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| |  |  |  |  |  | | --- | --- | --- | --- | --- | |  | |  | | --- | | 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.

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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

1. **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.

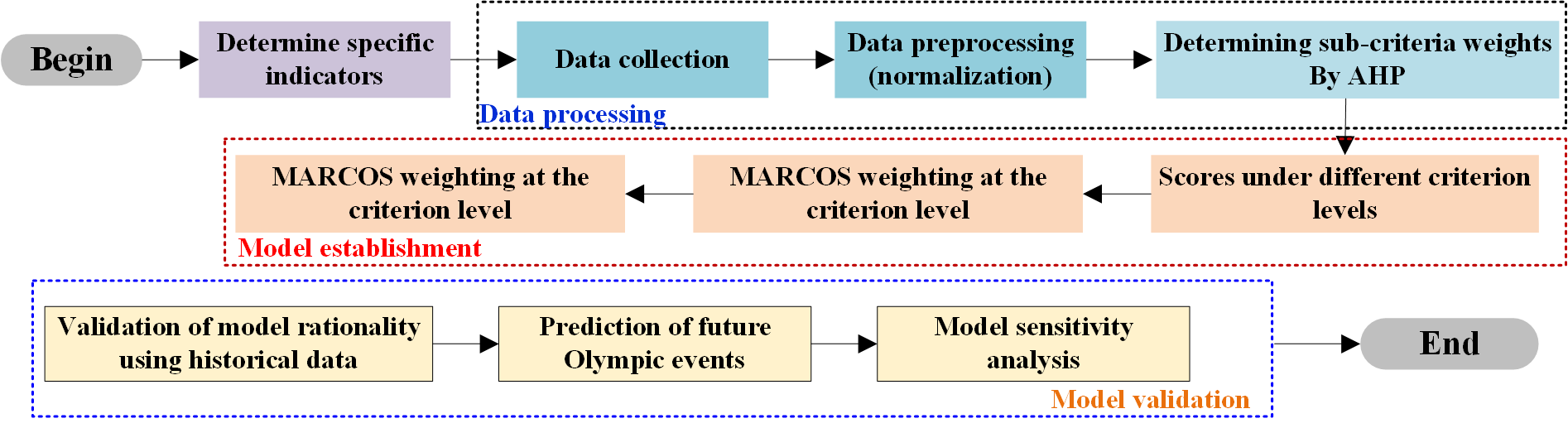
**2.2 Problem restatement**

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 1.1** Symbol definition

|  |  |
| --- | --- |
| Notation | Definition |
|  | Popularity Index |
|  | Gender Equality Index |
| S | Sustainability Index |
|  | Inclusivity Index |
|  | Relevence and Innovation Index |
|  | Safety and Fair Competition Index |
|  | Dimensional weights |
|  | The i-th Sport’s Score on the j-th Dimensions |

1. **Question 1**

**3.1 Question Restatement**

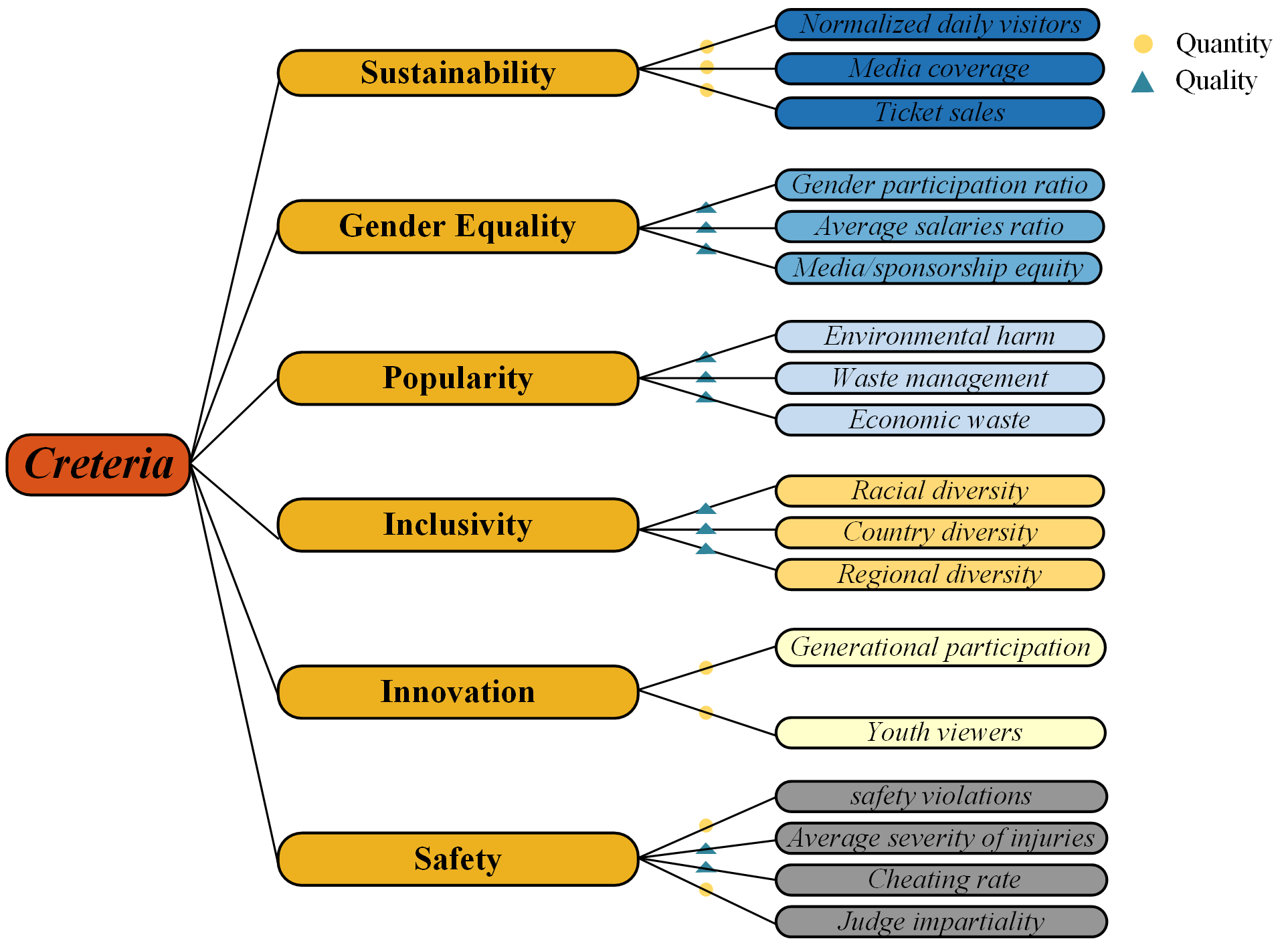
The team, HiMCM Olympic Consultants (HOC), has been tasked with assisting the International Olympic Committee (IOC) in evaluating potential sports, disciplines, and events (SDEs) for inclusion in the 2032 Summer Olympics. To support the IOC’s decision-making process, a set of criteria has been established, 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**

* 1. **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

* + 1. **Popularity Index**

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

|  |  |
| --- | --- |
|  | (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.

* + 1. **Gender Equity Index (Inequality Index Approach)**

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:

|  |  |
| --- | --- |
|  | (2) |

Where andrepresent the number of female and male participants, respectively, and denote the average salaries for female and male athletes. measures media and sponsorship equality, scaled to [0,1]. This formula quantifies the Euclidean dist2ance 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 不同的运动的结果**

* + 1. **Sustainability Index: Additive Penalty Model**

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

|  |  |
| --- | --- |
|  | (3) |

where represents the environmental penalty from weighted emissions. denotes the waste management penalty. 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.

* + 1. **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:

|  |  |
| --- | --- |
|  | (4) |

Whererepresent racial, country, and regional diversity indices for participant k. 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,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 represents the relative importance of criterion compared to criterion . The matrix is reciprocal, meaning that .

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:

|  |  |
| --- | --- |
|  | (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:

|  |  |
| --- | --- |
|  | (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):

|  |  |
| --- | --- |
|  | (7) |

Therefore, we can conclude that:

|  |  |
| --- | --- |
|  | (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:

|  |  |
| --- | --- |
|  | (9) |

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

|  |  |
| --- | --- |
|  | (10) |

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

|  |  |
| --- | --- |
|  | (11) |

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

|  |  |
| --- | --- |
|  | (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:

|  |  |
| --- | --- |
|  | (13) |

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 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.

* + 1. **Inclusivity Index (III): Exponential Aggregation**

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

|  |  |
| --- | --- |
|  | (14) |

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

* + 1. **Safety and Fair Competition Index**

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

|  |  |
| --- | --- |
|  | (15) |

Where: denotes normalized safety violations, and is the average severity of injuries (scaled 0–1). reflects the rate of cheating (e.g., drug violations per total checks). 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.

**Fig.4 不同的运动的结果()**

1. **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, representing the performance of about 40 sports across 6 dimensions. Each element 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 which contains the evaluation scores for  sports across 6dimensions mentioned above:

|  |  |
| --- | --- |
|  | (7) |

where represents the score of the i-th sports on the j-th dimensions. To ensure comparability between dimensions, the scores inare normalized using vector normalization

|  |  |
| --- | --- |
|  | (8) |

Where  represents the normalized value for the i-th sport and j-th dimension. The normalized decision matrixis used in subsequent computations. The weights for each dimension are optimized using a Recurrent Neural Network (RNN), trained on historical data. This data includes the scores for all dimensions and binary inclusion labels, where indicates the sport was included in a given Olympics, and  indicates exclusion.

**4.1 Input and Output Design**

**Input:** Each input to the RNN corresponds to a normalized vector for sports i.

**Output:**

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

|  |  |
| --- | --- |
|  | (9) |

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

**2🡪Probability ** The RNN predicts **** the probability of excluding sport i, using a sigmoid function:

|  |  |
| --- | --- |
|  | (10) |

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

**4.2 Loss Function**

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

|  |  |
| --- | --- |
|  | (11) |

Whereis the total number of training samples,  is the true label for sport i,and  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 matrixand the learned weights 

**4.3.1 Determination of Ideal and Anti-Ideal Solutions**

The ideal and anti-idealsolutions for each dimension  are defined as followed:

|  |  |
| --- | --- |
|  | (12) |

**4.3.2 Utility Score Computation**

The utility scores  and for sport iii are calculated as:

|  |  |
| --- | --- |
|  | (13) |

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

**4.3.3 Utility Score Computation**

The utility coefficient  for sport i is defined as the ratio of  and :

|  |  |
| --- | --- |
|  | (15) |

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

**4.3.4 Classification and Decision-Making**

The utility coefficient  serves as the input to the final decision-making stage, where the RNN transforms into a probability  using the sigmoid activation:

|  |  |
| --- | --- |
|  | (16) |

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

|  |  |
| --- | --- |
|  | (17) |

1. **Question3-4 - Model application**

**5.1 模型的验证**

**Fig.5 神经网络示意图**

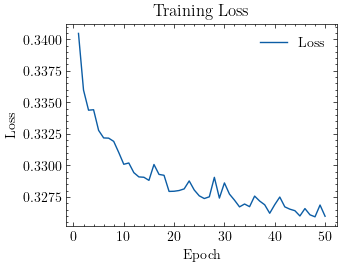
**输入我们的训练数据**

**Athletics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 2000 | 2004 | 2008 | 2012 | 2016 | 2020 |
| **P** | 0.6223 | 0.5740 | 0.6138 | 0.6108 | 0.6049 | 0.5789 |
| **G** | 0.6561 | 0.6222 | 0.6689 | 0.6434 | 0.6594 | 0.7204 |
| **S** | 0.4087 | 0.4664 | 0.3664 | 0.3305 | 0.2671 | 0.4598 |
| **I** | 0.5904 | 0.4654 | 0.4982 | 0.5156 | 0.3245 | 0.6155 |
| **R** | 0.1375 | 0.1288 | 0.1126 | 0.2052 | 0.1698 | 0.1542 |
| **SF** | 0.2010 | 0.2163 | 0.2300 | 0.1923 | 0.2450 | 0.2631 |

**Badminton**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 2000 | 2004 | 2008 | 2012 | 2016 | 2020 |
| **P** | 0.6342 | .6235 | 0.6386 | 0.6400 | 0.6396 | 0.6342 |
| **G** | 0.9212 | 0.9186 | 0.9195 | 0.9174 | 0.9241 | 0.8980 |
| **S** | 0.7295 | 0.7307 | 0.7225 | 0.7236 | 0.7373 | 0.7393 |
| **I** | 0.5923 | 0.5880 | 0.5748 | 0.6039 | 0.5879 | 0.5952 |
| **R** | 0.1245 | 0.1320 | 0.1270 | 0.1175 | 0.1356 | * 0.1355 |
| **SF** | 0.8423 | 0.8543 | 0.8450 | 0.8452 | 0.8498 | 0.8342 ​ |

****

**图6. Loss下降**

**六个维度的权重**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **P** | **G** | **S** | **I** | **R** | **SF** |
| **Weights** | |  | | --- | |  | | 0.427475 | |  | |  | | 0.06661 | |  | | --- | |  |   0.107052 | 0.044465 | 0.229257 | 0.125142 |

**图7. 验证结果往年数据**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 1960 | 1964 | 1968 | 1972 | 1976 | 1980 |
| Athletics |  0.5707 | 0.5709 | 0.5706 | 0.5710 |  0.5705 |  0.5705 |
| Badminton | 0.5708 | 0.5597 |  0.5883   | 0.5501 | 0.5984 | 0.5406 |

**5.2 模型的验证**

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:

* : The order of the Auto Regressive (AR) component, representing the number of past observations used to predict the current value.
* : The degree of differencing required to make the series stationary. This accounts for trends in the data.
* : 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:

|  |  |
| --- | --- |
|  | (18) |

Where:

* + is the value of the time series at time ,
  + ,,…, are the coefficients to be estimated,
  + is the error term at time .

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:

|  |  |
| --- | --- |
|  | (19) |

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

1. **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:

|  |  |
| --- | --- |
|  | (20) |

Where:

* + is a constant term (optional),
  + is the error term at time ,
  + ,,…, 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.8 ARIMA 绘制典型的运动的六个维度评分**

**新的运动对应的数据**

**Fig.9 ARIMA 绘制典型的运动的六个维度评分(相似图7)**

1. **模型**
2. **Weakness and Strengths**

**6.1 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.
  1. **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.

1. **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.

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