

# Beyond the Store Page: Clustering Steam Games by Player Engagement and Pricing

Antonio Mark Allen B.

*College of Computing and Information Technologies  
National University Manila  
Manila, Philippines  
antoniomb1@students.national-u.edu.ph*

Mago, Karl Mattheus W.

*College of Computing and Information Technologies  
National University Manila  
Manila, Philippines  
magokw@students.national-u.edu.ph*

**Abstract**—Steam is one of the largest PC game marketplaces, but its store page does not show how players actually interact with games. Many games have similar prices but very different playtime, review counts, and popularity. In this study, we use unsupervised machine learning to group Steam games by engagement and pricing features. We tested several clustering algorithms, including K-Means, Agglomerative Hierarchical Clustering, and Gaussian Mixture Models (GMM). We used Principal Component Analysis (PCA) to reduce the number of features while keeping at least 90% of the data's variance. Our results show that K-Means gave the clearest and most stable clusters. The final model used a filtered dataset of paid games with non-zero playtime, resulting in three clusters that show different patterns of engagement and market behavior. We also ran an experiment with a dataset that included all games, showing that including games with zero playtime can inflate evaluation scores and make the clusters harder to interpret. These findings help explain how pricing, engagement, and popularity are related among Steam games.

**Index Terms**—Steam games, clustering, K-Means, PCA, player engagement, pricing, unsupervised learning

## I. INTRODUCTION

Steam has tens of thousands of games with varying prices, release dates, and levels of popularity [1]. Store pages display prices and discounts, yet these indicators do not necessarily correspond to actual player engagement. Some low-cost games accumulate extensive playtime and review activity, whereas certain higher-priced titles attract minimal attention [2]. Consequently, it is difficult to construct meaningful groupings of games using only visible store information.

Unsupervised learning provides mechanisms for identifying natural structures in data without predefined labels. In this study, clustering techniques are applied to segment Steam games using variables such as average playtime, review counts, ownership estimates, peak concurrent users, and the proportion of positive feedback. The objective is to uncover groups that reflect real player behavior rather than surface-level characteristics.

### A. Problem Statement

Steam games differ a lot in popularity and engagement, even when their prices are similar. There is no easy way to label games by how engaged their players are. This study uses pricing and engagement features to group Steam games into meaningful categories.

### B. Objectives

This project aims to preprocess and engineer features from a Steam dataset, use principal component analysis (PCA) to reduce dimensionality, train and compare clustering models such as K-means, hierarchical clustering, and Gaussian Mixture Model, choose the best model using internal evaluation metrics, and interpret the clusters with profiling statistics and visualizations.

### C. Scope and Limitations

This study looks at clustering paid Steam games and does not include free-to-play games. The results may be affected by extreme values, missing playtime data, and skewed distributions. While PCA helps reduce dimensionality, the results still depend a lot on the chosen features and preprocessing methods.

## II. REVIEW OF RELATED LITERATURE

Game platforms such as Steam generate large datasets reflecting player engagement, pricing dynamics, and review responses across thousands of titles. Prior work in data science and game analytics has demonstrated that features derived from playtime, review volume, and pricing can be effective for understanding performance patterns. For example, Lim analyzed the relationship between hours played per dollar and game quality, showing that simple ratio metrics can reveal differences in value-for-money even when raw playtime and price vary widely across titles [3]. This underscores the importance of feature transformations such as ratios or logarithmic scaling when interpreting behavioral differences among games.

Supervised learning approaches have also been applied to Steam data to predict game “success,” typically defined using engagement proxies. Chan utilized SteamSpy metadata, including price, genre, ownership estimates, review scores, and playtime, to train a Random Forest classifier and found that engagement and review-related features were strong predictors of above-median playtime, while price exhibited weaker influence [4]. Although supervised models can provide strong predictive performance, they rely on predefined labels and do not inherently reveal latent structures. This motivates the use of unsupervised clustering techniques to uncover patterns without prior categorization.

Clustering large behavioral datasets introduces challenges related to feature scaling, dimensionality, and validation. Rousseeuw's silhouette method remains a foundational metric for evaluating cluster quality by comparing intra-cluster cohesion with inter-cluster separation, particularly in scenarios where ground-truth labels are unavailable [5]. Within game analytics, Drachen and colleagues highlight additional concerns, including the interpretability of clusters and the risk that numerically strong solutions may still lack practical meaning if features are poorly chosen [6]. These perspectives emphasize the necessity of combining careful feature engineering with multiple validation metrics, such as silhouette, Davies–Bouldin, and Calinski–Harabasz indices.

Another important consideration involves the distributional characteristics of engagement variables. Liang and Yang observed that PC game playtime follows a heavily skewed distribution, where a small subset of titles dominates long durations while the majority receive limited interaction [7]. They showed that logarithmic transformations can mitigate the influence of extreme values and improve modeling stability. This supports methodological choices in clustering, including the preference for ratio-based or log-scaled attributes rather than relying solely on raw magnitudes that may dominate distance computations.

In summary, prior research indicates that (1) engagement and pricing variables contain meaningful signals, (2) unsupervised clustering is suitable for exploratory segmentation without labels, (3) numerical validation must be complemented by interpretability, and (4) appropriate feature transformation is crucial when handling skewed behavioral metrics. These principles guide the methodological decisions in this study, including the use of PCA for dimensionality reduction, comparison across clustering algorithms, and the construction of features designed to yield interpretable groupings.

### III. METHODOLOGY

#### A. Dataset

The dataset used in this study was obtained from Kaggle and contains structured information about Steam games. The dataset includes variables related to pricing, popularity, and engagement, such as:

TABLE I  
DATASET ATTRIBUTES (STEAM GAMES DATASET)

Attribute	Description
name	Steam game title
price	Current game price (USD)
release_date	Date when the game was released
positive	Number of positive user reviews
negative	Number of negative user reviews
owners	Estimated ownership range
average_playtime_forever	Average total playtime (minutes)
median_playtime_forever	Median total playtime (minutes)
required_age	Minimum required age
dlc_count	Number of DLCs available
metacritic_score	Metacritic rating score (if available)
achievements	Number of achievements
recommendations	Number of Steam recommendations
supported_languages	Supported languages
categories	Steam categories (e.g., Single-player, Co-op)
genres	Steam genres (e.g., Action, RPG)
tags	User-generated Steam tags

This dataset was selected because it contains both economic indicators (price, discount) and player engagement indicators (reviews, playtime, concurrent users), making it suitable for clustering games based on value and engagement patterns.

#### B. Data Cleaning and Preprocessing

Several preprocessing steps were applied before clustering to ensure consistency and reduce noise.

1) *Filtering*: The dataset was filtered to include only paid games, since free-to-play titles often follow different engagement and monetization patterns compared to paid games. This filtering improves fairness when comparing price-based behavior.

2) *Handling missing and invalid values*: Missing or invalid values were handled through removal or imputation depending on the feature. Rows with incomplete values for core clustering features were excluded to prevent errors in PCA and clustering.

3) *Release date transformation*: The release date was converted into a numerical feature called: *release\_age\_years*

This was computed as the number of years since the game's release. This transformation allows the model to capture how older games may accumulate reviews, owners, and playtime differently compared to newer releases.

4) *Feature standardization*: Before applying PCA and clustering, all numerical features were standardized using z-score normalization (mean = 0, standard deviation = 1). This prevents large-scale features (such as owners or reviews) from dominating the clustering process.

#### C. Feature Set Construction

To explore clustering behavior under different assumptions, multiple feature sets were created. However, two key datasets were selected for the final analysis because they provide the most interpretable and defensible results.

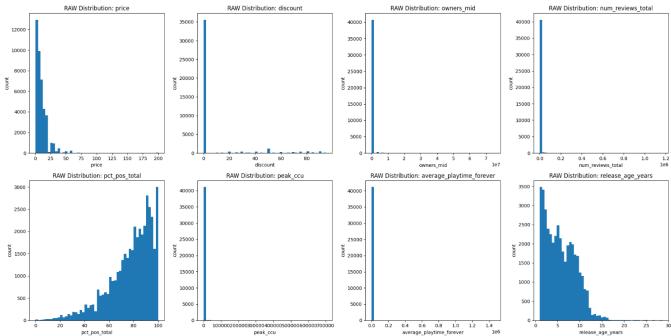


Fig. 1. Raw distribution

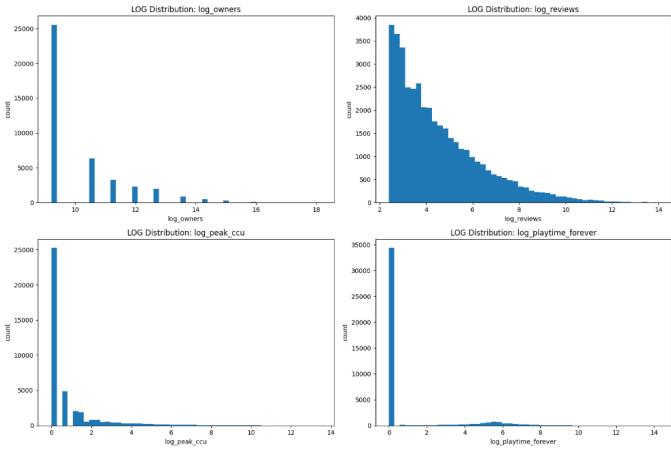


Fig. 2. Log distribution

1) *Main Dataset: X2 Balanced:* The main dataset contains paid games where the average lifetime playtime is greater than zero. This decision was made to reduce a common issue in Steam datasets: 0-playtime bias. Games with zero recorded playtime can artificially increase clustering scores because they form an easy-to-separate group. While this may improve metrics, it does not reflect meaningful engagement segmentation among active games. Therefore, X2 was used as the final model because it represents games that have actual recorded engagement.

2) *Supporting Dataset: X3 Ratios:* The supporting dataset includes all paid games and uses ratio/log-based engagement features. These features reduce the dominance of raw magnitude values such as playtime and reviews. X3 was included to support the discussion by showing how the inclusion of all paid games (including low-engagement and zero-playtime titles) affects the overall cluster structure of the dataset.

#### D. Dimensionality Reduction

Principal Component Analysis (PCA) was applied to reduce the dimensionality of the dataset and improve clustering efficiency. PCA was used to transform the standardized features into a smaller set of orthogonal principal components. Only enough components to preserve at least 90% of the total

variance were retained (PCA90). This reduces noise while maintaining most of the dataset's information.

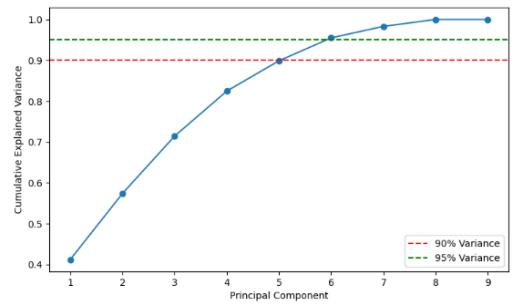


Fig. 3.

#### E. Clustering Algorithms

Three clustering algorithms were tested to evaluate which method produced the most stable and interpretable results:

1) *K-Means:* K-Means was treated as the primary baseline clustering method due to its simplicity and strong interpretability. Multiple values of k were tested.

2) *Agglomerative Hierarchical Clustering:* Hierarchical clustering was tested using common linkage methods. This method was included because it can capture nested cluster structure and does not require probabilistic assumptions.

3) *Gaussian Mixture Models (GMM):* GMM was tested as a probabilistic alternative to K-Means. Unlike K-Means, GMM allows soft cluster boundaries and can model elliptical clusters.

#### F. Evaluation Metrics

Because the dataset is unlabeled, clustering performance was evaluated using internal clustering metrics:

Silhouette Score (higher is better): measures how well-separated clusters are

Davies–Bouldin Index (lower is better): measures overlap between clusters

Calinski–Harabasz Index (higher is better): measures cluster compactness vs separation

These metrics were used to guide cluster selection, but the final decision also considered interpretability and cluster size balance.

## IV. RESULTS AND DISCUSSION

This section presents the results of the proposed clustering approach for Steam games. The clustering experiments were conducted using multiple feature sets and algorithms; however, the final analysis focused on the most interpretable and defensible results. Two main outputs are discussed: X2 Balanced as the main clustering model

X3 Ratios as a supporting result, since it highlights how engagement-to-price style features naturally separate high-traction games from the long tail of Steam titles.

### A. PCA Dimensionality Reduction Results

Before clustering, Principal Component Analysis (PCA) was applied to reduce feature dimensionality while preserving the majority of information contained in the dataset. The goal of PCA in this study was not to “improve” the dataset artificially, but to provide a stable, low-dimensional representation that makes clustering more efficient and less noisy. For the datasets used in the final analysis: X2 Balanced (playtime > 0) used 6 principal components to retain at least 90% cumulative explained variance.

X3 Ratios (ALL) also used 6 principal components to retain at least 90% cumulative explained variance.

The PCA results show that the first principal component (PC1) explains roughly 40% of the variance in both datasets, while PC2 contributes approximately 15–16%. This indicates that the dataset contains a strong dominant structure that PCA captures early, making it suitable for clustering.

Dataframe	Principal Component	Cumulative Explained Variance
X2	PC1	41.24%
	PC2	57.41%
	PC3	71.46%
	PC4	82.48%
	PC5	89.90%
	PC6	95.50%
X3	PC1	39.95%
	PC2	56.33%
	PC3	70.24%
	PC4	80.45%
	PC5	89.26%
	PC6	96.34%

Fig. 4. PCA Explained Variance Summary

**Key observation:** Since PCA90 only required 6 components out of 9 features, the clustering process can be performed with reduced computational cost while still retaining most of the dataset’s information.

### B. Selection of the Main Clustering Model

The study evaluated clustering performance across multiple algorithms, including K-Means, Gaussian Mixture Models (GMM), and Hierarchical clustering. The performance of each configuration was measured using standard internal clustering evaluation metrics: Silhouette Score (higher is better)

Davies–Bouldin Index (lower is better)

Calinski–Harabasz Index (higher is better)

For the final model selection, interpretability and defensibility were prioritized over simply choosing the highest metric value. This is because clustering is unsupervised, and internal metrics alone cannot guarantee that the resulting groups are meaningful for real-world interpretation. The final main model was chosen as: X2 Balanced (playtime > 0) + PCA90 + KMeans (k = 3) This configuration was selected because it produced: reasonable silhouette performance among tested values

cluster sizes that were not overly imbalanced clusters that were interpretable based on pricing, popularity, and engagement features

Dataframe	k	Silhouette	Davies--Bouldin	Calinski--Harabasz
X2	2	0.269	1.422	2741.3
	3	0.273	1.349	2176.3
	4	0.211	1.465	1998.1
	5	0.199	1.350	1850.4
	6	0.411	1.277	16883.2
X3	2	0.267	1.463	14588.3
	3	0.229	1.414	12738.2
	4	0.247	1.270	12164.4
	5			
	6			

Fig. 5. KMeans results for X2 across k = 2 to 5

### C. Main Clustering Output: X2, KMeans k = 3

1) *Cluster size distribution:* The main dataset (X2) contained 6,782 games (paid titles with playtime greater than zero). The KMeans model produced three clusters with the following distribution: Cluster 0: 2,133 games (31.45%)

Cluster 1: 879 games (12.96%)

Cluster 2: 3,770 games (55.59%)

This distribution indicates that the model does not collapse into one dominant group. Instead, it provides three distinct segments that represent different engagement and pricing behaviors.

TABLE II  
X2 MAIN DATASET: CLUSTER SIZES (K-MEANS, k = 3)

Cluster	Count	Percentage (%)
0	2133	31.45
1	879	12.96
2	3770	55.59

2) *Cluster profiling using mean statistics:* To interpret the clusters, mean values were computed across the main features used in the balanced dataset. The following features were analyzed:

- price
- discount
- release\_age\_years
- owners\_mid
- num\_reviews\_total
- pct\_pos\_total
- peak\_ccu
- average\_playtime\_forever

TABLE III  
X2 MAIN DATASET: CLUSTER MEANS (K-MEANS, k = 3)

Cluster	Price	Discount	Release Age (Years)	Owners (Mid)	Total Reviews	% Positive	Peak CCU	Avg. Playtime
0	23.601	3.421	6.031	1254156.118	20973.847	85.660	1470.802	1655.160
1	4.295	67.311	7.242	207292.378	2018.233	78.297	70.191	1328.688
2	10.275	0.473	7.753	108505.305	552.242	76.202	4.968	284.024

The mean profile reveals strong differences across clusters, especially in popularity-related features (owners\_mid, reviews, peak\_ccu), and engagement-related features (average\_playtime\_forever).

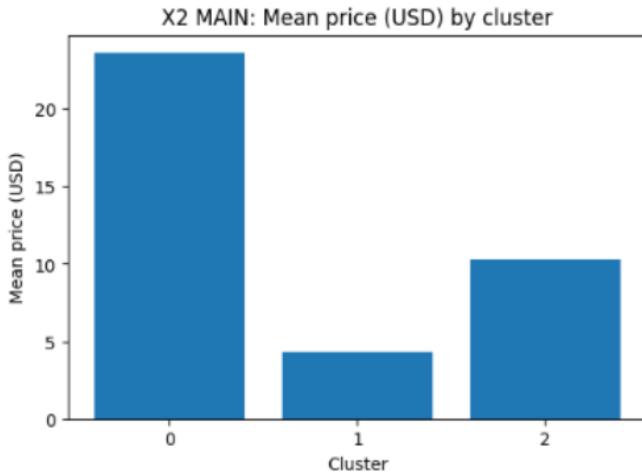


Fig. 6.

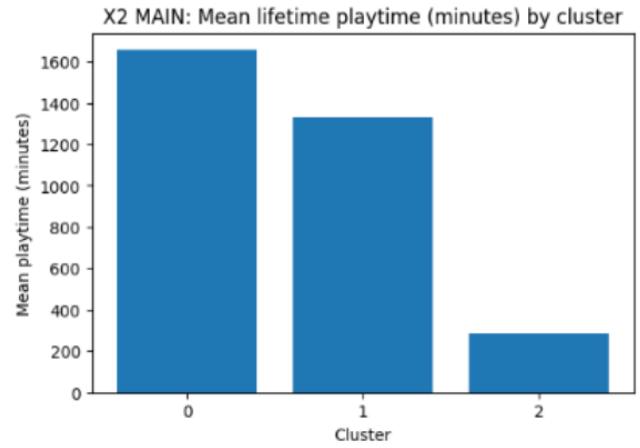


Fig. 8.

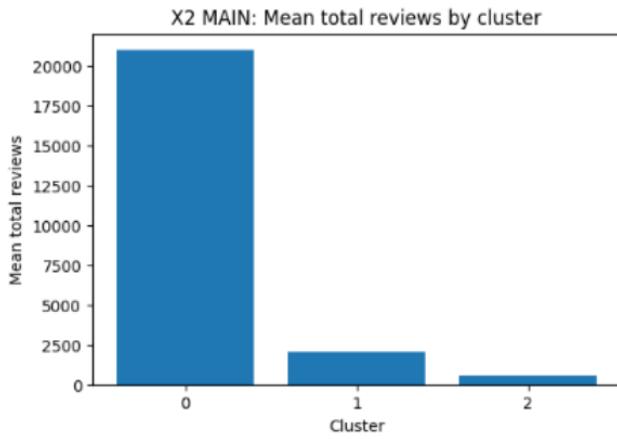


Fig. 7.

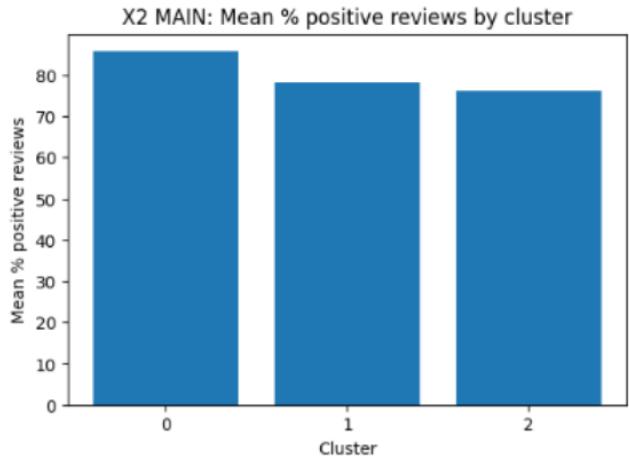


Fig. 9.

3) *Cluster profiling using median statistics:* Because Steam data is highly skewed (a small number of games dominate owners and reviews), medians were also computed. Medians are important because they represent the “typical” game in each cluster more accurately than means.

TABLE IV  
X2 MAIN DATASET: CLUSTER MEDIANES (K-MEANS,  $k = 3$ )

Cluster	Price	Discount	Release Age (Years)	Owners (Mid)	Total Reviews	% Positive	Peak CCU	Avg. Playtime
0	19.990	0.0	5.407	350000.0	4733.0	88.0	66.0	674.0
1	2.990	70.0	7.502	75000.0	545.0	81.0	3.0	202.0
2	9.795	0.0	8.437	35000.0	287.0	79.0	1.0	145.5

Notably, the medians confirm that the clusters differ not only due to extreme outliers, but also in their typical pricing and engagement patterns.

#### D. Interpretation of the X2 Clusters

Based on the profiling tables and the top examples per cluster, the three clusters can be interpreted as follows:

Cluster 0 (31.45%): High-Traction, High-Engagement Titles

Cluster 0 contains the most popular and high-engagement games. This cluster has:

- the highest owners\_mid
- the highest num\_reviews\_total
- the highest peak\_ccu
- the highest average\_playtime\_forever
- high pct\_pos\_total

The median price is also higher than the other clusters, suggesting these are established paid titles that still generate strong engagement. Examples in this cluster include:

- Tom Clancy's Rainbow Six Siege
- Rust
- Garry's Mod
- The Witcher 3
- Elden Ring

These examples confirm that Cluster 0 represents mainstream games with strong player retention and community activity.

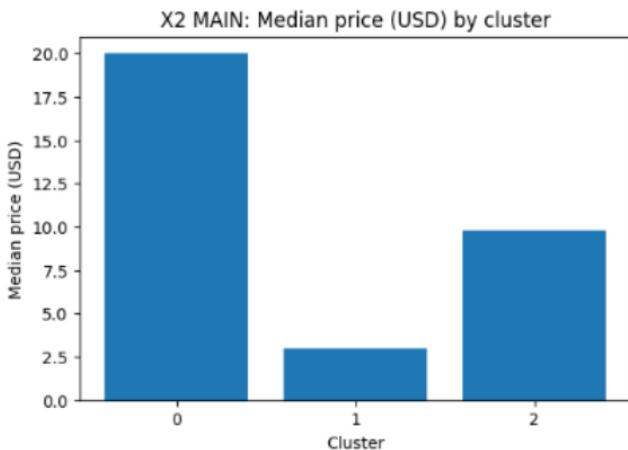


Fig. 10.

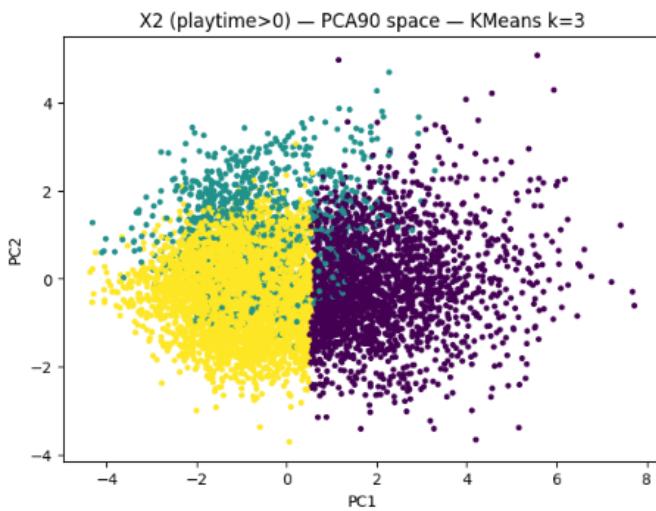


Fig. 11. PCA scatter plot for X2 (PC1 vs PC2)

**Cluster 1 (12.96%): Discount-Driven Mid-to-High Engagement Purchases**

Cluster 1 is characterized by:

- very low price
- extremely high discount levels (mean discount ~67%)
- moderate-to-high playtime
- moderate popularity indicators (owners, reviews)

This suggests that Cluster 1 represents games that are often purchased during sales and promotions, but still provide meaningful engagement. Examples include:

- Metro Exodus
- Metro 2033 Redux
- Rising Storm 2: Vietnam
- LIMBO

These titles align with the interpretation of “value purchases,” where users likely acquire the game during discounts and then spend significant time playing.

**Cluster 2 (55.59%): Low-Traction, Low-Engagement Long-Tail Games**

Cluster 2 is the largest cluster. It contains games with:

- low owners
- low reviews
- extremely low peak\_ccu
- low lifetime playtime
- slightly lower pct\_pos\_total

The median owners\_mid and review counts are much smaller, indicating these are not widely played games. Many titles in this cluster appear to be smaller indie games or niche releases that do not reach large audiences. This cluster represents the “Steam long tail,” where most games exist but receive minimal engagement.

#### E. Supporting Result: X3 Ratios (ALL), KMeans k = 2

To support the main findings, the study also examined X3 Ratios (ALL). Unlike X2, this dataset includes all paid games, including those with zero playtime. X3 uses ratio-based and log-scaled engagement features, which emphasize relative engagement differences rather than raw playtime values. The clustering on X3 produced two clusters: Cluster 0: 8,128 games (19.76%)

Cluster 1: 33,008 games (80.24%)

TABLE V  
X3 SUPPORT DATASET: CLUSTER SIZES (K-MEANS, k = 2)

Cluster	Count	Percentage (%)
0	8128	19.76
1	33008	80.24

**1) Interpretation of X3 clusters (short but strong):** The X3 result strongly separates Steam games into: Cluster 0: high-traction, high-engagement titles

Cluster 1: the long-tail majority with minimal traction

Cluster 0 contains games with significantly higher owners\_mid, reviews, and peak\_ccu, while Cluster 1 contains the majority of games with low visibility and minimal engagement. This supporting result is consistent with the expected structure of the Steam market, where a small percentage of games generate most of the player activity.

**2) Why X3 is used as supporting and not main:** X3 includes games with zero average playtime. As observed in earlier experiments, the presence of zero average playtime games can artificially increase silhouette scores by creating an easy separation between “played” and “not played.” While this produces clean metric values, it may not represent meaningful segmentation of engaged players. Therefore, X3 is used as supporting evidence for market structure, while X2 remains the main model for interpreting engagement and pricing among active games.

#### F. Summary of Findings

The clustering results provide a clear segmentation of Steam paid games: A smaller group of high-traction games that dominate owners, reviews, and engagement

A discount-driven cluster that represents value purchases with strong playtime

A large long-tail cluster that contains most games with low traction and low engagement

These clusters can be used to support insights related to pricing strategy, player engagement, and the Steam marketplace structure.

## V. CONCLUSION

Clustering Steam games based on pricing and engagement-related features yields meaningful groupings that effectively summarize marketplace performance. Among K-Means, Hierarchical Clustering, and Gaussian Mixture Models tested on various feature sets, K-Means consistently produced the most interpretable results according to the Silhouette, Davies–Bouldin, and Calinski–Harabasz evaluation metrics. The final clustering model utilized the X2 dataframe, with principal component analysis (PCA) reducing dimensionality to six components that captured 90% of the variance, and K-Means clustering with  $k = 3$ . This approach identified three distinct clusters: (1) mainstream games with high engagement and visibility, (2) heavily discounted games exhibiting moderate engagement, and (3) lower-visibility titles characterized by low engagement and limited community activity. A supplementary experiment employing the X3 dataset, which included all paid games and ratio or log-based features, demonstrated that incorporating games with extremely low or zero playtime alters the cluster structure and diminishes interpretability, despite higher overall clustering scores. These findings indicate that unsupervised learning serves as an effective exploratory tool for identifying broad behavioral segments in large digital game marketplaces, particularly when feature engineering mitigates the influence of extreme engagement values.

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