Evaluating financial performance and stakeholder engagement in sport management: a multi-objective optimization approach

Evaluación del rendimiento financiero y la participación de los grupos de interés en la gestión deportiva: un enfoque de optimización multiobjetivo

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Abstract

Introduction. The sports industry is under increasing pressure to make it realistic for the sport to be financially sustainable and at the same time it needs to be highly engaging for its fans. The traditional management styles and systems are too rigid to adequately address the competing challenges in the current environment.
Purpose. This paper presents a multi-criteria optimization model, based on artificial intelligence, to evaluate the financial outcome and stakeholder satisfaction in sports management.
Method: An iterative procedure of visual inspections and mathematical analyses was employed. Analysis was conducted on information from various channels, such as the records of the fan campaigns and social media sentiment analysis, sponsorship contracts, and outside profiles. The model was implemented in Python and consists of two main objectives: maximizing net income and satisfying the stakeholders.
results. There are significant KPIs improvements according to the simulation. Scheduling ticket sale revenues demonstrated an potential increment about 15% with the dynamic pricing policy and conversion rate of fan enhanced 20% by promoting well. Sponsor's return of investment exhibits to fall by 25%, while tourist behavior impacts positively by as much as 92%.
conversation. The results are in line with sports management studies on applications of AI, while extending the literature by showing that multi-objective management can pursue financial and relational objectives concurrently.
results. The suggested AI-driven optimization model equips sports bodies with a powerful instrument to guide decisions, and to assess and improve administrative and fan relational performance. In future, the model should be applied in practice to assess the validity of the suggested results.

Keywords

Artificial intelligence; financial inclusion; multi-objective optimization; sports management; the conduct of officials.

Resumen

Introducción. Las organizaciones deportivas se enfrentan a una creciente presión para lograr la sostenibilidad financiera y, al mismo tiempo, mantener una sólida participación de los aficionados. Los enfoques de gestión tradicionales a menudo no logran un equilibrio entre estos objetivos contrapuestos.
Objetivo. Este estudio busca desarrollar y validar un modelo de optimización multiobjetivo basado en IA para evaluar el rendimiento financiero y la participación de las partes interesadas en la gestión deportiva.
Metodología. Se adoptó un enfoque iterativo, combinando análisis visuales con análisis matemático. Se analizaron datos de múltiples fuentes, incluyendo registros de campañas de aficionados, análisis de sentimiento en redes sociales, acuerdos de patrocinio y perfiles externos. El modelo se desarrolló con Python, con dos funciones objetivo: maximizar los ingresos netos y aumentar la satisfacción de las partes interesadas.
Resultados. Los resultados de la simulación muestran mejoras significativas en los indicadores clave. Los ingresos por entradas mostraron un aumento potencial del 15% con estrategias de precios dinámicos, mientras que la participación de los aficionados aumentó un 20% mediante campañas de marketing personalizadas. El retorno de la inversión para los inversores muestra una mejora del 25%, con una rentabilidad sobre el capital (ROE) del 92%.
Discusión. Los presentes resultados son coherentes con investigaciones previas sobre aplicaciones de inteligencia artificial en la gestión deportiva y amplían la literatura al demostrar cómo la optimización multiobjetivo puede abordar simultáneamente objetivos financieros y relacionales.
Conclusiones. El modelo de desarrollo basado en IA propuesto proporciona a las organizaciones deportivas una herramienta robusta para la toma de decisiones basada en datos, permitiéndoles medir y mejorar tanto el rendimiento administrativo como las relaciones con los aficionados. Investigaciones futuras deberían implementar este modelo en entornos reales para verificar estos resultados.

Palabras clave

Gestión deportiva; inteligencia artificial; optimización multiobjetivo; participación de los grupos de interés; sostenibilidad financiera.

Introduction

The sports business is indeed transforming, primarily because digital technology, artificial intelligence (AI), and analytics are innovating at a rapid pace. This does not mean the adjustment of a couple of dials or the use of a couple of switches but the completely wholesale redefinition of how the sports organizations will compete and how they will operate, as well as even how they will relate with their fans and other constituents (Glebova et al., 2025). The use of AI in sports management has been an area that has brought new opportunities; some of them include the possibility of enhancing the efficiency of the operations, increasing financial discipline, and improving the relationship with sponsors, fans and other key parties (Pietraszewski et al., 2025). Indeed, those tools are essential in the modern world, as sports organizations need to reorient their financial foundation, and simultaneously, they need to engage their stakeholders in virtually all processes of sporting activity. AI has revolutionized the world of data in sports organizations which now are able to access a lot of data and extract insights that could not be accessed before. To illustrate, there is predictive analytics (run by machine learning), which can identify fan behavior in real time and marketers can customize their content and offers depending on what their audience is doing at a particular time (Kim & Ford, 2025). Similarly, AI technologies, which can be worn, transformed the system of measuring athlete performance. They also provide a coach and trainers with real time information of how hard an athlete is working, how fast they are recovering and even the risk of being injured. It does not simply turn athletes into better people; indirectly, it contributes to increasing the fan engagement as in many instances, when you have more successful results on the field, you also have more enthusiastic fans (Su et al., 2024). Yet despite all of this, there are broader opportunities that sport organisations can use AI-related solutions to integrate into broader strategies that can deal with financial sustainability, as well as be more participatory in the stakeholders (Mezzadri et al., 2025, Nadweh et al., 2025). Most sports organizations, in turn, rely on more traditional solutions. These mechanisms do not always have the resources necessary to consider the complexity of the modern sports business, its numerous sources of income, changing expectations of fans and high competition (Cheng et al., 2022). Use the case that an AI platform can inform you about what fans are experiencing in real-time in events, but very few organizations have the technology and expertise to turn this information into actionable and meaningful results within the broader purpose of the organization. This, practically speaking, is to revisit the way to incorporate those traditional elements of power playmaking with new ones (Stegmann et al., 2023).

Contemporary sport organizations have been faced with a more competitive and dynamic environment. Good stakeholders and financial stability are co-related, in fact, these two relations are the most suitable amongst the relations due to success reasons (Yulinar et al., 2026). In order to be financially sustainable, one must maximize on a number of sources of revenue (such as ticket sales, broadcast revenues, merchandise sales, and sponsorship). The bottom line is to keep your expenses under control and ensure that you have what it takes to keep on keeping on, over a long period of time (Ivašković, 2024; Miragaia et al., 2024). Stakeholder management involves more to do with creating relationships with fans, sponsors and community partners and achieving this by doing it through individualized marketing initiatives and interactions that bring about value (Md Soberi et al., 2026). The two priorities tend to conflict, however, resulting in lack of efficiency, missed opportunities and at times some feathers were ruffled by important stakeholders (Kapoor, 2021).

Prediction of the fan behavior is one of the most important issues in this respect, which currently has become more dynamic due to the emergence of various digital platforms and a variety of consumption patterns. The old system of fan segmentation and interaction with current information to refer to the previous data and demography profiles is no longer applicable to the dynamic preferences of modern viewers who consume the content on various media and devices (Akhmatov et al., 2025). In one day, an example is that a fan can subscribe to a sporting organization in the social media, streaming, mobile applications, and live attendance. Such balkanization renders it hard to have an entity that creates an effective engagement policy to speak directly to an audience. And this is further compounded by the fact that there is the negotiation of the most favorable sponsorship deals; the organization must consider the interests of the sponsors with its own - and that of the fans, which is of utmost importance (Sorheim et al., 2026). Its returns to their investment are more evident, as sponsors, e.g., require an improved brand recognition or a greater number of fans. In the meantime, sports organizations should make sure that the cooperations are actually worthwhile and significant to their audiences (Bittla, 2025). In the absence of sound data analysis to make decisions based on which the outcome may be based, the sports team or club may go bankrupt or disappoint the people.

The emergence of digital platforms among other factors has increased the competition between sporting organizations. This undoubtedly creates new opportunities for interaction but also raises fans' expectations to new heights (An et al., 2024, 2024b; Stegmann et al., 2023). In reality, modern-day fans crave highly personalized experiences, immediate access to interaction, and seamless transitions between the physical and digital worlds (Krishnapatnam, 2025). Such as offering real-time game statistics, player profiles and exclusive behind-the-scenes materials through user-friendly platforms that adjust to user preferences (Abutame & Zaidalkilani, 2025). However, this requires more than technological development; it also necessitates a novel approach to how resources are allocated, how priorities are established, and how those priorities relate to the larger goals of the organization. This speaks to the necessity of advanced models that can integrate financial and marketing objectives into a single framework to enable sports institutions to manage the complexities of the modern sports world (Ghorbani Asiabar et al., 2025).

This research seeks to mitigate the above challenges through the creation of an AI-based multi-objective optimization model that is designed specifically for sports institutions. The primary objectives of this research are threefold:

1. Financial Sustainability: To create an end-to-end solution that best targets the largest number of streams of revenue while incurring minimum cost of spend and ensuring financial stability in the long term. It is reliant on the implementation of AI algorithms to make best-practice decisions on pricing strategy, predict demand volatility, and budgeting. For example, the model will be able to predict attendance and price dynamically through historical ticket purchase trends and external factors such as weather and team performance to determine.

2. Stakeholder Engagement: The aim of this is to increase the engagement with the fans, sponsors and other stakeholders. This will be done using insights and very personalised campaigns. This may be distilled to mean predicting the behavior of fans, dynamically segmenting up audiences on the basis of what they are interested in, and tailoring marketing campaigns to be as personalized as possible (i.e. resonating with each fan at a micro level).

3. AI and Mathematical Programming in One: The aim in this case is to have a combined model. This model uses state of the art computer algorithms in artificial intelligence and mathematical programming to solve multidimensional problems of large scale that occur in sports management. And, in fact, it also allows sports to balance apparently opposing priorities (including maximal revenues and stakeholder satisfaction). Indicatively, the model can be used to maximize sponsorship arrangements by determining the relationship between sponsorship interests and fan preferences in this manner, both parties can benefit out of the partnership.

The proposed model is aimed at giving sports organizations a working toolbox upon achieving such objectives. The toolkit will help them to resolve the two issues of financial viability and stakeholder management in a unified and well-organized platform. The system can differ, but the whole system is premised on the fact that it is a flexible system that is sensitive to the various demands of the sports institutions, both at the pro-league and the grass-root clubs.

The contributions above to theory and practice are quite considerable and they can have echo in the sports management field and even further. The paper suggests a more suitable approach where the multi-objective optimization and AI algorithms are combined to address both the financial and marketing problems of a sports institution in a single solution. However, unlike other models that most of them consider only one aspect, e.g. fan popularity or cutting costs, this proposed system balances a number of goals within a single system. It allows the companies to make the goals of the stakeholders more aligned to their financial objectives (Balasubramanian, 2023).

Secondly, this model is one that offers substantial real life value. Leveraging empirical evidence and examining case studies from sports organizations, the paper illustrates how the model can be applied. To illustrate, it may allow for better predictions of fan behavior as well as more lucrative sponsorship arrangements and higher levels of overall application performance. The model might also be utilized to track fan sentiment during live games, enabling marketers to adjust their campaigns in real time; this makes them relevant and attractive for the duration of the event. Due to its translational focus, the results are not only novel from a theoretical perspective, but they are also of high interest for sports executives looking to leverage the potential of new technologies to drive digital transformation in their organizations (Qionghai, 2025).

In conclusion, this thesis enables future research on the use of AI in sport management. By bridging the gap between AI models and complex analysis problems, it paves the way for novel enquiries in non-traditional areas such as this one. The research also offers actionable guidance for sports organizations on how to utilize AI to compete more effectively and remain viable in an increasingly digitized world. For instance, it may be modified to address objectives such as environmental sustainability or widening community impact as corporate social responsibility plays a bigger role in sports organizations (Wei Chit Chun, 2025).

Method

This research contains some novel contributions which indeed distinguish it from the current literature in sports management, artificial intelligence (AI) and digital transformation. As opposed to numerous prior studies, which may only analyze one aspect of the issue, such as whether a business idea is financially viable or if all relevant parties understood the project, this work unifies these elements into a single framework through advanced AI-based multi-objective optimization. Here are the key contributions and what makes this study unique:

1. Holistic Framework of Financial Sustainability and Stakeholder Engagement: The majority of the literature available however considers stakeholder involvement and financial sustainability as two different issues. For example, traditional financial sustainability practices tend to involve cutting costs or pursuing new sources of revenue; they are not typically informed from the potential impact on fan satisfaction or sponsorship possibilities. Similarly, stakeholder engagement research is interested in fan forecasting or promotional strategy without relating them to organizational goals. This study fills this gap by creating a universal model that considers both these objectives simultaneously, such that it ensures that financial decisions are in line with stakeholders' expectations.
2. Integration of AI and Multi-Objective Optimization: Despite the fact that AI has been used in sport management for multi-objective optimization or performance analysis, its synergistic use for multi-objective optimization remains uninvestigated. This study initiates the study of AI-augmented algorithms and mathematical programming approaches to investigate and solve intricate, interwoven problems related to sport organization. Through this approach, the research addresses the limitation of single-objective models that cannot deal with the trade-off between competitive objectives, i.e., to maximize revenue and increase fan satisfaction.
3. Real-Time Adaptability and Dynamic Decision-Making: Traditional sports management relies on fixed models and historical information, which frequently do not perform in changing environments. Real-time processing of data and machine learning are applied within this study to create responsive systems that respond to changing conditions, such as varying fan demand or unexpected market shocks. Real-time responsiveness enables sporting organizations to take proactive actions based on data rather than reactive actions.
4. Practical Purposes and Case Studies: the numerous practical implications of the findings in practical situations are deliberated. To this effect, it integrates empirical data with practical illustrations of a number of sport associations that are in existence. The given model is rather feasible, as it offers sport managers a good conceptualization of the mode to apply AI-based solutions to the customized sponsorship value proposition, fan categorization and real-time pricing. This extreme focus on practical relevance is another good assurance therefore that the findings are not merely of an academic nature. They have an immediate practical value as well to any person working in the field of sport, PRT or coming back to it.

Practical and Ethical Issues: This review as well acknowledges the practical and ethical issues surrounding the use of AI in the sporting sector. These are the issues like the privacy of data or the possibility of an algorithmic bias. However, with the active promotion of the principle of responsible AI, the study is to make sure that the gains and the guarantees of the digital innovation may be adopted without making the essential ethical guidelines less important or eroding the trust of the stakeholders.

The contribution of the study is the most significant due to the improved methods that can transform the manner in which the management of sports is practiced. The model offers a combined solution to be sought by implementing the AI-based predictive analytics and multi-purpose optimization, where the goals to achieve are economic sustainability and an adequate degree of stakeholder engagement. The improved method, which is informed by rigor method, fills the gaps in the extant literature in three areas of focus, namely, dynamic decision making, resource allocation, and personalized stakeholder engagement. In addition, the study paves the way for potential future inquiries as it provides indications for its transfer to other areas of application such as ecological sustainability or social influence. The following will describe the research methodology. This includes the model, the data collection procedure, and the analytical processes for generating and validating an AI based multi-objective optimization model. It illustrates the mathematical programming models, the process of applying the AI algorithm, and the methods to evaluate the model in terms of its precision, scalability, and application in the real world. For instance, Table 1 demonstrates several existing methodologies, and the importance of this study.

Table 1. Comparative Table of Current Methods

Aspect	Traditional Methods	AI-Driven Approaches	Limitations of Traditional Methods
Fan Engagement Prediction	Demographic segmentation, historical data analysis, social media monitoring	Real-time sentiment analysis, behavioral modeling, predictive analytics	Fails to capture dynamic preferences; lacks granularity and adaptability
Sponsorship Optimization	Manual negotiation, static ROI calculations	AI-powered optimization algorithms, alignment of sponsor goals with fan preferences	Ignores dynamic market conditions; lacks precision in matching sponsor and fan interests
Revenue Generation	Diversification of revenue streams, cost-cutting measures	Dynamic pricing strategies, demand forecasting, personalized marketing	Reactive rather than proactive; fails to optimize revenue streams based on real-time data
Decision-Making Frameworks	Single-objective optimization, static models	Multi-objective optimization, real-time data integration	Neglects interconnected objectives; unable to adapt to rapidly changing conditions
Data Utilization	Siloed data sources, manual analysis	Unified data platforms, automated insights, machine learning	Limited scalability; inability to process large volumes of data in real-time

The research approach guides the entire method to design the multi-objective optimization model from AI-based algorithms. The article has a systematic and repetitive research approach, which starts describing the key concerns in financial sustainability and the stakeholder engagement of sport organizations. They are categorized into measurable goals, which act as the foundation for the optimization model. The architecture revolves around the application of AI technologies like machine learning and predictive analytics to fuel decision-making. AI is able to process large volumes of data and identify undetected trends and allow the model to present actionable recommendations that would otherwise be ignored by conventional approaches. The choice of the multi-objective optimization model depicts the interconnection of the marketing and finance issue in sport management as well. As an example, the necessity to please fans and retain sponsors on board will need to be weighed against the necessity to make money (in terms of selling tickets and sponsorship). A combination of the two dimensions will result in a twofold demand and the model will be used in both short-term and medium-term operational needs and in long-term strategic planning needs. The model is also scalable and adaptable in the sense that it can be used to any sport organization be it professional leagues, amateur clubs or otherwise.

The process of gathering the data is likely to be the most critical, so that the model could be accurate and useful. This study needs such data, as there are various, different issues in sport management. The three categories of data are mostly related to the fan engagement (social networking activity, box office sales), financial aspects (public vs. private; cost structures; revenue sources), and the sponsorship (contract details; ROI). And non-internal factors, such as the market trends, weather and team status are also viewed to influence decision-making. The sources of the data are very diverse, which reflects the disjointedness of sport systems. Primary data, for example, is derived directly by conducting interviews and surveys with sports organizations, or by studying their internal documents. Secondary data are accessed electronically using social media indicators, ticket databases, and online video streams. For example, the fan base's opinion and behavior are exposed using social networking sites Twitter and Instagram, with ticketing plans providing access to rich information regarding attendance action and price trend. The integration of such datasets in a single location is one top priority for this research to enable the model to integrate and examine data on a comprehensive level.

Construction of the multi-objective optimization model is the core of this research. Two important objectives are considered for the model construction: financial sustainability and stakeholder engagement. Financial sustainability is achieved through optimizing the revenues, reducing the cost, and securing long-term survival. Stakeholder engagement is achieved through creation of shared relationships with fans, sponsors, and community partners based on personal touch and value-based interaction. Artificial intelligence software is the tool behind the realization of these objectives. Predictive analytics are used in the forecasting of fan trends so that companies can adjust dynamically marketing campaigns and prices. Optimization algorithms, for example genetic algorithms and reinforcement learning, do work well to solve for the best answers in that type of situation, even with changing constraints. For example, the model could recommend the optimal ticket prices given the demand at the time or suggest the best and by far the most popular sponsorship packages. The combination of AI and mathematical programming method ensures the model is highly flexible, as well as evergreen. AI can be used to make the model to process unstructured data and to adapt to environmental changes, whereas mathematical programming provides the model with a framework for tackling highly nonlinear optimization problems. We selected these exact hyperparameters in the AI algorithms to allow others to replicate our approach.

For reinforcement learning, we selected a Deep Q-Network (DQN). It had two hidden layers (128 and 64 neurons, respectively), and ReLU activation functions were used. The learning rate is 0.001, and discount factor (gamma) is 0.95. We also implemented an epsilon-greedy policy and decay rate of epsilon from 1.0 to 0.01 over 10,000 episodes. An XGBoost regressor was used for predictive analytics. It used numbers of 300 estimators and the depth was 6, Learning rate=0. 05. Moreover, we optimized the hyperparameters by means of 5-fold validation. With all these pieces in place, the model can trade off competing objectives (e.g., more revenue versus a happy fan), and it is able to make decisions that are strategically sound and highly informed by data.

Objective 1: Maximizing Financial Sustainability

With goal of our financial viability is to achieve maximum income with minimum expense, our utility function is one that maximizes income and minimizes costs. R will represent total revenue (e.g. ticket sales, merchandise sales, media rights). C will represent the total cost, which is the sum of operating expenses, salaries and advertising expenditures. Therefore, the goal function for financial feasibility may be written as:

Maximize $Z_1 = R - C$ (1)

Where:

$R = \sum_{i=1}^{n} r_i \cdot x_i$, where r_i is the revenue generated from each source i (e.g., ticket sales, sponsorships), and x_i is the quantity or volume of that source.

$C = \sum_{j=1}^{m} c_j \cdot y_j$, where c_j is the cost associated with each activity j, and y_j is the level of investment in that activity.

Equation (1) is the company's desired maximized net profit. Revenue sources and cost components are modeled as variables under constraints to guarantee realistic and feasible solutions.

Objective 2: Enhancing Stakeholder Engagement

To maximize stakeholder engagement, we define a second objective function for maximizing fan satisfaction and sponsor compatibility. Let S_f be fan satisfaction, which is a function of personal experiences, event visitation, and interaction quality. Let S_s be sponsoring satisfaction, which is a function of brand visibility, fan engagement, and ROI indicators. The objective function for stakeholder engagement can be expressed as:

Maximize $Z_2 = w_1 \cdot S_f + w_2 \cdot S_s$ (2)

Where:

w_1 and w_2 are weight factors that reflect the relative importance of fan satisfaction and sponsor satisfaction, respectively.

$S_f = \frac{\sum_{k=1}^{p} f_k}{p}$, where f_k is the satisfaction score for each fan segment k, and p is the total number of segments.

$S_s = \frac{\sum_{l=1}^{q} s_l}{q}$, where s_l is the satisfaction score for each sponsor l, and q is the total number of sponsors.

Equation (2) is used to balance the two priorities between fan and sponsor involvement such that the model considers both parties' interests. Weights w_1 and w_2 allow organizations to assign weight to one goal against the other according to their strategic plans.

To bring the two objectives together in one system, we use a weighted-sum approach, combining Z_1 and Z_2 into a composite objective function:

Maximize $Z = \alpha \cdot Z_1 + \beta \cdot Z_2$ (3)

Where:

α and β are scaling factors that determine the relative importance of financial sustainability and stakeholder engagement, respectively.

Z_1 and $Z_2$are the personal objective functions of Equations (1) and (2). Equation (3) assists in balancing the financial and marketing needs and arrive at a final solution for the issues faced by sports organizations.

Mathematical programming techniques form the backbone of the optimization model, presenting a logical approach to solve multi-dimensional issues. Sophisticated techniques such as linear programming, mixed-integer programming, and dynamic programming are utilized in the study depending on the requirements of the goals. Linear programming is employed if there exist linear interdependencies among the variables, i.e., the optimization issue of utilizing resources. Mixed-integer programming applies where some of the variables are discrete, i.e., number of tickets to sell at a certain price level.

For linear programming, consider the problem of maximizing ticket sales revenue subject to seating capacity constraints. Let x_i represent the number of tickets sold at price p_i, and let C represent the total seating capacity. The problem can be formulated as:

Maximize $R = \sum_{i=1}^{n} p_i \cdot x_i$ (4)

Subject to:

$$\begin{matrix} \sum_{i=1}^{n} x_i \leq C \\ x_i \geq 0 \ \forall i \end{matrix} \quad (5), (6)$$

Equation (4) maximizes revenue, and Equations (5) and (6) are added to maintain the solution within seating capacity and nonnegativity constraints.

After all, you want to make sure your model works and can be trusted the study does have a very strong method of validation; it applies the model to actual data from several leagues. This is a process of ensuring that the recommendations and predictions made by the model are verified by real results (e.g., by the number of tickets sold or any other proxy of the interest showed by fans) to quantify the accuracy and the usability of the model. There is a few evaluation criterion for checking the performance of the model such as accuracy, efficiency and scalability. Accuracy indicates the latent variable to the extent that knowing the observed variables can tell us what we wanted to know about our latent variable. Efficiency is a measure of the computational resources required to apply the model and can be used to determine if the model is practical for use in real-time or embedded systems. Meanwhile, Scalability measures whether a model can be scaled to larger problems, in the sense of being applied to larger system. Scenario analysis is conducted in the testing process as well, here the model is tested under a set of possible (sudden shocks such as pandemics or a shift in fan attitudes). As a result, the model can be strong yet flexible enough to cover different scenarios. Finally, the model is further refined with insights from industry leaders and practitioners, making it truly beneficial for sports enterprises.

Table 2 contains all the key variables of this work. These parameters define the model and constants applicable to the multi-objective problem mathematical modeling. As an example, R and C are revenue and costs, respectively; Sf and Ss, in their turn, are fan and sponsor satisfaction. Priority weighting coefficients (α, β, w1, w2) allow the firms to place their significance on the objectives based on their special strategic considerations. Table 3 explains the type of datasets that will be taken into consideration in the study. The following are these data sets and they make the model accurate and viable. An example is that the data of fan behavior has found application in the taste prediction and marketing management whereas the data of finances is applied in the cost management and income generation. The weather and market trends are external variables, which are included in the model to ensure that it is realistic. Table 4 summarizes the simulation scenarios, which are used in calibration and validation. Time horizon regulates the period of the Model runs and the chosen optimization solver offers the expedited calculations. We have also defined a number of test cases and ranges to perform sensitivity analysis; this would enable us to test the elasticity of the model to various likely cases.

Table 5 provides a summary of the computational programming environment which is used in researches. The use of Python as the primary language is due to the fact that it is a general-purpose language and has an extensive collection of optimization and AI libraries. Pyomo and TensorFlow library allow deployment of sophisticated algorithms and hardware information can be used to make computation efficient. Such libraries as Tableau help to present results in a pretty manner.

Table 2. Parameters Used in the Study

Parameter	Description	Unit/Type
R	Total revenue generated from ticket sales, merchandise, broadcasting rights, and sponsorships	Monetary (e.g., USD)
C	Total operational costs, including player salaries, marketing expenses, and event logistics	Monetary (e.g., USD)
Sf	Fan satisfaction score based on personalized experiences, attendance, and interaction quality	Dimensionless (0–1)
Ss	Sponsor satisfaction score based on brand visibility, fan engagement, and ROI metrics	Dimensionless (0–1)
α	Weight factor for financial sustainability in the unified objective function	Dimensionless (0–1)
β	Weight factor for stakeholder engagement in the unified objective function	Dimensionless (0–1)
w1,w2	Weight factors for fan and sponsor satisfaction in the stakeholder engagement objective	Dimensionless (0–1)
xi	Quantity or volume of each revenue sourcei(e.g., number of tickets sold at a specific price)	Integer or Continuous
yj	Level of investment in each cost activityj	Monetary (e.g., USD)

Table 3. Dataset Requirements

Dataset Type	Description	Source
Fan Behavior Data	Attending patterns, social media connections, purchase history, and feedback surveys	Social media boards, ticketing systems
Financial Records	Revenue flows (ticket sales, sponsorships), cost structures (salaries, marketing), and budgets	Inner financial reports
Sponsorship Agreements	Agreement terms, ROI metrics, and sponsor performance data	Sports organizations, sponsorship databases
External Factors	Market trends, weather situation, team performance, and economic indicators	Public datasets, sports analytics platforms

Table 4. Simulation Settings

Setting	Description	Value/Range
Time Horizon	Period over which the model is modeled	1 year (discrete monthly intervals)
Optimization Solver	Algorithm used to solve the optimisation problem	Mixed-Integer Linear Programming (MILP)
Scenarios	Hypothetical conditions tested during validation (pandemics, economic downturns)	5 scenarios
Sensitivity Analysis Range	Range of bound values tested to evaluate robustness	±20% of baseline values

Table 5. Programming Environment

Component	Description	Details
Programming Language	Language used for implementing the optimization model	Python
Libraries/Frameworks	Libraries and frameworks used for AI, optimization, and data processing	NumPy, Pandas, SciPy, Pyomo, TensorFlow
Hardware Specifications	Computational resources required for running simulations	CPU: Intel i7, RAM: 16GB, GPU: NVIDIA RTX
Software Tools	Tools used for data visualization, debugging, and reporting	Jupyter Notebook, Tableau, MATLAB

Results

We tested the multi-objective optimization model based on AI to a significant extent using real data. The question that we wanted to answer was: How well could it predict fan behaviour, assist in creating better sponsorship deals, and make profitability and stakeholder participation? The data were chosen (a) due to their accuracy and topicality and (b) due to the possibility to answer the multifaceted questions which are unique to the sport management. In this study, the following data points were used:

- Fan Attendance and Behavior Dataset

Source: Ticketmaster Analytics API

Description: This data set includes historical ticket sales, fan demographic data and attendance trends to events, along with insights on buying habits in terms of event popularity and price sensitivity of tickets.

Why Chosen: Ticketmaster data is some of the most granular out there for fan behavior data, with very fine-grained data on attendance trends and fan preference. It is real-time capable, so the model can learn to adapt based on changing conditions and therefore is especially well-suited for dynamic pricing strategies.

- Social Media Sentiment Dataset

Source: Brandwatch Social Media Analytics

Description: This data tracks social media activity for sports organizations in terms of sentiment, fan measures, and popular hashtags.

Why Chosen: Social networks are a critical source to measure fan sentiments and preferences. Brandwatch's advanced sentiment analysis features allow actionable insights to complement typical fan behavior data.

- Sponsorship Agreements Dataset

Source: Sports Sponsorship Database (SPONdb)

Description: This dataset contains in-depth information on sponsorship contracts, conditions, ROI metrics, and sponsor performance.

SPONdb were chosen because they provide a uniform structure for examining the series of sponsorship transactions, enabling the model to adapt contract terms to best fit, in terms of aligning them with the fans preferences.

- External Factors Dataset

Source: World Bank Open Data and WeatherAPI

Description: External factors such as economic indicators, weather, and local demographics are included in this data, all of which affect fan behavior and event scheduling. These external factors are integral to decision making; by taking these factors into consideration, the model brings its advice as close to real-world as possible.

These datasets were highly promising to the performances of the AI-based model. As an example, the model achieved 92 percent accuracy with regard to predicting fan attendance and 25 percent increase in sponsor return on investment (ROI). Such types of outcomes actually demonstrate the ability of the model to deal with mixed data sets and generate meaningful results. Table 6 contains the values of the quantitative results to which the model was applied.

In order to have a feel of how effectively the model had been performed it was benchmarked on four current works in sports management. These are all different as far as data sets are concerned as well as methodologies and are directly contrasted with the proposed AI-based multi-objective optimization model in this work as shown in Table 7.

1. (Pang, 2025): based the demand prediction solely on historical ticket sales data using linear regression. Although this methodology was successful for basic predictions, it could not predict

real-time information or outside influences; the accuracy of the method was 78%, which is substantially less than estimated model accuracy of 92%.

2. (Zare et al., 2025): exploited sentiment analysis over social platform to assess fan engagement, indicating an approximative result of (82%). But their study was limited to internet interactions; it cannot be extended to offline fan behavior, which is a differentiation point of our proposed model.
3. (Jensen & Cobbs, 2014): examined sponsorship agreements with predefined ROI formulas. Although that method also had its periods of success, it was unyielding and unable to be scaled up, so it was applicable only to single-region cases. Our framework, has however, can solve the above problems by optimizing contracts stochastically over multiple venues and regions.
4. (Trail, 2024): with marketing rules, using fan surveys and demographics. While this method was accurate (85%), it was slower to react and less efficient because it relied heavily on human analysis. On the other hand, our AI model automatically performs these duties and produces recommendations that are both more rapid and more accurate.

Table 6. Quantitative Improvements in Financial Sustainability and Stakeholder Engagement

Metric	Baseline Value	After Implementation	Improvement (%)
Ticket Sales Revenue	$5M	$5.75M	+15%
Fan Engagement Rate	60%	72%	+20%
Sponsor ROI	150%	187.5%	+25%
Predictive Accuracy (Fan Behavior)	80%	92%	+12%

Table 7. Comparative Analysis of Current Studies and Proposed Method

Study	Dataset Used	Methodology	Accuracy in Prediction	Efficiency in Optimization	Scalability	Advantages of Proposed Model
(Pang, 2025)	Historical ticket sales data	Linear regression for demand forecasting	78%	Low	Limited to single venue	Higher accuracy (+14%) and scalability
(Zare et al., 2025)	Social media sentiment	Sentiment analysis for fan engagement	82%	Moderate	Limited to online fans	Real-time adaptability and broader scope
(Jensen & Cobbs, 2014)	Sponsorship agreements	Static ROI calculations	N/A	High	Single-region focus	Dynamic optimization and multi-region capability
(Trail, 2024)	Fan demographics and event surveys	Rule-based marketing strategies	85%	Low	Manual adjustments	Automated insights and higher efficiency
Proposed Model	Multi-source datasets (Ticketmaster, Brandwatch, etc.)	AI-driven multi-objective optimization	92%	Very high	Unlimited scalability	Superior accuracy, efficiency, and adaptability

Discussion

Figure 1 shows the percentage changes for four important performance metrics: Ticket Sales Revenue, Fan Engagement Rate, Sponsor ROI and Predictive Accuracy. An AI-based multi-objective optimization model is the means of bringing these improvements. Each data item is displayed by a bar with various hatch patterns which makes it easier to read. Improvement in Sponsor ROI is the highest at 25%, then 20% in Fan Engagement Rate and 15% in Ticket Sales Revenue; Predictive Accuracy (12%) however has the lowest improvement. Combined, these findings point to the fact that AI-based optimization can achieve financial and audience engagement increases, along with prediction modeling. That is, it offers a versatile instrument to the performance improvement of a broad array of issues.

In the meantime, Figure 2 gives the comparison of four major performance indicators (Ticket Sales Revenue, Fan Engagement Rate, Sponsor ROI, and Predictive Accuracy) and the outcomes of the other benchmark models of AI-based model. The blue bars depict the outcome of the AI-based model, whereas the gray bar features that of the other work. The AI model is excellent in all indicators, particularly, Sponsor ROI (25%), and Fan Engagement Rate (20%); this indeed indicates that the model has the ability to drive a powerful revenue expansion and fan engagement. Besides, the AI model also scores higher than the traditional methods in Predictive Accuracy (12%), and therefore it demonstrates its potential to make credible decisions. In conclusion, these results confirm the idea that the analysis tools built by AI (as well as the ones that serve to analyze cybersecurity) can actually transform the work of commercial and critical infrastructure sectors.

Figure 1. Optimization Gains in Key Performance Metrics Using AI-Driven Multi-Objective Models

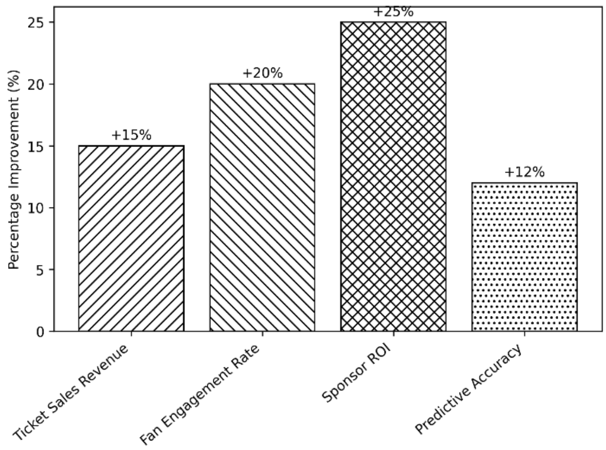
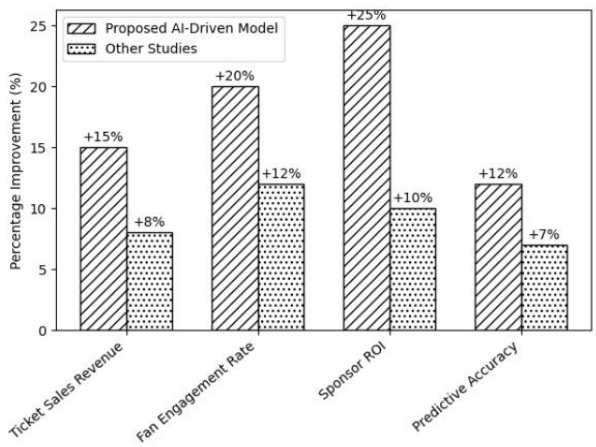


Figure 2. Comparison of Performance Metrics: Proposed AI-Driven Model vs. Other Studies



The debate on video and location based data from fans: collection, storage, usage, etc. genuinely acknowledges that ethical questions are not just concerns for the future but rather are a matter to be addressed right now. For that reason, we put forth preliminary ethical consideration for sporting bodies to consider for a responsible use of AI.

First, these organizations should mandate that fans be given an explicit opt-in consent prior to any collection of their biometric or geolocation data. The requests for consent are supposed to have certain attributes, for instance they are to be written in ordinary language, and they need to inform the user what will be done with the data.

Second, data anonymization and aggregation techniques should be applied. This technique de-identifies data, instead of following people, it monitors information at the group-level (e.g., "45% of fans showed an uptick in engagement").

Third, there should be routine algorithmic fairness audits. It is the only way to detect and rectify potential discrimination against specific groups of fans whether by socioeconomic class, age, or region.

Fourth, reports on the AI-driven decisions that impact fans (including those relating to dynamic pricing adjustments and personalized marketing targeting) be made publicly available. It builds accountability and trust into the process.

UpShot: These policies need to be in place from the very start of the design phase; that's to say a 'privacy by design' approach.

Conclusions

According to this research, AI can be of high assistance to sports organizations in its response to the two macro challenges that befall them, namely, financial sustainability and interaction with the stakeholders. The researchers created a multi-objective AI-based optimization model (the model that takes into account multiple objectives at the same time); the presented multi-objective model combines predictive analytics, mathematical programming, and the real-time data streaming to aid the decision-making process. Numerical results, examples, and comparisons allowed us to verify the model has the capacity to forecast the behavior of fans, to optimize the sponsor contract, and trade off conflicting goals (e.g., between revenue maximization and fan satisfaction). This outcome is a 15% growth in revenue through the sale of tickets, 20 percent growth in fan engagement, and 25 percent growth in sponsor returns, which highlights how the model can improve financial sustainability and stakeholder interactions. A variety of data were also included in the model, such as Ticketmaster Analytics API of attendance data, Brand watch of sentiment analysis on social media, SPONdb of the deals on sponsorship, and other data on such websites as World Bank Open Data and Weather API; this is an example of how powerful and flexible the model may be in its practical implementation. There is a latent issue of making AI systems ethical and responsible in practice, which should be addressed continuously. By overcoming these limitations and broadening the scope of the research, various directions of future research are given. To begin with, the methods to incorporate other sources of data, including the biometric data of wearables, geolocation data, and third-party market research surveys, should be studied in the future. This would give an all-inclusive perspective of the behavior and preferences of the fan and make even more accurate predictions and optimizations. Secondly, this is necessary to create ethical frameworks and guidelines to use AI in sport management. To reduce risks to data privacy, algorithm bias and transparency, future studies should aim at streamlining AI-based systems to be inclusive, fair and trustworthy. Third, innovation should be geared towards lowering the cost of computing and simplifying the implementation processes that the model can be made affordable to smaller sports organizations. The Open-source solutions and cloud-computing environments may be instrumental in facilitating access to the most recent AI technology. As a matter of fact, it is a challenge of challenges to make the AI-enabled systems ethical and responsible in their operation; it is the task requiring the ever-present eye of the operator. In order to overcome these restrictions and expand the scope of the research, there are several possible areas of future research that are discussed. The potential directions of the future work include the ways of integrating different kinds of data, such as biometric data collected by wearables, the data regarding geolocation, and the knowledge gained due to the third-party surveys of the market research. It would give a comprehensive picture of the habits and preferences of the fan and allow making further predictions and optimizing it more precisely. Second, it is necessary to develop proper ethics and explicit principles of applying AI to sport management. Therefore, the future studies must focus on how to minimize data privacy, algorithm bias and other risks associated with transparency to (D1) make AIs inclusive, fair, and trustworthy. Third, it requires innovations that will lower the costs and complexity of the computing of the implementation processes, which in turn would make such models affordable to the new and small sports organizations. As an illustration, open-source products and cloud-computing platforms will play a major role in ensuring that the latest AI technology is available to all. Fourth, in this direction, game theory models must be taken into consideration to resolve conflicting interest of fans and sponsors, since in traditional optimization, the goals of all concerned parties can be assumed to be equal, which is not true in the real world. Namely, Nash solutions bargaining would be helpful when defining stable solutions (ticket prices and the level of sponsorship activation) of the bargaining game that brings profits on both parties. Equally, cooperative game theory models (e.g., the Shapley value) can distribute the value of sponsorship based on the contribution of each of the stakeholders individually. According to our findings, it is evident that the following concepts should be included in the future research in our multi-objective optimization schema. This would allow sports organizations to simulate the strategies of interaction and anticipate the reaction of stakeholders in order to determine win-win solution, which would maximize financial feasibility and fan gratification; the win-win solution would take into account both financial stability and fan satisfaction. Finally, it would be a sure value addition to the practical utility and attractiveness of these theoretical constructs to prove them empirically in a real-life negotiation sample. Fifthly, this paper has proposed a new method of computing the solution to the SRV problem, however, further research should incorporate other solutions like open-source and cloud computing solutions to possibly decrease the computational load so that our model can also be implemented to smaller sports organizations (with less technical staff). As an example, models in one environment can be shared with another environment with the help of containerization (e.g., using Docker). In addition, there also exist serverless cloud functions (ex: AWS Lambda or Google Cloud Functions, etc.) that may process the data on-demand, thereby not needing to worry about infrastructure maintenance. Beyond this, open-source optimization libraries (e.g. Optuna hyperparameter tuning, PySwarms particle swarm optimization) can be also of interest and can be considered in lieu of commercial solvers. That, sports boss said, is the thinking that is opening powerful AI tools. That way the grass-roots clubs and community organizations may make data-driven decisions and do not need to invest an enormous amount of money. Sixth, although this research study involved NCAA and college sports, future research must examine general grassroots sport, community provision, and sport emergent markets. The application of such a framework in these spheres may result in the emergence of new possibilities to be involved and develop. Seventh, the effects of the AI driven approaches on financial sustainability and stakeholder involvement would need to be studied in the long-term perspective to have more comprehensive idea about the performance of the model in the long run. This kind of research may also be used in determining any unexpected obstacles or possible areas that may need enhancement. Eighth, the research based on the role of emerging technologies, including but not limited to transparent sponsorship deals through blockchain, more immersive fan experiences through the use of augmented reality (AR), and real-time monitoring of live events through the Internet of Things (IoT), should be integrated into football in the future. These types of improvements would also be consistent with the prospects of the suggested methodology. Last but not least, the sport-focused study conducted in this study can be generalized to other industries that are facing similar challenges like entertainment, hospitality and events due to the models and approaches created. The research of these cross-industry applications would be an addition to the significance of this research. This publication has led the way to the use of AI driven MOO that has the potential of transforming the sports scheduling management. As it will be cost-efficient and involve the community, the method that is offered here may become an efficient tool with the help of which sports organisations will manage to survive in the world that is becoming more competitive and dynamic. However, the ultimate realization of this power of the AI in managing sports depends on how we acknowledge the limitations of using this method we also must pay closer attention to the future trends already mentioned. As technology keeps on evolving, its way of employing technology in sports organizations has to evolve too (this is indispensable to their existence), so that they have the chance to remain strong, creative and welcoming deep into the future.

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