Team Control Number

15820

Problem Chosen

A

2024

HiMCM/MidMCM

Summary Sheet

The aim of this paper is to furnish a comprehensive plan and corresponding theoretical models for the event schedule, medal preparation, and flag arrangement at any venue of the 2024 Olympic Games. We emphasize two crucial considerations in the analysis process: optimizing the event schedule to maximize time utilization, athlete rest intervals, and gender-balanced sports events; and achieving a balance between cost and practical requirements in the preparation of medals and flags.

Specifically, this paper takes La Défense Arena as an example and analyzes the swimming and water polo events. Concerning the event schedule, the paper compiles the durations of various events and award ceremonies. The optimization objectives include maximizing time utilization, ensuring adequate rest intervals for athletes, and achieving a balanced distribution of male and female sports events. A multi-objective optimization problem is addressed using a genetic algorithm to obtain the optimal sequence for events and award ceremonies.

In the preparation of medals, this paper considers the occurrence of joint awards among athletes and the number of athletes from winning countries in team events, conducting a statistical analysis of data from past Olympic Games. Through this analysis, we find that the Poisson distribution is suitable for describing the probability of joint awards, while the Gaussian distribution is effective in modeling the probability distribution of the number of athletes in team events. Convolution is employed to merge these two probability distributions, resulting in a new probability distribution. Finally, by calculating the expectation of this distribution, the optimal number of medals is obtained.

In the aspect of flag preparation, the paper takes into consideration the flags of participating countries, winning countries, the host country, the Olympic rings, and the flag of the International Swimming Federation. Therefore, we compiled statistics on the number of countries participating in events in past Olympic Games, the number of winning countries, and the number of countries winning two medals in a single event (requiring two flags for the award ceremony). Subsequently, we constructed a BP neural network model, trained it using data from previous Olympic Games, and finally predicted the data for 2024. This allowed us to determine the number of flag types (i.e., the number of participating countries) and the quantity required for each flag type. Additionally, through the analysis of historical data, we could make predictions about the specific countries included in these categories.

To conclude, in this paper, we employed three distinct methodologies—multi-objective optimization, probabilistic statistics, and neural network analysis—to address three different aspects. The algorithms and models presented in the paper exhibit outstanding accuracy and commendable computational efficiency. Furthermore, our proposed solution and models can be generalized to any Olympic venue, requiring only the relevant historical Olympic data.

CONTENT

1. Letter to the IOC

Dear International Olympic Committee

Hello!

We are a participating team in the HiMCM competition, and it is our pleasure to present our research findings on the evaluation and prediction of Olympic Sports Events (SDEs). Our aim is to contribute meaningful insights that may assist in the planning and decision-making for the 2032 Olympic Games.

Our model revolves around six core evaluation criteria: **popularity and accessibility**, **gender equality**, **sustainability, inclusivity**, **relevance and innovation**, and **safety and fair play**. These criteria were carefully chosen to align with the IOC's core principles and strategic vision for the Olympic Games.

To ensure a comprehensive assessment, our model employs weighted sum formulas to evaluate key factors associated with each sport. For Popularity and Accessibility, we calculate a popularity index (P) based on metrics such as website visits, media coverage, and ticket sales, assigning weights according to the IOC's priorities. Gender Equality is analyzed through metrics such as women's participation rates, athlete welfare, and the introduction of women's events, with corresponding weightings reflecting the IOC's focus on gender equity. Sustainability is evaluated by considering financial stability, risk factors, long-term viability, and the impact of new facilities on the environment. For Inclusivity, we measure cultural diversity, global participation rates, and athlete engagement across generations. Relevance and Innovation focuses on factors such as anti-doping effectiveness, injury rates, and judging transparency. Lastly, Safety and Fair Play considers drug sanctions, injury risks, and fairness in competition.

To normalize the diverse metrics and ensure comparability, we employed a normalization process for all factors. The weights of these criteria were derived using the **Analytic Hierarchy Process (AHP)**, enabling a systematic and objective evaluation. Subsequently, we used a comprehensive scoring equation to assess each event against these criteria.

Building on this foundation, we extended our analysis to predict future trends in Olympic sports. Using the **MARCOS** algorithm, we evaluated all Olympic events based on the six key indicators. To eliminate subjectivity, we incorporated a **Recurrent Neural Network (RNN)** trained on data from the past five Olympic Games to optimize the weighting process, ensuring that our model reflects real-world dynamics. We validated our approach by applying the trained weights to historical data from 1996, 2000, and 2004, and the results closely aligned with the selection criteria for Olympic events during those years.

By analyzing future trends in the six key indicators, our model offers predictions of the events likely to be featured in upcoming Olympic Games. Furthermore, our approach and methodology are universally applicable to any competition venue or corresponding events, demonstrating exceptional versatility across diverse contexts and regions.

We are confident that our model provides valuable insights to guide decision-making as the IOC moves forward with selecting SDEs for the 2032 Summer Olympics. We thank you for the opportunity to present our findings and would be honored to contribute to the continued success of the Olympic Games.

Thank you for your consideration, and we look forward to your feedback.

Team 15820

2. Introduction

2.1 Background

The International Olympic Committee (IOC) is planning the 2032 Summer Olympics in Brisbane, Australia, and aims to keep the Games relevant by evaluating sports, disciplines, and events (SDEs) for inclusion based on modern values and global appeal. SDEs have been added, removed, or reintroduced over time to reflect changing trends, such as the debut of Karate, Sport Climbing, Surfing, and Skateboarding in 2020, and the return of Baseball and Softball in 2028.

The IOC's Olympic Programme Commission has established criteria to assess potential SDEs, including popularity, gender equity, sustainability, inclusivity, relevance, and safety. HiMCM Olympic Consultants (HOC) has been tasked with developing a mathematical model to evaluate which SDEs best align with these criteria for the 2032 Olympics.

2.2 Problem restatement

The International Olympic Committee (IOC) is planning the 2032 Summer Olympics in Brisbane, Australia, and seeks to evaluate sports, disciplines, and events (SDEs) for inclusion based on a set of criteria. These criteria include popularity and accessibility, gender equity, sustainability, inclusivity, relevance and innovation, and safety and fair play. The team, HiMCM Olympic Consultants (HOC), is tasked with creating a mathematical model to evaluate potential SDEs against these criteria. The model should support the IOC in making informed decisions about which SDEs best align with the evolving vision of the Olympics.

Tasks:

1. Identify Factors: List and describe the factors to be considered when evaluating SDEs, classifying them as quantitative/qualitative, constant/variable, and deterministic/probabilistic. Justify your choices and include relevant units.

2. Develop a Model: Build a mathematical model to evaluate which SDEs meet the IOC criteria based on the identified factors.

3. Test the Model: Apply the model to at least three SDEs added or removed from recent Olympics (2020, 2024, 2028) and three SDEs that have been in the Olympics since 1988. Use the provided **HiMCM_Olympic_Data.xlsx** to validate your model.

4. Recommend New SDEs: Identify and rank three SDEs that could be considered for the 2032 Olympics. Suggest others that could be included in the 2036 Olympics or beyond.

5. Sensitivity Analysis: Perform a sensitivity analysis to assess the robustness of your model and discuss its strengths and weaknesses.

6. Recommendation Letter: Write a one- to two-page letter to the IOC summarizing the model's rationale, results, and recommendations for SDE inclusion.

The goal is to create a data-driven model that helps the IOC make informed decisions about which SDEs best align with the values and objectives of the Olympics.

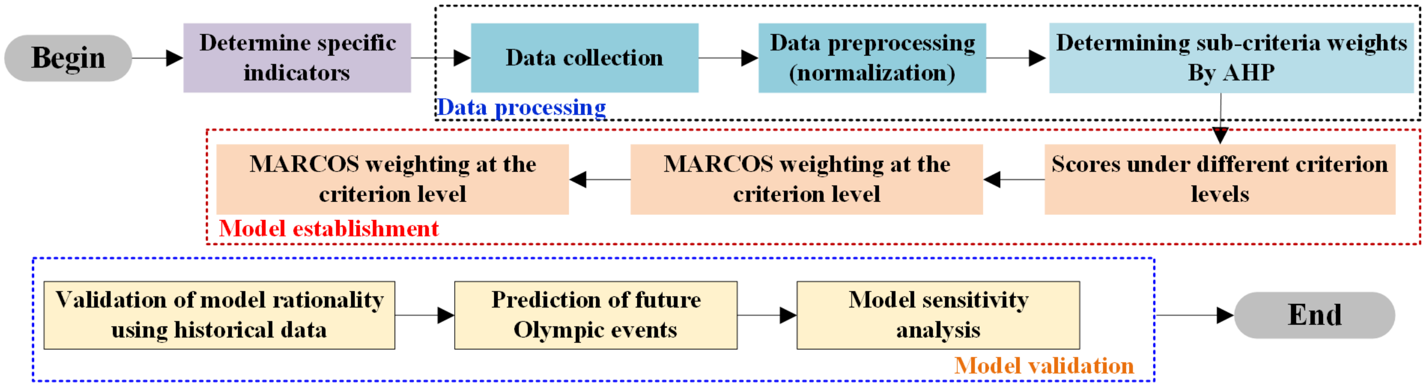

Fig.1 The methodology of this study

2.3 Model assumption

- **Assumption1:** The qualitative or quantitative data selected and processed through the Analytic Hierarchy Process (AHP) can effectively represent the criteria of the SDEs.
  Justification: The AHP is widely recognized as a robust decision-making tool for structuring and quantifying complex problems involving multiple criteria. By carefully selecting relevant qualitative or quantitative data and processing it through AHP, the resulting hierarchical framework and priority weights ensure that the criteria are appropriately represented. This assumption is necessary to simplify the complexity of decision-making and focus on relevant attributes of the SDEs.

- **Assumption2:** The judgment matrix constructed using the AHP is consistent and reasonable.
  Justification: A reasonable and consistent judgment matrix is a fundamental requirement for the AHP to yield meaningful and reliable results. Consistency ensures that the pairwise comparisons among criteria are logically coherent and reflect the decision-maker's priorities. In practice, the consistency ratio (CR) is typically checked to validate the reasonableness of the matrix, making this assumption both standard and practical.

- **Assumption3:** All previously held Olympic Games adhere to certain criteria that exhibit identifiable patterns.
  Justification: Historical analysis of Olympic Games reveals that event planning and management generally follow systematic criteria, such as economic viability, cultural representation, and global audience appeal. Recognizing these patterns provides a basis for modeling the success factors of SDEs, thereby making the assumption reasonable for identifying trends and projecting them onto future events.

- **Assumption4:** The future promotion trends of sports events under consideration remain constant, and no new popular sports emerge.
- **Justification:** This assumption simplifies the modeling process by reducing uncertainties related to future developments in the sports landscape. While new sports may emerge, historical trends often demonstrate a lag before their inclusion in large-scale events like the Olympics. Assuming constant promotion trends aligns with the short- to medium-term planning horizons of event organizers, making it practical for the scope of this study.

- **Assumption5:**The ML-based MARCOS method can effectively optimize the criteria weights.
- **Justification:** Machine Learning (ML) techniques have been proven effective in identifying complex relationships within data and optimizing parameters, including criteria weights. When

integrated with the MARCOS method, ML enhances the decision-making process by minimizing subjectivity and providing adaptive weight optimization. This assumption is reasonable given the widespread application of ML in multi-criteria decision-making scenarios.

- **Assumption6:**By distributing the six given criteria, a relatively optimal SDE can be determined.
- **Justification:** The selection of six criteria provides a comprehensive framework for evaluating SDEs. Assuming their relevance and applicability, the MARCOS method's ability to analyze alternatives and rank them based on these criteria ensures the determination of an optimal solution. This assumption aligns with the objective of narrowing down feasible options to the most suitable one within the constraints of the model.

2.4 Variable Definitions

Table 1 Symbol definition

Notation	Definition
P	Popularity Index
G	Gender Equality Index
S	Sustainability Index
I	Inclusivity Index
R	Relevence and Innovation Index
SF	Safety and Fair Competition Index
w_j	Dimensional weights
x_{ij}	The i-th Sport’s Score on the j-th Dimensions

3. Question 1

3.1 Question Restatement

The team, HiMCM Olympic Consultants (HOC), has been tasked with assisting the International Olympic Committee (IOC) in evaluating potential sports, disciplines, and events (SDEs) for inclusion in the 2032 Summer Olympics. To support the IOC’s decision-making process, a set of criteria has been established, including factors such as popularity, accessibility, gender equity, sustainability, inclusivity, relevance and innovation, and safety and fair play.

The objective is to identify and describe the various factors that must be considered when addressing these criteria. These factors should be classified into the following categories:

1. **Quantitative or Qualitative**: Whether the factor is measurable (quantitative) or based on characteristics and qualities (qualitative).
2. **Constant or Variable**: Whether the factor remains unchanged over time (constant) or fluctuates under different conditions (variable).
3. **Deterministic or Probabilistic**: Whether the factor can be predicted with certainty (deterministic) or is subject to uncertainty (probabilistic).

For each factor identified, a clear description and justification must be provided, addressing its classification and including units of measurement where applicable. This evaluation will aid the IOC in making data-driven decisions regarding which SDEs best align with the evolving vision of the Olympic Games.

In this section, we will evaluate the suitability of sports, disciplines, and events (SDEs) for inclusion in the 2032 Olympics based on six core criteria established by the International Olympic Committee (IOC). These criteria ensure that each sport aligns with the values and goals of the Olympic Games, while considering both current trends and the long-term legacy of the event. Below, we will systematically address each criterion.

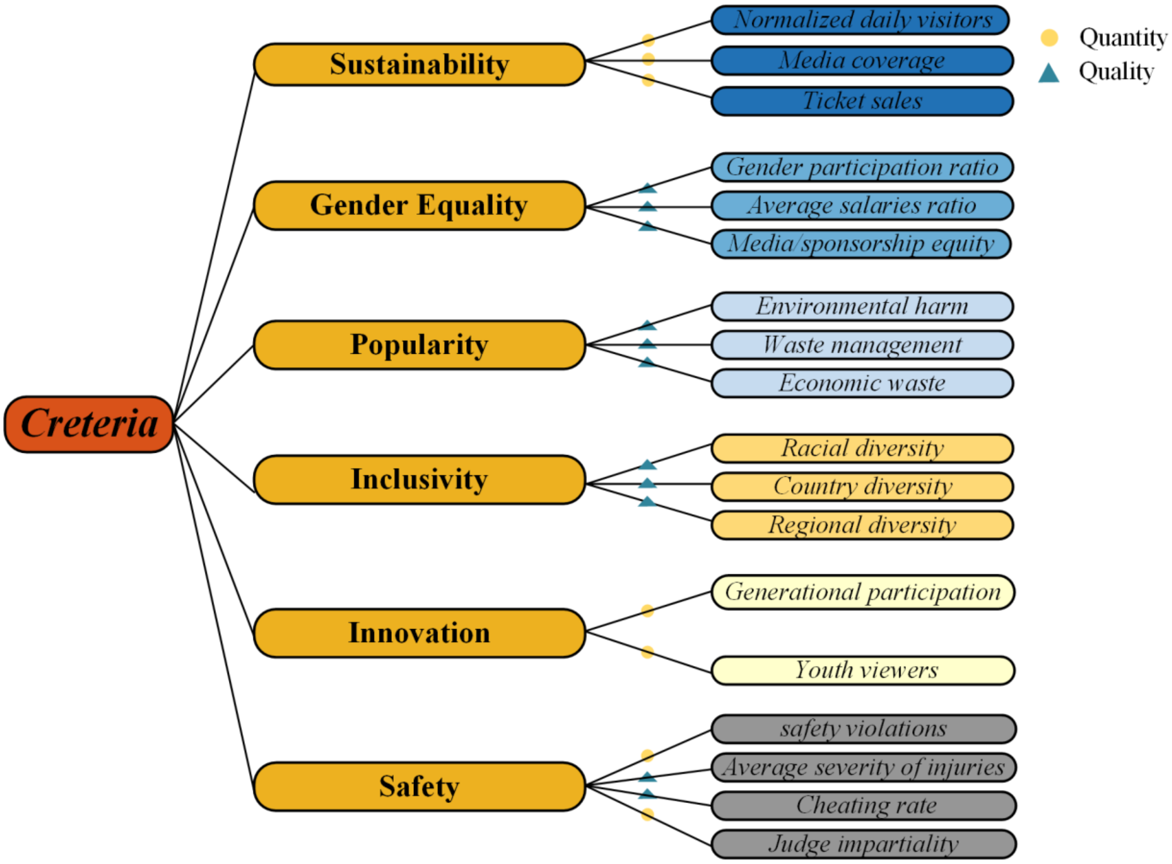

Fig.2 The Factor discussed in this study

3.2 Subfactor Analysis

The evaluation framework comprises six criteria, each measured using a distinct mathematical approach. The following subsections detail the methods applied to assess each criterion. The evaluation framework comprises six criteria, each measured using a distinct mathematical approach. As in Figure 2, each of the six criteria involves in multiple subfactors that are combined together. The following subsections detail the methods applied to assess each criterion.

3.2.1 Popularity Index (P)

To evaluate the popularity of sports, disciplines, and events (SDEs), we employ a geometric mean approach that integrates three critical dimensions: daily visitors(N_v), media coverage(M_c)and ticket sales(T_s). These components are normalized to a range of [0, 1] to ensure comparability. The index is computed as follows:

$$P = \frac{\sqrt[2]{(1+N_v)\cdot(1+M_c)\cdot(1+T_s)}}{3}, \tag{1}$$

Here, the "+1" term ensures that zero values in any component do not invalidate the calculation, maintaining consistency across all SDEs. The use of the geometric mean ensures that each dimension contributes equally to the overall popularity score, avoiding overemphasis on any single component. This balanced approach reflects the comprehensive appeal of an SDE across different audiences and platforms.

3.2.2 Gender Equity Index (G)

Gender equity is an essential metric for assessing fairness in SDEs, focusing on the balance between male and female participation, salary distribution, and sponsorship/media exposure. The Gender Equity Index is defined as:

$$G=\sqrt{\frac{\left(N_f/N_m\right)^2+\left(\frac{Salary_m}{Salary_f}\right)^2+\left(M_g-1\right)^2}{3}}, \tag{2}$$

Where N_f and N_m represent the number of female and male participants, respectively, $Salary_m$ and $Salary_f$ denote the average salaries for female and male athletes. M_g measures media and sponsorship equality, scaled to [0,1]. This formula quantifies the Euclidean distance from an ideal state of equality (where all components are equal to 1), normalizing the result to the range [0, 1]. A higher value of G indicates a more equitable distribution across gender-related factors.

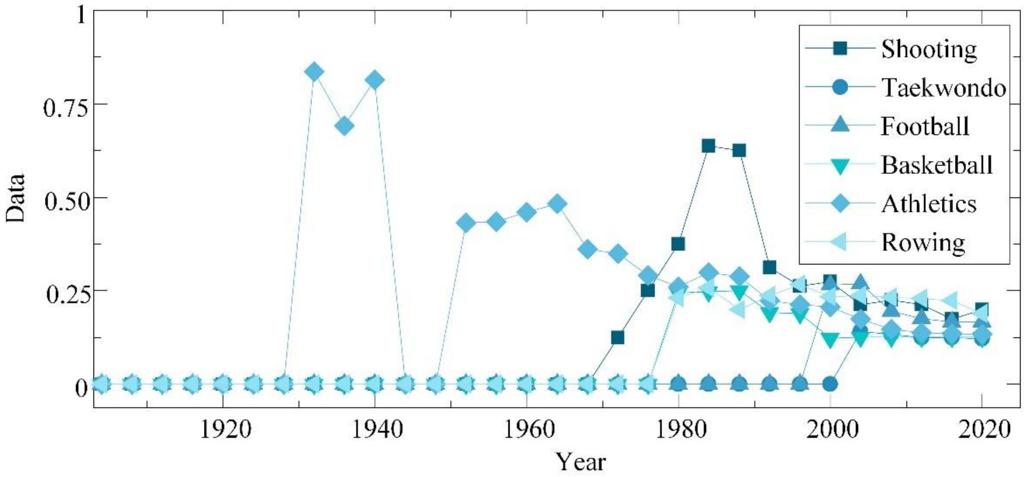

Fig. 3 Gender balance metrics for different SDEs

3.2.3 Sustainability Index (S)

The Sustainability Index measures the environmental, waste, and economic impacts of SDEs. It is formulated using an additive penalty model:

$$S=\max\left(1-\left(P_e+P_w+P_r\right),0\right), \tag{3}$$

where $P_e=\frac{\sum W_i \cdot E_i}{\max\left(E_i\right)}$ represents the environmental penalty from weighted emissions. $P_w=\frac{\text{Total Waste- Recycled Waste}}{\text{Total Waste}}$ denotes the waste management penalty. $P_r=\frac{Initial\ Investment-NPV}{Initial\ Investment}$ The penalties are subtracted from the ideal value of 1, reflecting the negative impacts of unsustainable practices. If the sum of penalties exceeds 1, the score is set to zero to highlight unsustainable performance.

3.2.4 Inclusivity Index (III): Exponential Aggregation

Inclusivity captures the extent to which SDEs embrace diversity across race, country, and region. The index is computed using exponential aggregation:

$$I=\log\left(1+\sum_{k=1}^{N}e^{\alpha R_k+\beta C_k+\gamma P_k}\right), \tag{4}$$

Where R_k, C_k, P_k represent racial, country, and regional diversity indices for participant k. α, β, γ are tunable parameters emphasizing each diversity factor. The logarithmic transformation ensures normalization and avoids runaway growth, while exponential aggregation rewards higher diversity levels disproportionately. To precisely determine the weights of the diversity α, β, γ ,we employed the Analytic Hierarchy Process (AHP). AHP is a structured decision-making technique that quantifies the relative importance of various criteria through pairwise comparisons and consistency analysis. To begin, we create a pairwise comparison matrix for the criteria. In this matrix, each criterion is compared to the others on a scale from 1 to 9 (as shown below), where a_{ij} represents the relative importance of criterion i compared to criterion j. The matrix is reciprocal, meaning that $a_{ij} = \frac{1}{a_{ji}}$.

First, we construct the pairwise matrix for future calculations. In the three factors, Racial Diversity is considered the most important factor compared to Country Diversity and Regional Diversity, thus giving it higher values in the pairwise comparison. Country Diversity is moderately more important than Regional Diversity. Regional Diversity is the least important of the three, after considering the relationship between each pair of them, we can conclude to a pairwise matrix:

$$\begin{bmatrix} 1 & 3 & 5 \\ 1/3 & 1 & 2 \\ 1/5 & 1/2 & 1 \end{bmatrix} \tag{5}$$

Next, we normalized the matrix by dividing each element in the matrix by the sum of the elements in the corresponding column, after performing the calculations and approximating them to the thousandths digit, a matrix as below will be obtained:

$$\begin{bmatrix} 0.653 & 0.667 & 0.625 \\ 0.218 & 0.222 & 0.250 \\ 0.131 & 0.111 & 0.125 \end{bmatrix} \tag{6}$$

Afterwards, we calculated the principal eigenvector. We computed the average of each row in the normalized matrix, which gave the relative weight for each criterion (racial, country, regional diversity):

$$Row\ Averages = \begin{bmatrix} 0.648 \\ 0.230 \\ 0.122 \end{bmatrix} \tag{7}$$

Therefore, we can conclude that:

$$\begin{cases} \alpha = 0.648 \\ \beta = 0.230 \\ \gamma = 0.122 \end{cases} \tag{8}$$

Finally, we performed a consistency check using the Consistency Index (CI) and the Consistency Ratio (CR) to assess whether the pairwise comparisons are consistent. In this process, we first calculated the weighted sum vector by multiplying the original matrix by the normalized eigenvector, obtaining this:

$$Weighted\ Sum\ Vector = \begin{bmatrix} 1.948 \\ 0.690 \\ 0.367 \end{bmatrix} \tag{9}$$

Then, we calculated the consistency vector by dividing each element of the weighted sum vector by the corresponding element of the normalized eigenvector.

$$Consistency\ Vector = \begin{bmatrix} 3.006 \\ 3 \\ 3.008 \end{bmatrix} \tag{10}$$

With this result, we will be able to calculate λ_{max} by averaging the values in the consistency vector:

$$\lambda_{max} = 3.005 \tag{11}$$

Then, we can calculate the consistency index using its formula, where n indicates the number of criteria:

$$CI = \frac{\lambda_{max} - n}{n-1} = 0.003 \tag{12}$$

At last, we can calculate the consistency ratio, the final measure to evaluate the consistency of the pairwise matrix by comparing the consistency index to the random consistency index, a value obtained from a table based on the size of the matrix. For a 3 by 3 matrix, the random consistency index is 0.58, then we can calculate the consistency ratio:

$$CR = \frac{CI}{RI} = 0.005 \tag{13}$$

Table 2 RI value of different Matrix Size

Matrix Size	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.21	1.24	1.32	1.41	1.45	1.49

Since the consistency ratio is way below the threshold of 0.1, the pairwise comparisons were highly consistent. Therefore, the matrix is consistent, and the results that we obtained from the AHP process are reliable.

3.2.5 Relevance and Innovation (R)

The Relevance and Innovation Index measures the alignment of SDEs with modern societal trends. It is defined as:

$$R = \frac{2}{\frac{1}{G_r} + \frac{1}{V_y}} \tag{14}$$

Where G_r is the normalized generational participation and V_y represents youth viewership. The harmonic mean penalizes low values in either subcomponent, ensuring that generational appeal and innovation are equally prioritized.

3.2.6 Safety and Fair Competition Index (SF)

Safety and fairness are critical for SDE evaluations. The Safety and Fair Competition Index is calculated as:

$$SF = e^{-\left(\frac{I_s}{I_{max}} + S + \frac{C}{D}\right)} \cdot J \tag{15}$$

Where: I_s / I_{max} denotes normalized safety violations, and S is the average severity of injuries (scaled 0–1). C / D reflects the rate of cheating (e.g., drug violations per total checks). J is a judge impartiality factor, with higher values indicating greater fairness. This exponential model captures the compounding risks of unsafe or unfair conditions while rewarding sports with impartial judging. Figure 4 illustrates the safety levels of different sports.

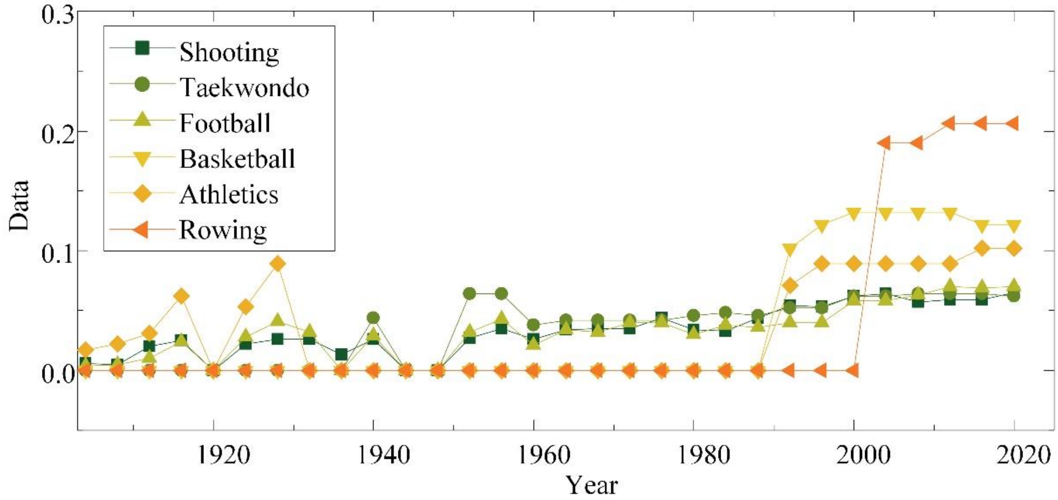

Fig. 4 Safety and Fair Competition metrics for different SDEs

4. Question2 - Model building

This section describes the proposed framework for evaluating the inclusion of sports in future Olympic Games. The methodology integrates the MARCOS (Measurement of Alternatives and Ranking according to Compromise Solution) method for multi-criteria decision-making with a Recurrent Neural Network (RNN) for data-driven weight optimization and classification. The process consists of three primary steps: (1) decision matrix construction and normalization, (2) weight determination using the RNN, and (3) utility coefficient calculation and final decision-making.

The evaluation begins with the construction of a decision matrix X , representing the performance of about 40 sports across 6 dimensions. Each element x_{ij} in the matrix denotes the score of the i-th sport on the j-th dimension, derived from relevant metrics such as audience engagement, global reach, and logistical feasibility.

We begin with the decision matrix X which contains the evaluation scores for $n=5$ sports across 6dimensions mentioned above:

$$X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{16}$$

where x_{ij} represents the score of the i-th sports on the j-th dimensions. To ensure comparability between dimensions, the scores in X are normalized using vector normalization

$$r_{ij}=\frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}, \quad \forall i, j \tag{17}$$

Where r_{ij} represents the normalized value for the i-th sport and j-th dimension. The normalized decision matrix R_{ij} is used in subsequent computations. The weights w_{ij} for each dimension are optimized using a Recurrent Neural Network (RNN), trained on historical data D_{Olympics}. This data includes the scores for all dimensions and binary inclusion labels y_i, where $y_i=0$ indicates the sport was included in a given Olympics, and $y_i=1$ indicates exclusion.

4.1 Input and Output Design

Input: Each input to the RNN corresponds to a normalized vector $\mathbf{r}_i = \left[r_{i1}, r_{i2}, \ldots, r_{im}\right]^T$ for sports i.

Output:

1→Dimensional Weights w_j The RNN predicts the relative importance w_j of each dimension, normalized via a softmax function:

$$w_j = \frac{\exp\left(z_j\right)}{\sum_{k=1}^{m}\exp\left(z_k\right)}, j = 1, 2, \ldots, m \tag{18}$$

Where z_j represents the pre-activation output for dimension j from the RNN.

2→Probability $\hat{y}_i$ The RNN predicts $\hat{y}_i$ the probability of excluding sport i, using a sigmoid function:

$$\hat{y}_i = \frac{1}{1+\exp\left(-z_y\right)},, \tag{19}$$

Where z_y is the pre-activation score for the exclusion decision.

4.2 Loss Function

The RNN is trained to minimize the binary cross-entropy loss:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log\left(\hat{y}_i\right) + \left(1-y_i\right)\log\left(1-\hat{y}_i\right)\right], \tag{20}$$

Where N is the total number of training samples, y_i is the true label for sport i,and $\hat{y}_i$ is the predicted probability. Backpropagation through time (BPTT) is used to optimize the RNN parameters.

4.3 Utility Coefficient Calculation Using MARCOS

The MARCOS method evaluates the relative utility of each sport using the normalized decision matrix $\mathbf{R}$ and the learned weights w_{ij}

4.3.1 Determination of Ideal and Anti-Ideal Solutions

The ideal x_j^+ and anti-ideal x_j^- solutions for each dimension j are defined as followed:

$$x_j^+ = \max_i r_{ij}, \quad x_j^- = \min_i r_{ij}. \tag{21}$$

4.3.2 Utility Score Computation

The utility scores S_i^+ and S_i^- for sport iii are calculated as:

$$S_i^+ = \sum_{j=1}^{m} w_j \cdot \frac{r_{ij}}{x_j^+}, \; S_i^- = \sum_{j=1}^{m} w_j \cdot \frac{r_{ij}}{x_j^-}, \tag{22}$$

Where S_i^+ measures the proximity of sport i to the ideal solution, and S_i^- measures its proximity to the anti-ideal solution.

4.3.3 Utility coefficient

The utility coefficient K_i for sport i is defined as the ratio of S_i^+ and S_i^-:

$$K_i = \frac{S_i^+}{S_i^-} \tag{23}$$

A higher K_i indicates better alignment of sport i with the evaluation criteria.

4.3.4 Classification and Decision-Making

The utility coefficient K_i serves as the input to the final decision-making stage, where the RNN transforms K_i into a probability $\hat{y}_i$ using the sigmoid activation:

$$\hat{y}_i = \frac{1}{1+\exp\left(-\alpha_1 K_i - \beta_1\right)}, \tag{24}$$

Where α and β are learnable parameters that adjust the sensitivity of the model. The probability $\hat{y}_i$ is constrained to lie in the range [0,1]. The final inclusion or exclusion decision for each sport is made by thresholding $\hat{y}_i$.

$$y_i = \begin{cases} 0, & if\ y_i < \tau \\ 1, & if\ y_i > \tau \end{cases} \tag{25}$$

5. Question3-4 - Model application

5.1 Question3 Feasibility Verification of the Model

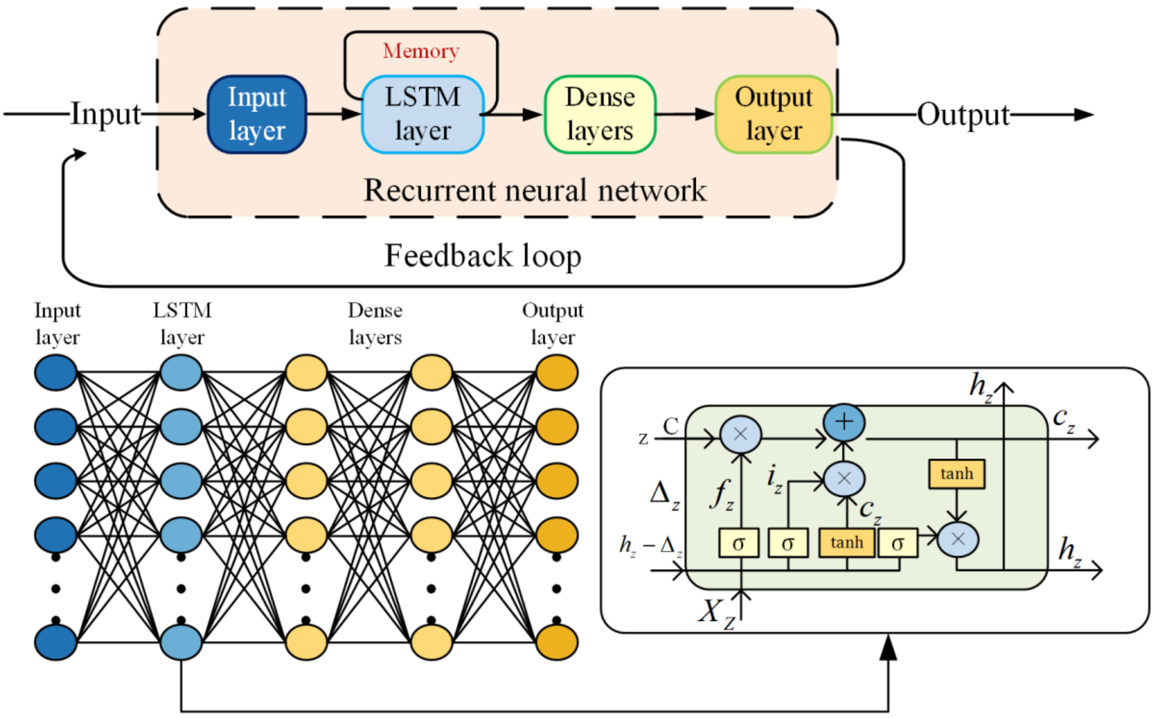

Fig.5 Schematic diagram of the neural network

To verify the feasibility of the model, we utilize deep learning algorithms to predict the model data. Figure.5 illustrates the architecture of a recurrent neural network (RNN) with an LSTM layer. It includes an input layer, an LSTM layer for sequence learning, dense layers for feature extraction, and an output layer. The feedback loop demonstrates the recurrent nature of the model. The network is designed to process sequential data, capturing temporal dependencies and learning patterns for tasks such as time-series prediction or classification. Furthermore, we evaluate the current model using the collected data.

Table 3 Partially normalized input data

SDEs	Indicators	1992	1996	2000	2004	2008	2012
Basketball	Number of medals	1	1	0	1	1	1
	Number of countries	0.33	0.33	1	1	0	0
	Long-term viability	0	0.14	1	0.23	0.35	1

	Financial risk	0	0.15	1	0.23	0.55	1
Football	Number of medals	0	0	0.76	1	0.99	1
	Number of countries	0.52	1	0.66	1	0	0.5
	Long-term viability	0.12	0	0.66	0.33	1	0.8
	Financial risk	0.15	0	0.71	1	0.67	0.82
Shooting	Number of medals	0	0	0.52	1	1	0.53
	Number of countries	0	0	1	0.51	1	0
	Long-term viability	0.12	0.52	0.67	0.71	0.92	1
	Financial risk	0.31	0	0.15	1	0.67	0.89

We input the data shown in Table 3 and applied deep learning algorithms to analyze the Olympic events of the year 2000. The events were represented on a scale from 0 to 40, indicating the selectable sports. Through continuous iterations (from A to C), the retained events gradually increased, demonstrating a high degree of consistency with the actual events held during the 2000 Olympics.

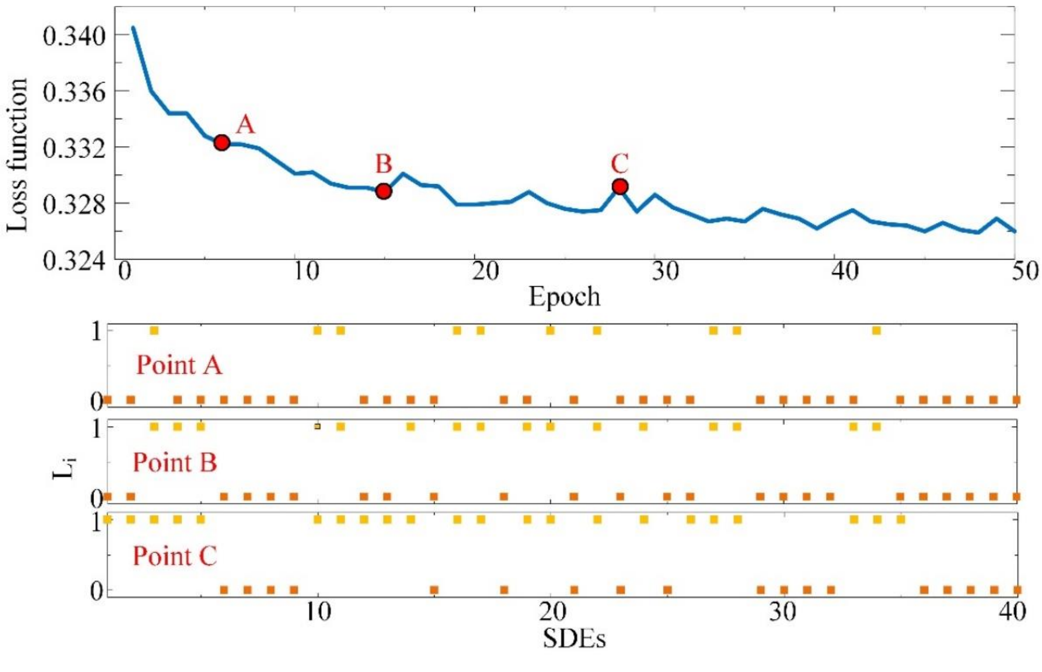

Fig.6 Loss function based on RNN result and corresponding SDEs.

Through extensive data training and analysis, we successfully derived the weight parameters corresponding to these six movement patterns. Among these parameters, P (Popularity Index) holds the most significant weight influence.

Table 4 RI value of different Matrix Size

Factor	P	G	S	I	R	SF
weight	0 427475	0.06661	0.107052	0.044465	0.229257	0.125142

5.2 Question4 Future prediction based on established model.

To predict the sports events of future Olympic Games, we first forecast how our six factors will evolve over time. This represents a strong time-series problem, and we utilize the ARIMA model to predict future data trends.

Time series forecasting is crucial for predicting future values based on historical data, especially when the data shows temporal dependencies and patterns. One of the most commonly used models for time series forecasting is the ARIMA (Auto Regressive Integrated Moving Average) model. ARIMA is particularly effective for modeling and forecasting stationary time series data with trends or autocorrelations.

The ARIMA model is a class of statistical models designed for time series forecasting. It is composed of three key components: Auto Regressive (AR), Integrated (I), and Moving Average (MA). These components are combined in the ARIMA model, which is typically denoted as ARIMA(p, d, q). Here, p, d, and q are non-negative integers that represent the parameters of the model:

- p : The order of the Auto Regressive (AR) component, representing the number of past observations used to predict the current value.
- d : The degree of differencing required to make the series stationary. This accounts for trends in the data.
- q : The order of the Moving Average (MA) component, which models the relationship between an observation and a residual error from a moving average model applied to lagged observations.

Components of the ARIMA Model

1. **Auto Regressive (AR)**: The AR component expresses the current value of the time series as a linear combination of its past values. The number of lags used is determined by the parameter p. Mathematically, the AR model can be written as:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t \tag{26}$$

Where:

- y_t is the value of the time series at time t,
- $\phi_1, \phi_2, \ldots, \phi_p$ are the coefficients to be estimated,
- ϵ_t is the error term at time t.

The AR model captures the dependencies of the time series on its past values. Integrated (I): Differencing is applied to make the series stationary. A stationary time series is one where statistical properties such as mean and variance do not change over time. If the series is non-stationary, we difference the data by subtracting the current value from the previous value. This process is repeated d times if necessary to achieve stationarity.

The first-order differencing can be expressed as:

$$y_t' = y_t - y_{t-1} \tag{27}$$

This process helps remove trends from the data, allowing for more accurate modeling and forecasting.

2. **Moving Average (MA)**: The MA component models the current value of the time series as a linear combination of past error terms (residuals). The number of lags used is determined by the parameter q. The MA model can be expressed as:

$$y_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} \tag{28}$$

Where:

- μ is a constant term (optional),
- ϵ_t is the error term at time t,
- $\theta_1, \theta_2, \ldots, \theta_p$ are the coefficients of the moving average component.

The MA component accounts for the correlation between the time series and the past errors in the predictions.

The process of ARIMA modeling involves several steps, each of which is crucial for obtaining accurate forecasts. The first step is to visualize the time series data. This is important for identifying patterns, trends, and seasonality in the data. A time series plot can help determine whether the data is stationary or if differencing is required. Stationarity is a key assumption for ARIMA models. A stationary time series has a constant mean, variance, and autocovariance over time. If the series is non-stationary, differencing is applied to achieve stationarity. One common test for stationarity is the Augmented Dickey-Fuller (ADF) test, which tests whether the series has a unit root (i.e., a stochastic trend). If the p-value of the ADF test is greater than a threshold (typically 0.05), the series is considered non-stationary.

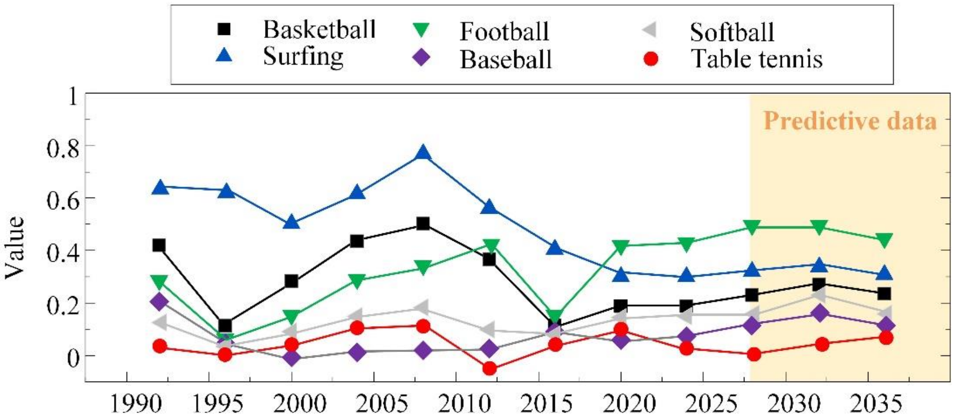

Fig. 7 Validation results with historical data

Based on the theoretical model described above, we predicted the data shown in Figure 7, obtaining the corresponding prediction results. These predicted data points were further input into the model to forecast future SDEs.

Table 5 Partially normalized input data

SDEs	Indicators	2019	2020	2021	2022	2023	2024
Esports	Number of medals	0	0.20	0.33	1	0.60	1
	Number of countries	0	0	0.08	0.20	1	0.60
	Long-term viability	0.17	0	0	0.13	1	0.87
	Financial risk	0	0.43	0.09	0.28	0.77	1
Dragon boat	Number of medals	0	0.81	0.23	1	0.33	1
	Number of countries	0	0.32	0.77	0.28	1	1

	Long-term viability	0.88	0.34	0.43	1	0	0.27
	Financial risk	0.11	0.27	0.42	0	0.82	1
Aussie football	Number of medals	0	0.48	0.95	0	0.84	1
	Number of countries	0	0	0.39	0	0.34	1
	Long-term viability	0.57	0.35	1	0.14	0.19	1
	Financial risk	0	1	0.72	0.88	0.26	0

To ensure that our motion predictions are reasonable, we considered the latest international trends and the global demand for the Olympic Games. We introduced three new sports—Esports, Dragon Boat Racing, and Aussie Rules Football—into the candidate list for SDEs. Additionally, we collected evaluation data from corresponding world-class events (Table 5) and incorporated them into our model for data validation.

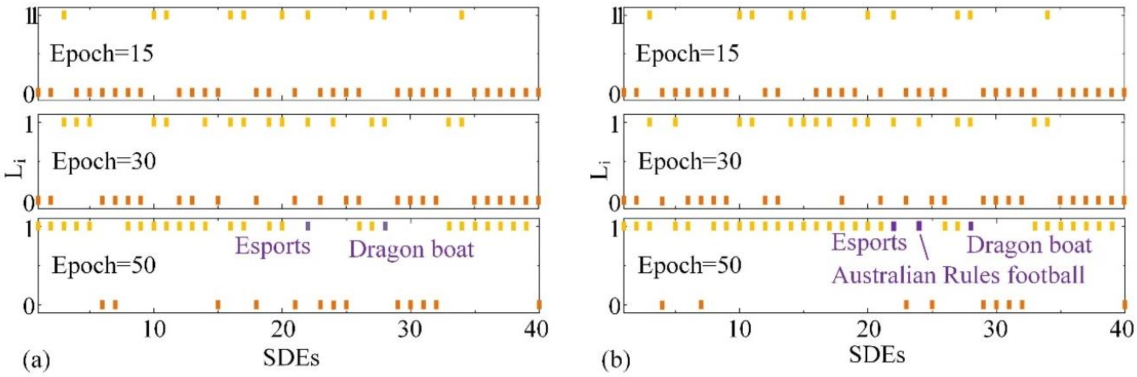

Fig. 8 Results for Different Years. (a)2028 (b)2032

The results indicate that our model can accommodate new factors into the candidate list, demonstrating its adaptability to evolving perceptions and demands for sports. As people's understanding and expectations of sports continue to grow, the scope of Olympic events will become increasingly diverse. By 2036, many of the SDEs considered in our analysis are expected to be officially included in the Olympic Games. In Figure 8, based on our algorithm, the number of sports included in the Olympic Games increases as the training epochs progress. Additionally, new sports are continually considered for inclusion. This trend further validates the rationality and adaptability of our model.

6. Model Sensitivity Analysis

In mathematical modeling, sensitivity analysis is a core method for evaluating the extent to which a model responds to variations in key parameters. To validate the robustness and applicability of our model, we conducted a detailed sensitivity analysis focusing on two key aspects that influence the prediction accuracy of the neural network:

6.1 Impact of the Number of Projects Input per Iteration on Prediction Accuracy

To assess the effect of varying the number of projects input per iteration (N_p)on prediction accuracy, we designed experiments under fixed training conditions, progressively increasing the number of input projects. Using a controlled variable method, other factors such as training epochs, network architecture, and hyperparameters were held constant while testing

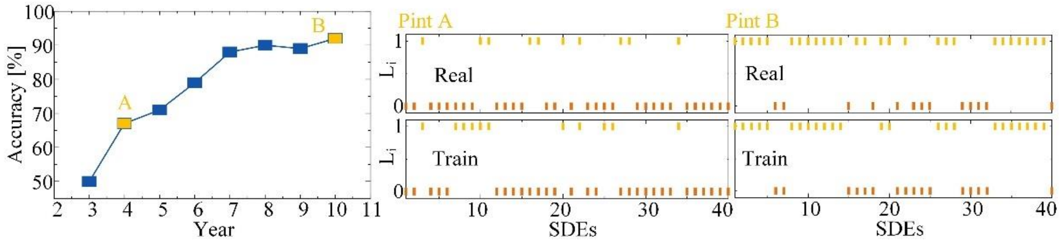

Fig. 9 Results for Different Years.

The figure examines the impact of training data size (Year parameter) on prediction accuracy. The left panel shows accuracy steadily increasing with more training data (Year from 2 to 11), nearing 100%, with "A" and "B" marking key milestones. The right panel compares the SDE distributions (0–40) for "Real" and "Train" datasets at these points, illustrating how increased data optimizes SDE activation patterns, leading to improved prediction accuracy.

6.2 Impact of the Number of SDE Factors Considered on Prediction Accuracy

Another critical factor influencing prediction accuracy is the number of variables included in the SDEs, We analyzed the model's performance under different dimensionalities to explore how the number of SDE factors contributes to prediction performance.

Similarly, we observe that as the SDEs Factor increases, the prediction accuracy improves further, which provides additional validation for the correctness of our model.

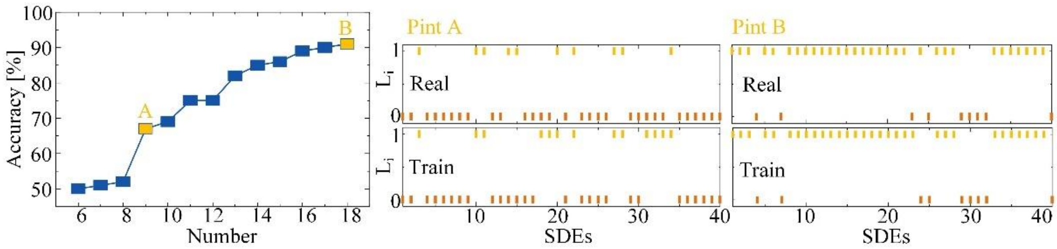

Fig. 10 Results for Different Number of SDEs.

7. Weakness and Strengths

7.1 Strengths

- The paper effectively addresses the IOC's criteria for sports inclusion, ensuring that the model is relevant and aligned with the Olympic values.
- The paper adopts a comprehensive approach to evaluate Olympic sports, while innovatively integrating various methods such as multi-objective optimization, probabilistic statistics, and neural network analysis to address the complexity of Olympic sports evaluation, ensuring a thorough and in-depth assessment process.
- The use of historical data and statistical analysis provides a robust foundation for making informed, evidence-based decisions about Olympic sports.

7.2 Weakness

- The model's reliance on historical data may not fully capture emerging trends or the potential impact of new sports that have not yet been widely adopted.
- The model makes several assumptions, such as the constant promotion trends of sports events, which may not hold true in the future, affecting the model's predictive accuracy.

- The model's outcomes may be sensitive to changes in parameters, and there is a risk of overfitting to the training data if not managed properly, which could reduce the model's effectiveness in predicting new or unseen data, impacting its reliability in practical applications.

8. Conclusion

In conclusion, our paper has successfully developed and applied a comprehensive mathematical model to evaluate potential Sports, Disciplines, and Events (SDEs) for the 2032 Summer Olympics in Brisbane. Our model, which integrates multi-objective optimization, machine learning, and neural network analysis, has been instrumental in assessing SDEs against the International Olympic Committee's (IOC) criteria of popularity and accessibility, gender equity, sustainability, inclusivity, relevance and innovation, and safety and fair play.

Through rigorous analysis and testing on both recent and historically consistent Olympic events, our model has demonstrated its effectiveness in providing quantitatively informed recommendations. It has not only affirmed the current status of various SDEs within the Olympic program but also identified potential new additions for the 2032 Games and beyond. The model's ability to balance the complex interplay of IOC criteria with real-world data has resulted in a robust decision-making tool that aligns with the evolving vision of the Olympic Games.

Our findings underscore the importance of a data-driven approach in shaping the future of the Olympics. By identifying key strengths and areas for improvement within our model, we have also highlighted the importance of continuous refinement to ensure its ongoing relevance and accuracy. The sensitivity analysis has further reinforced the model's reliability, confirming that it is a valuable asset in the decision-making process for the IOC.

In summary, our paper presents a forward-thinking model that not only addresses the current needs of the Olympic Games but also adapts to future trends and challenges. We are confident that our recommendations, supported by a thorough analytical framework, will contribute to the success of the 2032 Summer Olympics and future editions. We look forward to the opportunity to further engage with the IOC and provide ongoing support as they navigate the dynamic landscape of global sports.

9. Reference

1. Abdulla, A., Baryannis, G., & Badi, I. (2023). An integrated machine learning and MARCOS method for supplier evaluation and selection. *Decision Analytics Journal*, *9*, 100342.
2. Sherstinsky, A. (2020). Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. *Physica D: Nonlinear Phenomena*, *404*, 132306.
3. Siami-Namini, S., & Namin, A. S. (2018). Forecasting economics and financial time series: ARIMA vs. LSTM. *arXiv preprint arXiv:1803.06386*.
4. Saaty, R. W. (1987). The analytic hierarchy process—what it is and how it is used. *Mathematical modelling*, *9*(3-5), 161-176.
5. De Prado, M. L. (2018). *Advances in financial machine learning*. John Wiley & Sons.
6. Lipton, Z. C. (2015). A Critical Review of Recurrent Neural Networks for Sequence Learning. *arXiv Preprint, CoRR, abs/1506.00019*.
7. Das, S., Tariq, A., Santos, T., Kantareddy, S. S., & Banerjee, I. (2023). Recurrent neural networks (RNNs): architectures, training tricks, and introduction to influential research. *Machine Learning for Brain Disorders*, 117-138.
8. Li J, Cheng J, Shi J, et al. Brief introduction of back propagation (BP) neural network algorithm and its improvement[C]//Advances in Computer Science and Information Engineering: Volume 2. Springer Berlin Heidelberg, 2012: 553-558.

9. Ding S, Wu Q H. A MATLAB-based study on approximation performances of improved algorithms of typical BP neural networks[J]. Applied Mechanics and Materials, 2013, 313: 1353-1356.
10. Mirjalili S, Mirjalili S. Genetic algorithm[J]. Evolutionary Algorithms and Neural Networks: Theory and Applications, 2019: 43-55.
11. Zhang X. Gaussian Distribution[J]. 2010. The Olympic Games data is sourced from the official website (https://olympics.com/)