representation. The lowest-ranking genres in this top 10 list include Puzzle, Sports, and Battle Royale.

This distribution provides an essential context for the data analysis, offering insight into how genre representation differs between PC and VR platforms. The differences in distribution suggest that certain genres are more prevalent in VR than in PC and vice versa.

4.2 Correlation between price and player's positive ratings

4.1.1. PC Games

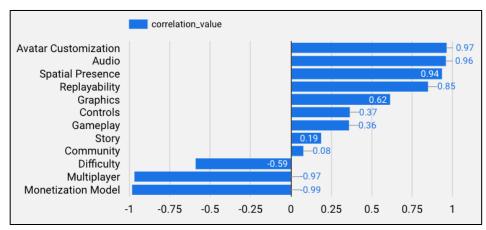


Fig. 15. Correlation Between Positive Ratings and Game Design Elements in PC Games

Fig. 15 presents the correlation values between various game design elements and price in PC games. Avatar Customization (0.97) and Audio (0.96) exhibit the highest positive correlations with price, meaning that as game prices increase, these features are rated more favorably. Spatial Presence (0.94) and Replayability (0.85) also show strong positive correlations, followed by Graphics (0.62), Controls (0.37), and Gameplay (0.36), which maintain moderate positive relationships with price.

Story (0.19) and Community (0.08) display weak positive correlations, indicating that these aspects have little direct association with price. Difficulty (-0.59) is the first feature with a negative correlation, meaning that as game price increases, difficulty ratings tend to decrease. Multiplayer (-0.97) and Monetization Model (-0.99) have the strongest negative correlations, suggesting that these elements are rated lower in higher-priced games.

4.1.2. VR Games

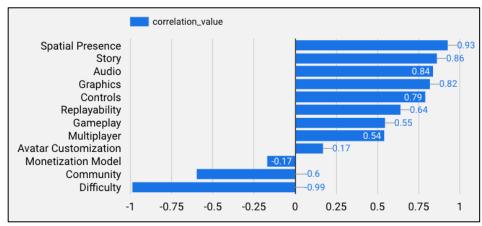


Fig. 16. Correlation Between Positive Ratings and Game Design Elements in VR Games

As shown in Fig. 16, in VR games, Spatial Presence (0.93) exhibits the highest positive correlation with price, meaning that more expensive VR games tend to provide significantly better immersive experiences. Story (0.86) and Audio (0.84) also show strong positive correlations with price, suggesting that higher-budget VR games are more likely to feature engaging narratives and high-quality sound design. Graphics (0.82), Controls (0.79), and Replayability (0.64) follow closely behind, maintaining notable positive relationships with price. Gameplay (0.55) and Multiplayer (0.54) also correlate positively with price, though to a slightly lesser degree.

Monetization Model (-0.17) and Community Engagement (0.06) exhibit minimal correlation with price, indicating that monetization strategies and community-driven aspects do not strongly depend on a game's cost in VR. Difficulty (-0.99) has the strongest negative correlation with price, meaning that as the price of a VR game increases, difficulty ratings tend to decrease significantly.

4.1.3. PC vs VR Games

The comparison of Fig. 15 and Fig. 16 highlights key differences in how price correlates with player ratings across various game design elements in PC and VR games. While both platforms share some similarities, notable differences emerge in how game price influences design priorities and player reception.

One of the most significant differences is in the correlation between price and Story, which is high in VR games (0.86) but low in PC games (0.19). This means that higher-priced VR games are strongly associated with better storytelling, whereas story

quality in PC games does not show a meaningful relationship with price. Audio quality, on the other hand, shows a strong correlation with price in both PC (0.96) and VR (0.84) games, indicating that sound design is consistently valued in premium titles regardless of platform.

Calculating the average percentage of high ratings across 12 game design elements, and computing the correlation between price and ratings separately for VR and PC games gave us two correlation values that can be seen in Fig. 17 below. We can see that VR games have a much higher total positive correlation (0.8) with price compared to PC (0.5).

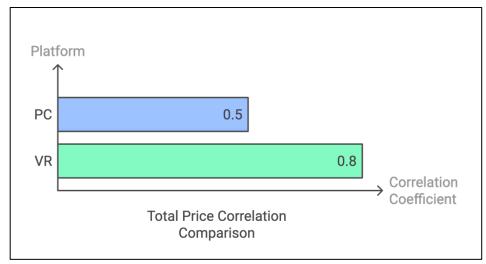


Fig. 17. Total Correlation Between Price Category and High Ratings: PC vs VR Comparison

4.3 Comparing Player Satisfaction Across VR and PC Games

Table 14. Percentage of PC and VR games with high ratings for each Game Design Element

Design Element	PC Games ▼	VR Games
Graphics	62.51	73.11
Audio	61.81	54.73
Gameplay	45.42	83.08
Monetization Model	37.3	49.14
Story	36.7	33.85
Avatar Customization	36.48	35.65
Spatial Presence	35.54	83.93
Replayability	27.06	65.46
Community	25.49	34.97
Controls	18.5	36.43
Multiplayer	14.65	33.51
Difficulty	4.39	4.55
Total Average	33.82%	49.03%

Table 14 presents the percentage of PC and VR games that received high ratings (4+ out of 5) across various game design elements. The overall average rating is higher for VR games (49.03%) than for PC games (33.82%), indicating that VR games generally receive more favorable reviews across most design aspects. However, the degree of satisfaction varies depending on the specific elements of game design.

Among the individual design elements, graphics stand out as one of the highest-rated features on both platforms. A higher proportion of VR games (73.11%) receive strong ratings in this category compared to PC games (62.51%), reflecting a 10.6% difference in favor of VR. In contrast, audio design follows a different trend. While PC games (61.81%) receive a relatively high percentage of positive ratings, VR games (54.73%) fall slightly behind, marking the only category where PC games outperform VR.

Gameplay mechanics show the most pronounced disparity between the two platforms. VR games (83.08%) receive overwhelmingly higher ratings than PC games (45.42%), representing a 37.66% difference—one of the largest gaps in the dataset. The largest difference is observed in spatial presence, where VR games (83.93%) significantly outperform PC games (35.54%), with a 48.39% gap—the most substantial observed. Similarly, VR games also hold a major advantage in replayability, with 65.46% of VR titles receiving high ratings compared to 27.06% of PC games, marking a 38.4% difference.

Storytelling elements show little variation between the two formats, with PC games (36.7%) and VR games (33.85%) receiving comparable ratings, showing only a 2.85% difference. Monetization models also show a higher percentage of positive

ratings in VR, with 49.14% of VR games receiving high ratings compared to 37.3% of PC games, a difference of 11.84%. Similarly, the multiplayer experience is rated more favorably in VR, with 33.51% of VR games receiving high ratings compared to 14.65% of PC games, showing an 18.86% gap. Finally, difficulty ratings remain fairly consistent across both platforms, with VR games (4.55%) and PC games (4.39%) receiving similarly low percentages of high ratings, showing only a 0.16% difference.

4.4 Highest rated Game Design Elements per Game genre

This analysis highlights the key game design elements that matter most across different genres in both PC and VR platforms, offering valuable insights for developers, designers, and publishers to optimize game features and enhance player experience.

4.4.1. PC Games

Table 15. Average ratings of Game Design Elements across PC Game Genres

Genre	Graphics	Audio	Avatar_Custo mization	Gameplay	Spatial_Pres ence	Story	Community	Monetization _Model	Replayablity	Difficulty	Multiplayer	Controls
Music	3.84	4.01	3.44	3.48	3.45	3.4	3.15	3.09	3.06	3	2.69	2.97
Entertainment	3.53	3.55	3.83	3.53	3.54	3.4	2.25	2.33	3.54	3.43	3.33	3
Puzzle	3.72	3.64	3.44	3.49	3.37	3.35	3.16	3.3	2.97	2.97	2.97	2.81
Horror	3.65	3.65	3.39	3.43	3.45	3.39	3.03	3.22	2.94	2.96	2.8	2.74
Adventure	3.65	3.62	3.44	3.42	3.32	3.29	3.15	3.11	2.99	2.96	2.91	2.75
Education	3.44	3.31	3.46	3.5	3.18	3.27	3.42	3.05	3.22	3.02	3.11	2.84
Casual	3.63	3.57	3.46	3.43	3.27	3.26	3.18	3.13	3.01	2.96	2.96	2.78
Shooter	3.58	3.57	3.45	3.51	3.37	3.13	3.02	3.04	3.09	2.93	2.83	2.99
Action	3.6	3.59	3.44	3.46	3.3	3.17	3.07	3.07	3.05	2.94	2.91	2.84
Battle_Royale	3.54	3.51	3.43	3.46	3.3	3.14	3.05	2.93	3.14	2.95	2.97	2.85
Role_Playing	3.57	3.54	3.48	3.37	3.25	3.26	3.12	2.86	3.06	2.92	2.89	2.68
Fighting	3.57	3.58	3.39	3.52	3.22	3.2	2.8	2.74	3.15	2.94	2.95	2.87
Strategy	3.5	3.42	3.45	3.41	3.21	3.19	3.14	2.91	3.17	2.95	2.91	2.7
Sports	3.41	3.34	3.28	3.46	3.2	3.12	3.1	2.98	3.23	2.96	2.97	2.89
Racing	3.43	3.33	3.4	3.45	3.22	3.08	2.97	3.1	3.15	2.97	2.9	2.88
Simulation	3.51	3.43	3.45	3.34	3.24	3.22	3.21	2.92	3.03	2.95	2.85	2.61
Survival	3.5	3.49	3.42	3.32	3.27	3.15	3.19	2.91	2.98	2.92	2.79	2.56

Table 15 presents the average ratings of various game design elements across different PC game genres. Each row represents a genre, while each column corresponds to a specific game element, such as Graphics, Audio, Gameplay, Spatial Presence, Story, Community, Monetization Model, Replayability, Difficulty, Multiplayer, and Controls. The values in the table indicate the average rating given to each element within that genre.

Graphics and Audio tend to have relatively high scores across all genres, with Music (3.84) and Puzzle (3.72) rating Graphics highly, while Audio receives the highest scores in Music (4.01) and Entertainment (3.55). Avatar Customization is consistently rated between 3.3 and 3.8 across genres, with the highest value found in Entertainment (3.83). Gameplay scores are relatively consistent across genres, with

Entertainment (3.53) and Strategy (3.41) at the higher end, while Spatial Presence scores range between 3.1 and 3.4, with Shooter (3.37) and Horror (3.45) being among the highest-rated.

Story ratings show variation across genres, with Horror (3.39), RPG (3.26), and Adventure (3.29) having the highest values, whereas genres like Shooter (3.13) and Sports (3.12) have lower ratings. Community engagement ratings are in the 3.0 to 3.4 range, with Education (3.42) and Adventure (3.15) scoring higher, while Entertainment (2.25) has the lowest rating.

Monetization Models generally have the lowest scores among all elements, with Fighting (2.74) and Strategy (2.91) being at the lower end, while Puzzle (3.30) and Casual (3.13) score slightly higher. Replayability ratings vary, with Entertainment (3.54) having the highest value, while genres like Horror (2.94) and Puzzle (2.97) have lower scores. Difficulty ratings are relatively close across genres, with Entertainment (3.43) and Music (3.00) at the higher end, and Strategy (2.95) and Simulation (2.95) at the lower end.

Multiplayer ratings are highest in Sports (2.98) and Fighting (2.95), while Music (2.69) and Horror (2.80) rate it the lowest. Controls ratings fluctuate, with Strategy (3.17) and Racing (3.15) having the highest values, and Survival (2.56) and Horror (2.74) ranking lower.

4.4.2. VR Games

Table 16. Average ratings of Game Design Elements across VR Game Genres

Genre	Spatial_Prese nce	Gameplay	Graphics	Replayablity	Audio	Monetization _Model	Avatar_Custo mization	Community	Story	Multiplayer	Controls	Difficulty
Music	4.04	3.86	3.61	3.82	3.98	3.41	3.52	3.56	3.26	3.13	3.42	3.05
Puzzle	4.08	3.77	3.9	3.44	3.65	3.63	3.4	3.44	3.46	3.28	3.14	3.01
Sports	4.05	3.91	3.65	3.85	3.34	3.46	3.56	3.37	3.26	3.33	3.24	3
Strategy	4.23	3.85	3.86	3.67	3.51	3.4	3.36	3.24	3.33	3.15	3.35	3
Casual	3.99	3.79	3.75	3.52	3.59	3.49	3.39	3.46	3.41	3.36	3.15	3.04
Shooter	4.06	3.83	3.69	3.68	3.45	3.63	3.42	3.36	3.31	3.19	3.28	3.02
Action	4.02	3.86	3.72	3.72	3.53	3.51	3.43	3.34	3.36	3.19	3.23	2.99
Education	3.94	3.71	3.76	3.31	3.47	3.71	3.71	3.85	3.29	3.58	2.76	3.06
Adventure	4.03	3.76	3.79	3.46	3.6	3.48	3.41	3.4	3.48	3.21	3.08	3
Survival	4.03	3.86	3.63	3.72	3.47	3.54	3.44	3.52	3.36	3.16	3.05	2.99
Entertainment	4.33	4	4	2.5	2.67	3.67	4	3.5	4	3	3	3
Fighting	4.02	3.82	3.76	3.64	3.35	3.5	3.51	3.37	3.28	3.16	3.26	2.97
Role_Playing	3.94	3.71	3.66	3.64	3.52	3.3	3.38	3.67	3.25	3.29	3.14	3
Racing	3.91	3.85	3.7	3.67	3.39	3.64	3.38	3.22	3.24	3.09	3.28	3
Simulation	3.99	3.81	3.61	3.67	3.37	3.4	3.46	3.49	3.27	3.12	3.09	3.02
Battle_Royale	3.92	3.68	3.57	3.44	3.43	3.39	3.44	3.35	3.23	3.36	3.02	3.03
Horror	3.92	3.77	3.64	3.44	3.48	3.36	3.44	3.36	3.36	3.18	2.84	2.95

Similar to Table 15, Table 16 presents the average ratings of various game design elements across VR game genres instead.

Unlike in PC games, Spatial Presence scores highly across all VR genres, with Strategy (4.23), Entertainment (4.33), and Shooter (4.06) receiving the highest ratings, while even the lowest-scoring genres, Education (3.94) and Battle Royale

(3.92), remain relatively high. This contrasts with PC games, where Spatial Presence varied more significantly across genres, showing that immersion is a more universal expectation in VR. Gameplay ratings remain strong across genres, similar to PC, with Entertainment (4.00), Sports (3.91), and Strategy (3.85) leading, while Adventure (3.76) and Role-Playing Games (3.71) have slightly lower ratings. In VR, the spread of Gameplay ratings is narrower than in PC games, where RPGs showed more differentiation.

Graphics ratings are consistently high across all genres, with Entertainment (4.00), Strategy (3.86), and Puzzle (3.90) leading, while Battle Royale (3.57) and Horror (3.64) are among the lower-rated. The highest PC game ratings for Graphics were around 3.84, meaning VR games tend to have slightly higher visual ratings overall, likely due to their dependence on high-quality visuals for immersion. Replayability in VR shows a different distribution compared to PC, with Sports (3.85), Music (3.82), and Shooter (3.68) being the highest-rated, while Entertainment (2.50) is significantly lower than in PC. This suggests that VR entertainment applications often provide one-time immersive experiences rather than repeatable gameplay sessions.

Audio ratings in VR are highest in Music (3.98), Adventure (3.60), and Education (3.47), whereas in PC, Shooter (3.57) and Fighting (3.58) had stronger Audio ratings. While VR ratings remain more concentrated, PC games had a broader range of Audio scores, showing that audio quality is prioritized differently between the two platforms. Monetization Model ratings remain among the lowest-rated elements in both VR and PC. The highest VR scores appear in Puzzle (3.63), Shooter (3.63), and Sports (3.46), while Strategy (3.40) and Fighting (3.50) rank lower, a pattern similar to PC games, where monetization was one of the least favored aspects across most genres.

Avatar Customization is rated highly in Entertainment (4.00), Sports (3.56), and Education (3.71), while Fighting (3.51) and Battle Royale (3.43) are at the lower end. In PC games, Avatar Customization followed a similar distribution, though the difference between highest- and lowest-rated genres is more pronounced in VR. Community ratings in VR are strongest in Education (3.85) and Entertainment (3.50), while Fighting (3.37) and Shooter (3.36) have lower ratings. This follows the same pattern as PC games, where Education and Entertainment showed higher Community engagement compared to competitive genres.

Story ratings are highest in Entertainment (4.00), RPG (3.48), and Strategy (3.33), while Sports (3.26) and Fighting (3.28) score lower. While RPGs and Adventure games had similarly high Story ratings in both VR and PC, Entertainment games score significantly higher in VR, suggesting a stronger focus on immersive storytelling. Multiplayer ratings in VR are strongest in RPG (3.29), Adventure (3.21), and Sports (3.33), while Fighting (3.16) and Shooter (3.19) score slightly lower. Compared to PC, Multiplayer scores in RPGs are higher in VR, suggesting that social VR role-playing experiences are more emphasized than in traditional PC games.

Controls ratings are highest in Shooter (3.28), Strategy (3.35), and Racing (3.28), while Education (2.76) and Horror (2.84) have the lowest ratings. PC games also

showed high Control ratings for Strategy and Racing, though Education did not rank as low as it does in VR. Difficulty ratings in VR are relatively even across all genres, with Education (3.06) ranking highest, while Fighting (2.97) and Horror (2.95) rank lowest. This differs from PC games, where Fighting had higher Difficulty ratings, suggesting that VR developers may prioritize accessibility over challenge in these genres.

4.5 Predicting what game genres have the biggest impact on ratings

Table 17. Predicted Average Ratings of Game Genres in VR vs. PC

	Prediction - Genre Influence on VR vs PC Ratings								
	VR Games		PC Games						
Genre	Predicted Average Overall Rating ▼	Genre	Predicted Average Overall Rating *						
Role-Playing Game	3.14	Battle Royale	2.89						
Strategy	3.14	Fighting	2.88						
Battle Royale	3.13	Sports	2.87						
Music	3.09	Music	2.86						
Shooter	3.09	Shooter	2.85						
Fighting	3.09	Action	2.85						
Sports	3.08	Racing	2.84						
Survival	3.08	Strategy	2.82						
Racing	3.07	Role-Playing Game	2.81						
Simulation	3.06	Casual	2.79						
Action	3.04	Adventure	2.78						
Casual	3.04	Simulation	2.78						
Adventure	3.02	Survival	2.77						
Puzzle	3.01	Horror	2.75						
Horror	2.97	Puzzle	2.73						
Education	2.95	Education	2.73						
Entertainment	2.36	Entertainment	2.64						

Table 17 presents the predicted average overall rating for different game genres in VR and PC gaming, based on the XGBoost regression model. The values represent the expected user satisfaction scores for each genre on their respective platforms.

In the VR Games category, the highest predicted ratings are for Role-Playing Games (3.14) and Strategy (3.14), both receiving the same expected satisfaction level. Battle Royale (3.13) follows closely behind, with only a minor difference from the top-rated genres.

Music (3.09), Shooter (3.09), and Fighting (3.09) share identical predicted ratings, forming the next group of highly-rated genres, slightly below the leading ones. Sports

(3.08) and Survival (3.08) also have nearly identical predicted values, ranking just below the previous group. Racing (3.07) and Simulation (3.06) follow closely, maintaining a small gap from the higher-scoring genres.

Further down, Action (3.04), Casual (3.04), and Adventure (3.02) show slight decreases in predicted ratings, with Puzzle (3.01) positioned just below them. Horror (2.97) ranks slightly lower than Puzzle, while Education (2.95) follows closely. The lowest-rated genre in this category is Entertainment (2.36), which is significantly lower than all other genres.

While Role-Playing Games and Strategy rank at the top in VR gaming, Battle Royale (2.89) receives the highest predicted rating in PC games. Fighting (2.88), Sports (2.87), and Music (2.86) follow closely, all within a narrow range. Shooter (2.85) and Action (2.85) maintain identical predicted scores, positioning them just below the leading group.

Further down, Racing (2.84), Strategy (2.82), and Role-Playing Games (2.81) show small differences, indicating a slightly lower expected satisfaction compared to their VR counterparts (3.14 for both Role-Playing and Strategy games). Casual (2.79), Adventure (2.78), and Simulation (2.78) are positioned closely together, showing minimal variation in their expected ratings. Survival (2.77) and Horror (2.75) rank just below them, while Puzzle (2.73) is next in line.

At the lower end of the predictions, Education (2.73) and Entertainment (2.64) receive the lowest ratings, with Entertainment ranking the lowest among all PC game genres. While Entertainment games score slightly higher in PC gaming (2.64) compared to VR (2.36), they remain the least favorably rated genre overall.

5 Discussion

5.1 Discussion of key findings

According to the results of this study, the answers to the research questions have been found. RQ1 dealt with identifying key game design features that significantly contribute to player enjoyment in PC versus VR games. The answer to this RQ shows that Spatial Presence, Graphics, Audio, and Gameplay are the features most consistently correlated with high ratings, although their impact on player satisfaction varies across platforms. Notably, Spatial Presence is markedly higher in VR, with 83.93% of VR games attaining strong positive reviews compared to only 35.54% of PC games. These findings imply that VR players place a particularly high value on immersion, aligning with typical expectations of virtual reality.

Similarly, Audio correlates strongly with overall positive ratings for both platforms; however, PC games slightly surpass VR in terms of the proportion of

games receiving excellent audio ratings (61.81% vs. 54.73%). This difference suggests that VR audio design may not fully meet player expectations, potentially due to higher scrutiny of spatial or 3D sound implementation in immersive environments. Furthermore, Gameplay and Replayability exhibit a considerable gap between the platforms. While 83.08% of VR games achieve high Gameplay ratings, only 45.42% do so on PC; Replayability follows a similar pattern (65.46% in VR vs. 27.06% in PC). These findings imply that players perceive VR's physical, interactive engagement as novel and more engaging over repeated play sessions, whereas PC games might depend more on broader content variety or community-driven interactions to sustain player interest. In the literature, [6] and related studies on user engagement suggest that a richer sense of presence and interactivity positively correlate with higher satisfaction, which aligns with our findings as well.

RQ2 examined how monetization strategies influence player satisfaction in free-to-play versus non-free-to-play games. The findings demonstrate a strong negative correlation between price and Monetization Model in PC games (-0.99), indicating that aggressive microtransactions or DLC practices in premium-priced PC titles provoke significant dissatisfaction. This aligns with previous studies [43] emphasizing player resistance to perceived paywalls in costly products. Additionally, the decline in multiplayer ratings for higher-priced PC games suggests that lower-cost or free-to-play multiplayer games often foster stronger communities and better reception, exemplified by popular titles like League of Legends and CS:GO[44], [45].

Further, correlations between game design elements and game price reveal additional insights. Avatar Customization, Graphics, Controls, and Replayability are positively correlated with higher-priced games, suggesting premium titles prioritize immersive visuals, refined controls, extensive customization, and prolonged gameplay value [46]. Additionally, a strong negative correlation was found between Difficulty and price, indicating cheaper PC games are often more challenging, possibly due to less refined mechanics or steeper learning curves, whereas premium-priced titles generally offer more accessible, user-friendly experiences [47].

Furthermore, storytelling exhibits a unique divergence across platforms: non-free-to-play VR games have a strong correlation with narrative quality (0.86), suggesting deeper engagement and investment in high-quality storytelling, whereas price has minimal influence on storytelling quality in PC games (correlation of 0.19). This indicates narrative excellence is achievable across price points in PC games, unlike VR, where premium pricing typically accompanies richer story-driven experiences.

On the other hand, VR games exhibit only a weak negative correlation between price and Monetization Model (-0.17). This result shows that higher-priced VR titles do not necessarily incur significantly worse perceptions of monetization, potentially because VR players are more accustomed to premium upfront costs and have not encountered widespread pay-to-win or microtransaction-heavy models [48]. It can also be noted that VR games received a higher proportion of positive monetization ratings (49.14%) compared to PC games (37.3%). Consequently, if a PC title is

marketed as free-to-play, players might be more accepting of monetization structures based on cosmetics or optional content, whereas a premium title that imposes further costs often faces harsh critique.

RQ3 dealt with the differences in player enjoyment between PC and VR game genres. The answer to this RQ indicates that VR games, on average, receive more favorable overall ratings (49.03% of VR titles showing high design-element ratings vs. 33.82% of PC titles). Additionally, it can be noted that the analysis by genre shows that Role-Playing Games (RPG) and Strategy perform exceptionally well in VR, each with predicted average ratings of around 3.14, whereas their PC counterparts score lower (around 2.81–2.82). In contrast, Battle Royale stands out in PC gaming with a predicted average rating of 2.89, though it still scores higher in VR at 3.13. These results imply that the immersive mechanics of VR appear to enhance the appeal of genres emphasizing narrative depth, strategic decision-making, or physical interaction. Another key observation is that VR outperforms PC in elements like Gameplay, Spatial Presence, and Replayability, suggesting that players perceive VR experiences as more novel and interactive. This conclusion is consistent with prior research on VR user experience [49] that highlights increased immersion as a defining advantage.

Furthermore, platform-specific genre preferences emerged clearly in the analysis. PC gaming is dominated by Casual and Adventure genres, indicating a broader appeal and focus on accessibility. In contrast, VR strongly favors Action and Simulation games due to their inherently immersive and interactive nature. Multiplayer interactions are perceived as more engaging and natural in VR due to enhanced physical presence, spatial audio, and body language cues, especially noticeable in RPG genres. Controls and precision mechanics, highly rated in Racing and Strategy games, are equally crucial in both platforms, but VR titles tend to emphasize accessibility over challenge, especially in Fighting and Horror genres.

Lastly, RQ4 addressed how generative AI techniques can be employed to identify the primary factors influencing positive player reviews across different game genres and platforms. According to the results, large-scale automated text summarization, sentiment analysis, and topic modeling were effective in revealing patterns that would otherwise be difficult to detect manually. The sentiment data derived from player comments enabled the analysis to highlight significant negative correlations, such as those between price and difficulty, or price and monetization, and to pinpoint specific areas (like VR audio design) that may need improvement. By capturing thematic clusters through topic modeling, one can identify recurring complaints about pay-to-win frustrations, perceived lack of fairness in skill-based mechanics, or dissatisfaction with short campaign lengths in expensive VR adventure titles. Previous studies for instance, Guzsvinecz note that such approaches can also unearth genre-specific nuances that might not emerge from manual coding alone [5]. Consequently, generative AI offers a more scalable, data-driven method to uncover which design features resonate with or repel players, making it possible for developers and

researchers to iterate on their products or studies with greater precision.

5.2 Implications of the study

The findings from this study offer practical and theoretical implications that can guide both industry practitioners and academic researchers. First, the clear distinction in player satisfaction between VR and PC platforms underscores the necessity for developers to tailor design strategies according to platform capabilities. The substantially higher ratings in VR for Spatial Presence, Gameplay, and Replayability highlight the importance of immersion and physical engagement, suggesting that VR developers might benefit from prioritizing robust motion controls, high-fidelity visuals, and refined interactive mechanics. Equally, PC developers should be mindful of elements like Audio design and monetization schemes. The results show a strong negative correlation between price and monetization in premium PC titles, indicating that players have limited tolerance for microtransactions in higher-priced games. This finding reinforces existing calls for transparent and fair monetization strategies, which can preserve goodwill and customer loyalty over time.

Another critical implication of this study is the value of integrating generative AI techniques into the game development and research cycle. The capacity to process large volumes of user feedback enables developers to identify latent patterns—such as frequent complaints about pay-to-win mechanisms or dissatisfaction with overly steep learning curves—in near real time. By adopting automated text summarization, sentiment analysis, and topic modeling, practitioners can track the evolution of player attitudes and pivot their design choices to better suit player preferences. This approach can extend beyond VR and PC to platforms such as mobile and console, especially as cross-platform gaming becomes increasingly commonplace.

Lastly, the differences observed across genres highlight that not all game categories benefit equally from VR's immersive attributes. Genres like RPG and Strategy, which thrive on deep interaction and narrative, may reap the greatest advantages. Conversely, purely casual or educational titles often face an uphill battle in achieving high ratings, underscoring that matching game content with the immersive strengths of VR or the diverse capabilities of PC is essential for fostering positive user experiences.

5.3 Limitations of the study

While this study provides valuable insights into player sentiment and game design trends in the post-pandemic gaming landscape, several limitations must be acknowledged. The focus on games released between 2020 and 2024, while justifiable due to shifts in player behavior, restricts the generalizability of findings to earlier or future game releases. Additionally, the presence of review bombing poses a challenge

to sentiment analysis, as artificially skewed ratings may not accurately reflect genuine player experiences [7]. Lastly, the reliance on Generative AI for text tokenization introduces potential biases, as AI models may misinterpret nuanced expressions such as sarcasm or humor, affecting the accuracy of sentiment classification [12]. Future research could address these limitations by incorporating a broader dataset spanning multiple time periods, employing filtering techniques to mitigate review bombing effects, and refining AI models to better capture linguistic subtleties.

Additionally, due to the limited resources available for this study and the high computational power required to process each individual review through the large language model (Phi-4), only the 100 most-rated reviews from a total of 4,856 PC and VR games were analyzed. This means certain lesser-known or niche games, which might provide unique insights into specific design elements, received less representation. As a result, the focus on top-rated reviews may emphasize mainstream preferences and trends, potentially overlooking nuanced perspectives from smaller player communities. Future studies could mitigate this sampling constraint by incorporating a larger cross-section of reviews for each game or by employing a stratified sampling approach that captures both popular and niche titles in equal measure, thus offering a more comprehensive view of the overall player sentiment landscape.

6 Conclusions and Future Work

In this study, the reviews of 4,856 PC and VR games—each represented by the 100 most-rated user comments—were analyzed using a generative AI approach to uncover the factors contributing to player enjoyment across different genres and platforms. The following points can be concluded:

- (1) VR games outperform PC games in overall ratings for key game design elements, particularly Spatial Presence, Gameplay, and Replayability. This suggests that the immersive nature of VR resonates strongly with players and offers a heightened sense of engagement and continued play.
- (2) Monetization strategies have a strong effect on user sentiment, especially in premium-priced PC titles. Players tend to react negatively to additional costs in already expensive games, whereas VR gamers show more lenience toward varying pricing schemes.
- (3) Genre-specific analysis shows that RPGs, Strategy, and Shooter experiences benefit most from VR's heightened interactivity and presence, while Battle Royale, Fighting, and Sports games maintain strong followings on PC, although their VR counterparts often still achieve higher predicted ratings.
- (4) Generative AI techniques, including text summarization and topic modeling, proved essential in processing large volumes of player feedback. These methods

effectively revealed nuanced themes, such as dissatisfaction with pay-to-win mechanics and the significance of balanced difficulty, thereby offering robust, data-driven insights into what makes a game enjoyable.

Due to these findings, it becomes evident that a deeper understanding of the interplay between immersive mechanics, monetization, and player expectations is critical to designing more engaging games. Developers and publishers can leverage these insights to refine price models, tailor difficulty settings, and optimize immersive elements to meet evolving player needs. Additionally, researchers may find value in applying these generative AI methodologies to other gaming contexts—such as console or mobile platforms—to assess whether similar patterns of player satisfaction emerge. After all, the ability to match game design features with specific audience preferences is increasingly vital in a gaming landscape that continues to expand and diversify, underscoring the importance of robust, data-oriented investigations into player experiences.

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Ethical Approval

This study was conducted in accordance with the ethical guidelines set forth by the University of Wollongong in Dubai. Given that this research involved the analysis of publicly available game reviews, it did not require formal approval from an institutional ethics review board. No personally identifiable data were collected, and all user-generated content was anonymized in adherence to ethical research principles.

Consent to Participate

Not applicable. This study utilized publicly available data from digital game distribution platforms (Steam and Meta Quest) without direct interaction with human participants. As such, no consent to participate was required.

Consent to Publish

Not applicable. The dataset used in this study consists of publicly accessible game reviews, and no proprietary or confidential information was disclosed. The findings of this research are presented in aggregate form to ensure no individual user can be identified.

Data Availability Statement

The datasets analyzed in this study were collected from publicly accessible sources, namely Steam and the Meta Quest Store. The processed dataset, including quantified game design elements and metadata, is available upon request. Code used for data processing and analysis is available upon request.

Authors' Contributions

Hisham Abdelqader conceptualized the study, designed the methodology, and carried out the data collection and processing. The data analysis and visualization were conducted by the author using generative AI and machine learning techniques. The manuscript was drafted and revised by Hisham Abdelqader. The author takes full responsibility for the integrity and accuracy of the study's findings.

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Competing Interests

The author declares no competing interests. The study was carried out independently, and no conflicts of interest, financial or otherwise, influenced the research process or its findings.