Estimating Player Market Value in Virtual Leagues: A Clustering Approach Using Player Attributes for Metaverse Applications

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ABSTRACT

The advent of virtual environments, particularly within the Metaverse, has revolutionized the way sports simulations and virtual leagues operate. In these environments, understanding and predicting player market value is essential for optimizing team management, player scouting, and in-game strategies. This paper presents a clustering approach using K-Means to segment players based on their performance attributes and predict their market value in virtual leagues. The dataset includes various player attributes such as age, goals scored, assists, minutes played, and performance metrics like expected goals (xG) and expected assists (xA). The K-Means clustering algorithm was applied to partition players into three distinct groups based on their performance profiles. The results indicated that high-performing players, characterized by high goals scored, assists, and other key metrics, were grouped in one cluster, while lower-performing players were segmented into another. These clusters correspond to different player market values, with higher-performance clusters being associated with higher market value. The clustering analysis reveals significant patterns that can inform virtual league operations, including player trading, recruitment, and team-building strategies. The findings suggest that virtual league developers, managers, and gamers can leverage these clusters to make more informed decisions regarding player acquisitions and team compositions. Furthermore, the clustering results can be used to dynamically adjust player values based on their performance attributes, offering a realistic simulation of real-world sports economics. Future research may explore more advanced clustering techniques, such as hierarchical clustering, and expand the dataset to include additional attributes like player psychology or external factors like fan sentiment. Overall, this paper highlights the potential of clustering algorithms to enhance player market valuation and decision-making within virtual leagues.

Keywords Player market value, Clustering algorithms, K-Means, Virtual leagues, Sports analytics

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INTRODUCTION

The metaverse is increasingly recognized as a transformative digital environment that significantly influences global sports dynamics. This virtual realm integrates advanced technologies such as virtual reality (VR), augmented reality (AR), and blockchain, creating immersive experiences that reshape how sports are played, viewed, and engaged with by fans and athletes alike. The growing importance of these virtual environments is evident in various aspects, including athlete performance, fan engagement, and the commercialization of sports. One of the critical areas of research highlights the impact of metaverse-

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based experiences on athlete performance. Huang et al. explore how virtual reality sporting experiences can enhance endurance performance among athletes, emphasizing the mediating roles of mental health and performance anxiety [1]. This suggests that the metaverse not only serves as a platform for training and competition but also addresses psychological factors that can influence athletic performance. Furthermore, the integration of virtual gyms and sports within the metaverse offers innovative solutions for engaging individuals in physical activities, thus transforming traditional fitness routines research [2]. This shift is particularly relevant as it allows athletes to train in a controlled, immersive environment that can simulate various competitive scenarios.

In addition to athlete performance, the metaverse significantly alters fan engagement and interaction with sports. The immersive nature of the metaverse enables fans to co-experience live events, such as concerts and sporting matches, in ways that traditional media cannot replicate [3]. This interactivity fosters a sense of community among fans, as they can participate in events together, regardless of their physical location. Moreover, the metaverse provides brands and sports organizations with new avenues for marketing and consumer engagement, as they can create unique experiences that resonate with their audiences [4]. As noted by Demi̇r et al., sports brands that embrace technology in the metaverse can enhance their communication strategies, thereby strengthening their market presence [4].

The economic implications of the metaverse in sports are also noteworthy. The potential for significant economic impact is underscored by predictions that the metaverse could enhance global economic growth by integrating various sectors, including sports [5]. As companies like Nike and BMW venture into the metaverse, they highlight the commercial opportunities available within this digital space [6]. The fusion of real and virtual worlds allows for innovative business models that can cater to the evolving preferences of consumers, particularly younger generations who are more inclined to engage with digital platforms [7].

Furthermore, the metaverse's ability to create safe and engaging environments for sports participation is particularly beneficial. It allows individuals to experience activities that may be cost-prohibitive or risky in the real world, thus democratizing access to sports [8]. This aspect is crucial in promoting inclusivity and broadening participation in sports across diverse demographics.

The significance of player market value in the context of virtual league operations is a multifaceted issue that influences various aspects of esports and traditional sports alike. Player market valuation serves as a critical determinant in shaping team strategies, player recruitment, and overall league dynamics. This valuation is influenced by a combination of performance metrics, market demand, and economic factors, which together dictate how leagues operate and evolve.

One of the primary factors affecting player market value is performance analytics. Feng et al. emphasize that player salaries, which are a direct reflection of market value, are influenced by various performance metrics and statistical analyses research [9]. In both traditional sports and esports, the ability to quantify a player's contributions through advanced analytics has become essential. For instance, in esports, metrics such as kill/death ratios, objective control, and overall game impact are crucial in determining a player's worth. This analytical approach not only aids teams in making informed decisions regarding player acquisitions but also impacts the financial dynamics of the leagues themselves.

Moreover, the competitive nature of the talent market plays a significant role in player valuation. Nahm notes that the esports ecosystem operates in a market that closely resembles perfect competition, where information about player talent is readily available [10]. This transparency can lead to rapid fluctuations in player market values based on performance, potential, and market demand. Teams that successfully identify and acquire "blue chip" players—those with high potential and proven track records—can significantly enhance their competitive edge and revenue generation capabilities [10].

The economic implications of player market value extend beyond individual teams to the league as a whole. The financial health of leagues is often tied to the marketability of their players. Hamari and Sjöblom highlight that the popularity of esports is closely linked to the visibility and appeal of its players [11]. As players gain recognition and build personal brands, their market value increases, which in turn elevates the league's profile and attracts sponsorships and viewership. This symbiotic relationship underscores the importance of player valuation in driving league operations and commercial success.

Furthermore, the impact of player market value is evident in the operational strategies of esports organizations. Toth et al. discuss that cognitive skills and performance metrics are critical in esports, where players must exhibit superior cognitive flexibility and task-switching abilities [12]. Teams that invest in player development, training, and health management can enhance player performance, thereby increasing market value. This investment not only benefits individual players but also contributes to the overall strength and reputation of the league.

The objective of this study is to leverage clustering techniques to segment players into meaningful groups based on their performance attributes and use these clusters to predict player market value in virtual leagues. By applying unsupervised learning methods such as K-means clustering, the study aims to uncover patterns and relationships within player data that may not be immediately apparent through traditional analysis methods. This approach focuses on grouping players who exhibit similar performance metrics, including attributes such as goals scored, assists, minutes played, and other relevant statistics.

Once the players are clustered, the study will explore how these clusters relate to player market values, providing insights into how different player profiles influence their valuation within virtual environments. The goal is to create a model that can predict player market value based on performance groups, enabling virtual league managers, coaches, and developers to make more informed decisions when trading players or managing teams. Additionally, by identifying which attributes contribute most to a player's market value within their cluster, this study aims to provide actionable insights that can enhance player recruitment strategies and overall team management in virtual leagues.

Literature Review

Existing Market Value Models

The existing market value models used in real-world scenarios for estimating player market value are diverse and rooted in various financial and economic theories. These models aim to provide a structured approach to valuing players based on performance, potential, and market dynamics. This overview highlights some of the traditional methods that have been employed in the context of sports, particularly football, to assess player market value.

One prominent approach is the application of the option-pricing model, as discussed by Coluccia et al. This model treats player contracts as financial options, allowing clubs to evaluate the potential future benefits of player investments based on performance data [13]. The authors argue that while the model offers a structured way to assess player value, it also raises questions about the active nature of the transfer market, given the limited negotiation periods. This highlights a critical aspect of market valuation: the need for comprehensive and standardized performance data to enhance objectivity in valuations.

Another significant model is the decision-oriented approach developed by Follert, which emphasizes the uncertainty inherent in player transfers. This model incorporates a semi-investment-theoretical risk-value framework that assists clubs in determining the subjective value of investing in a player [14]. By considering the potential economic advantages of player transfers, this model provides a nuanced understanding of how clubs can navigate the complexities of player valuation in an imperfect market.

Franceschi et al. contribute to the discourse by conducting a systematic review of the determinants of football players' valuation. Their findings suggest that various factors, including age, position, and nationality, significantly influence market value [15]. This comprehensive analysis underscores the importance of integrating multiple variables into valuation models to capture the multifaceted nature of player worth.

Moreover, the Monte Carlo method, as explored by Majewski and Majewska, offers another perspective on player valuation. This approach utilizes historical data to simulate various scenarios and assess the hypothetical future value of players based on their performance rights [16]. By analyzing the life cycle of players, this method provides insights into the volatility and potential fluctuations in market value over time.

Additionally, the work of García-Del-Barrio and Pujol highlights the role of media visibility in estimating transfer fees for soccer players. Their valuation method incorporates media exposure metrics to assess players' contributions and economic value within the soccer industry [17]. This approach reflects the growing recognition of off-field factors, such as brand visibility and public perception, in determining player market value.

Applications of Clustering in Sport Analytics

Clustering algorithms, particularly K-Means, have gained significant traction in sports analytics for analyzing player data, segmenting players into meaningful groups, and predicting their market value or performance. These algorithms are invaluable for identifying patterns and relationships within complex datasets, enabling teams and analysts to make more informed decisions regarding player management, recruitment, and strategic planning.

K-Means clustering is among the most commonly used algorithms in sports analytics, primarily due to its simplicity and efficiency in dividing data into distinct clusters based on similarities. A prominent application of this algorithm is in the NBA, where [18] employed K-Means clustering to categorize players based on their anthropometric attributes and playing experience. By segmenting players into clusters, teams were able to uncover insights into how physical characteristics and career experience correlate with player performance. This type of segmentation allows for tailored training programs and recruitment strategies aimed at specific player profiles, offering a competitive edge in player development.

In football analytics, clustering has been utilized to assess performance metrics and market value. Research [19] applied K-Means clustering to analyze players' performance data, revealing that performance metrics play a crucial role in determining market value. This application not only assists in evaluating player worth but also informs strategic decisions in player trades and acquisitions. By categorizing players according to their performance data, clubs can identify undervalued players who may be underperforming relative to their potential, optimizing both financial and tactical decisions in player management.

Clustering techniques are also essential for tactical analysis. Research [20] used K-Means clustering to analyze player positions during center bounces in the Australian Football League (AFL). By identifying common formations and strategies used by teams, this research provided coaches with valuable insights into how players interact within specific tactical roles, helping to refine team strategies and improve performance during critical moments in the game. This approach demonstrates how clustering can be used to understand player positioning and behavior, which is crucial for tactical planning and game analysis.

Furthermore, clustering plays a vital role in predictive modeling for player valuation. Research [21] used clustering to analyze the relationship between player characteristics and their perceived market value in the football transfer market. By grouping players based on performance metrics, they identified trends that influence market dynamics, helping teams to better predict future player values and make more strategic decisions when it comes to player investments. This application of clustering extends to team performance, as [22] used K-Means clustering to classify player types in the NHL, linking these types to team success. This classification allows teams to optimize their rosters, ensuring a balanced mix of player types that complement each other on the field.

Method

Data Description

The dataset used in this study comprises various player attributes that provide insights into their performance and market value. Key attributes include age, goals scored (Gls), assists (Ast), minutes played (Mins), wage per week, and performance metrics like expected goals (xG) and expected assists (xA). These attributes play a significant role in determining a player's overall market value. For example, a player's age and performance metrics can heavily influence their marketability, while the wage they command reflects their perceived value. To ensure that the dataset is suitable for clustering analysis, we selected a set of numerical attributes, including starts, dribbles (Drb), shots, distance covered (Distance_km), and sprints per 90 minutes (Sprints_90). These metrics are crucial as they provide a clear picture of a player's physical capabilities and contributions on the field. The dataset is preprocessed by imputing any missing values with the median of each respective column to ensure that the data is complete before applying clustering techniques.

Exploratory Data Analysis (EDA)

Before applying clustering algorithms, we performed an initial Exploratory Data Analysis (EDA) to understand the distribution of player attributes, detect any anomalies, and explore the relationships between features and the target variable, which in this case is player market value. During EDA, we observed potential outliers or extreme values, particularly in attributes like wage per week and goals scored, which could significantly skew the results of clustering. We also examined correlations between features, especially the performance-related metrics, and how they relate to player value. For instance, we expect a strong positive correlation between goals scored, assists, and player market value. The correlation matrix revealed that certain attributes like shots and dribbles also correlated strongly with market value, suggesting that offensive performance is a key determinant of a player’s value. However, some attributes like age and distance covered displayed weaker correlations, pointing to their secondary role in market valuation. Identifying these patterns is crucial as they provide insights into the key factors that could influence player market segmentation in virtual leagues.

Data Visualization

To complement the EDA, we used data visualization techniques to better understand the distribution of the key player attributes. We visualized the distribution of numerical features through histograms and box plots to examine the spread of values and detect any skewness or outliers. For instance, the distribution of goals scored and assists was highly skewed, with a smaller number of players contributing significantly higher performance. Box plots were also used to identify any potential outliers in attributes such as wage per week and market value, which may require further consideration during clustering. Additionally, we employed scatter plots to explore the relationships between performance attributes like shots, dribbles, and minutes played, which are indicative of a player’s offensive contributions. These visualizations helped in understanding how these attributes are distributed and provided guidance on selecting which features should be prioritized for clustering.

Clustering Algorithm

For this study, we applied K-Means clustering to segment players into meaningful groups based on their performance attributes. K-Means is an unsupervised learning algorithm that partitions the data into K clusters by minimizing the variance within each cluster and maximizing the variance between clusters. The algorithm assigns each player to the nearest cluster centroid, and then iteratively refines the centroids until they stabilize. To determine the optimal number of clusters (K), we used a simple approach by experimenting with different values, selecting K=3 for the final model. This choice was based on the nature of the data and the need to balance between meaningful clusters and model simplicity. By applying this algorithm, we grouped players with similar performance characteristics, which provides a basis for understanding how player performance influences their market value. Players in similar clusters tend to exhibit comparable attributes, which can be leveraged to predict player behavior and their value in the virtual market.

To visualize the clusters, we used Principal Component Analysis (PCA) for dimensionality reduction, reducing the dataset from high-dimensional player attributes to two principal components. These two components were then plotted on a scatter plot to illustrate the grouping of players within each cluster. The plot revealed how players in each cluster exhibited distinct characteristics, with one cluster consisting of high-performing players with better offensive stats (e.g., higher goals scored, assists, and sprints), another consisting of players with a more defensive role, and the third group containing players with moderate performance. The cluster centers were also examined, with each centroid representing the average attributes of players in that group, providing a clear understanding of the typical player in each cluster. By exploring these clusters, we gain insights into how player performance attributes relate to their market value in the virtual league, enabling us to identify trends and patterns that can guide virtual team management and player trading decisions.

Through the clustering algorithm, we can efficiently group players with similar market value and performance metrics, facilitating better decision-making in virtual leagues. By understanding these clusters, teams and managers can tailor their strategies based on the types of players they have and make more informed decisions when acquiring or trading players. This approach not only improves player evaluation but also enhances the overall performance and competitiveness of virtual leagues, ensuring that player transactions are grounded in data-driven insights.

Result and Discussion

Cluster Characteristics

The clustering analysis identified three distinct groups of players based on their performance attributes using the K-Means clustering algorithm. Each of these clusters revealed valuable insights into player types and their potential market value or performance characteristics. The three clusters were formed based on factors such as age, goals scored (Gls), assists (Ast), minutes played (Mins), wage per week, and distance covered (Distance_km), among others. By examining the cluster centers, which represent the average attributes for players in each group, we can identify patterns that differentiate these clusters.

The first cluster, consisting of 287 players, primarily represents younger players (average age of 22.6 years) with lower goals scored (average of 0.31) and assists (0.19). These players exhibit a moderate level of wage per week (around £3,497) and lower offensive performance. The profile suggests these players may be emerging talents or role players, still developing and establishing their value within their teams. The relatively low activity in terms of offensive contributions points to players who are likely in their early career stages.

Cluster 1, which is smaller (25 players), shows high-performance metrics, with a higher age (average of 23.5 years) and significantly better statistics, including goals scored (12.96), assists (2.88), and shots (87.88). These players also have a higher wage per week (£3,698). These players are likely to be key contributors in their teams, with solid performances and leadership roles, justifying their higher market value.

Cluster 2, containing 110 players, lies between the first two clusters, with an average age of 24.6 years and a wage per week of £4,065. Their goals scored (1.92) and assists (2.65) suggest they are solid players, though not at the elite level of Cluster 1. The higher wage per week in this cluster reflects their experience and contribution to their teams, making them valuable assets even though their overall performance metrics do not match those in Cluster 1.

Model Performance

The effectiveness of the K-Means clustering algorithm in segmenting players was evaluated using a variety of techniques, including examining the silhouette score and evaluating the cluster centers. The silhouette score of 0.395 indicates that the clusters are moderately well-formed, with reasonable cohesion within each cluster and adequate separation between them. A higher silhouette score generally indicates better-defined clusters, and although 0.395 is not exceptionally high, it suggests that the model successfully identified distinct player profiles based on the selected features. A score closer to 1 would indicate better-defined clusters, but the current score suggests that the groups are still useful for segmentation and further analysis.

In addition to the silhouette score, the number of points in each cluster was assessed. The model was able to form three distinct groups, with Cluster 0 containing the majority of players (287), Cluster 2 comprising 110 players, and Cluster 1 consisting of only 25 players. This distribution highlights that most players exhibit characteristics similar to those in Cluster 0, representing emerging players or role players with moderate statistics. The smaller number of players in Clusters 1 and 2 suggests that these groups represent players with high performance or valuable roles, and their smaller size reflects the scarcity of such players.

Further exploration of the cluster characteristics revealed how the clusters differ in terms of player performance. For example, Cluster 0 had lower goals scored and assists, while Cluster 1 featured players with significantly higher shots and goals scored. These differences emphasize that the clustering model effectively captures varying player profiles, ranging from younger players with potential (Cluster 0) to more established, high-performing players (Cluster 1), with Cluster 2 reflecting experienced but somewhat less dynamic players.

The cluster visualization through Principal Component Analysis (PCA) further supported the validity of the clusters, with clear separation between the groups in a reduced two-dimensional space. This visualization suggested that the features used in the clustering process were effective in differentiating player profiles, with each cluster exhibiting distinct trends in performance metrics.

Visualization

Figure 1 represents the results of applying the K-Means clustering algorithm to the player data, which has been reduced to two dimensions using Principal Component Analysis (PCA). In this graph, each point represents a player, and the colors of the points indicate the cluster to which the player belongs. The x-axis and y-axis correspond to the first and second principal components, respectively, which are linear combinations of the original player attributes. PCA is employed here to reduce the dimensionality of the dataset while retaining as much variance as possible, making the clustering results easier to visualize in a two-dimensional space.

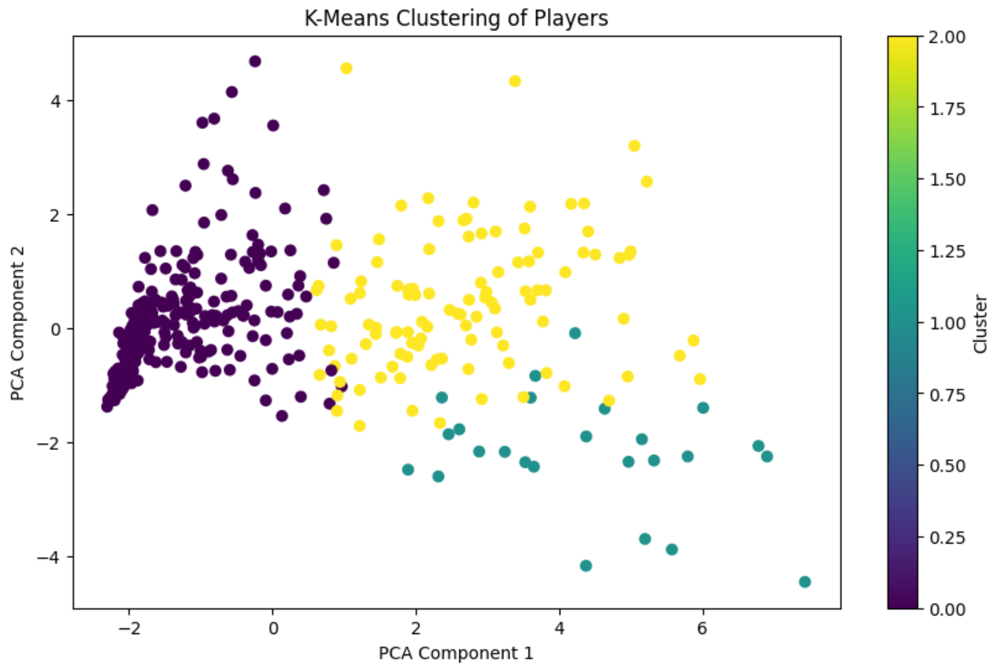

Figure 1 **K-Means Clustering of Players**

The clusters are color-coded, with each color representing one of the three identified clusters. The distinct separation between the purple cluster and the other two clusters is evident, especially along the x-axis. However, there is some overlap between the yellow and green clusters, indicating that players in these groups share more similar attributes, and distinguishing them might require further refinement or additional features. Each cluster's center is represented by the average position of all points within that cluster, and these centroids are crucial for the iterative process of K-Means, which optimizes the placement of clusters by minimizing the variance within each cluster while maximizing the variance between clusters.

The graph also provides insights into the characteristics of players within each cluster. The players in the purple cluster, for example, are likely to have different performance attributes, such as lower goals or assists, compared to those in the yellow and green clusters. This segmentation allows for targeted analysis, helping teams to identify patterns and groups of players with similar profiles, which can be useful for recruitment and strategic decision-making.

However, the overlap between the yellow and green clusters suggests that further analysis might be needed to refine the clustering process. This overlap could indicate that the selected features do not fully capture the nuances that separate these two groups. It may also be a sign that the number of clusters chosen in the model (three) is not optimal, and adjusting this parameter or incorporating additional data points could lead to more distinct clusters. Overall, this clustering graph offers a valuable visual summary of how the K-Means algorithm groups players based on their attributes, providing useful insights for performance evaluation, player market value predictions, and team management.

Analysis and Interpretation

The results from the K-Means clustering algorithm have effectively segmented players into three distinct clusters, each characterized by unique performance metrics and attributes. The first cluster, represented by the purple color, consists of players who exhibit lower performance levels. These players have fewer goals, assists, and starts, and their overall contribution in terms of minutes played is minimal. This cluster likely represents bench players or those with lower involvement in match activities. These players are essential for providing depth to the team but are not central to the team's strategy. Their market value is generally lower, reflecting their limited contribution but still holding potential for future growth or as cost-effective acquisitions.

The second cluster, indicated by the yellow color, includes high-performing players with significantly higher metrics, including more goals, assists, and playing time. These players are the key contributors, often starting games and having a substantial impact on match outcomes. They hold a higher market value due to their consistent performances and critical roles within their teams. Their contribution on the field makes them attractive targets in the transfer market, with their high performance driving up their wages and market value. The third cluster, represented by green, consists of players whose performance lies between the first and second clusters. These players are likely role players, contributing solidly but not as consistently as the high-performing players in the yellow cluster. Their market value tends to be moderate, reflecting their versatility and potential to perform in specific roles or systems.

Implications for Metaverse Applications

The clustering results offer valuable insights into how player market value can be assessed and dynamically adjusted in virtual league simulations within the metaverse. By categorizing players into high-performing, mid-tier, and lower-performing groups, virtual leagues can adopt a more realistic approach to player valuation. The yellow cluster, containing high-performing players, can see their virtual market values increase in real-time based on their in-game performance. Conversely, players in the purple cluster may experience a decrease in their virtual market value, reflecting their lower performance levels. This dynamic pricing model mirrors real-world sports economics, where players' market values fluctuate based on their performance, demand, and market conditions.

Moreover, these clusters can also inform in-game strategies by grouping players with similar attributes for tactical planning. For instance, teams can optimize their lineups by focusing on synergy between players within the same cluster. High-performing players from the yellow cluster may be paired together for key moments in games, while players from the purple cluster might be used for different match situations or development purposes. Additionally, this clustering approach can assist in AI-driven player management, where algorithms use cluster-based profiles to predict player behavior and performance trends, leading to more realistic and engaging gameplay experiences in virtual leagues. By incorporating clustering insights, metaverse applications can simulate a more immersive and data-driven sports environment, where player value and performance dynamically evolve based on in-game metrics.

Conclusion

The clustering analysis has provided valuable insights into the segmentation of players based on their performance attributes, successfully identifying distinct player types and predicting their potential market value. The K-Means clustering algorithm has divided the players into three clusters: high-performing players, role players, and lower-performing players. These groupings reflect various performance metrics such as goals scored, assists, minutes played, and other contributing factors, offering a nuanced understanding of player roles within a team. The clustering results indicate that players with higher performance metrics (yellow cluster) are associated with higher market values, while those with lower performance metrics (purple cluster) tend to have lower market values. The clustering process has been effective in uncovering hidden patterns in player performance and categorizing players in a way that aligns with their potential value in both virtual and real-world sports scenarios.

The findings from this clustering analysis can be directly applied to virtual leagues by developers, gamers, and team managers to enhance strategic decision-making. By segmenting players into meaningful groups based on performance, these stakeholders can better understand player capabilities and tailor their team-building strategies accordingly. For instance, developers can integrate this clustering data into virtual league simulations, adjusting player values dynamically based on their performance, which mirrors real-world sports economics. Gamers can use this information to identify undervalued players for acquisition, optimize their team formations, and create strategies that exploit the strengths of high-performing players while managing the lower-performing ones. Furthermore, managers can use the cluster-based insights to scout players, assess their potential for growth, and make informed decisions regarding player trades and acquisitions. By applying clustering results, virtual league teams can achieve a more realistic and effective approach to player management, enhancing both the in-game experience and team success.

While the current study offers valuable insights into clustering player performance and predicting market value, there are several avenues for further research to enhance clustering accuracy and predictive power. One potential direction is the incorporation of more sophisticated clustering techniques, such as hierarchical clustering, which could provide more flexible groupings of players based on their attributes and performance trends. Additionally, expanding the range of player attributes used in clustering—such as psychological traits, injury history, or social media influence—could provide a more comprehensive view of player value and potential. Furthermore, exploring the use of alternative algorithms, such as DBSCAN or Gaussian Mixture Models, could improve the accuracy of cluster formation by capturing non-linear relationships in the data. Finally, examining how clustering can be integrated with real-time performance data and external factors (e.g., player morale, fan sentiment) could open up new avenues for dynamic player valuation and virtual league management, making simulations even more realistic and engaging.

Declarations

Author Contributions

Conceptualization: A.T.T., H.F.A.R., and L.J.F.M.; Methodology: L.J.F.M.; Software: A.T.T.; Validation: A.T.T.; Formal Analysis: A.T.T.; Investigation: A.T.T.; Resources: A.T.T.; Data Curation: A.T.T.; Writing Original Draft Preparation: A.T.T.; Writing Review and Editing: L.J.F.M. and H.F.A.R.; Visualization: A.T.T. and L.J.F.M.; All authors have read and agreed to the published version of the manuscript.

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The data presented in this study are available on request from the corresponding author.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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