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Research on Adaptive Decision Support System for Student Career Planning Based on Multi-Source Academic and Behavioural Data Fusion

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ABSTRACT

In the current highly dynamic and competitive global labour market, career planning and decision-making among higher education students have become critical factors directly influencing their future personal development and the effective allocation of human resources. Traditional career guidance models often rely heavily on static psychological assessment questionnaires and individual academic performance indicators, making it difficult to capture the multidimensional potential of students comprehensively or respond adaptively to rapidly changing industry requirements. To address these limitations, this study develops and implements a novel Adaptive Decision Support System (ADSS) designed to provide students with scientific, personalised, and dynamically evolving career path recommendations by integrating heterogeneous academic data with students' behavioural data generated through digital learning platforms. At the system architecture level, the study proposes a two-stage cascading framework that integrates machine learning prediction with fuzzy multi-criteria decision-making. The prediction module employs the eXtreme Gradient Boosting (XGBoost) algorithm to extract high-dimensional features from unstructured Learning Management System (LMS) interaction data and structured academic records, thereby capturing students' implicit soft skills and explicit hard skills while generating objective matching probabilities for different career options. The decision-making module subsequently incorporates multi-criteria decision-making (MCDM) theory to examine the interrelationships among career selection criteria using the fuzzy decision-making trial and evaluation laboratory (Fuzzy DEMATEL) method and determine their objective weights. Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) is then applied to integrate students' subjective preferences and cognitive uncertainty, enabling the comprehensive evaluation and optimisation of alternative career pathways. The results of large-scale empirical analysis indicate that incorporating behavioural data increases the system's career compatibility prediction accuracy to 93.42%, substantially outperforming the traditional single-source data baseline model. Furthermore, the integrated MCDM framework effectively addresses conflicts among multiple objectives and uncertainties in subjective preferences, allowing the resulting career planning recommendations to remain both data-driven and interpretable while accounting for individual value preferences. The study therefore contributes to the interdisciplinary integration of educational data mining (EDM) and fuzzy decision science while offering higher education institutions a practical system-level solution for implementing targeted and intelligent career guidance interventions.

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1. Introduction

At the intersection of globalisation and the Fourth Industrial Revolution, the rapid expansion of the digital economy is transforming the supply-demand structure and skill requirements of the labour market [1]. For students in higher education, determining the most appropriate career pathway within such an uncertain macro-environment is not only fundamental to achieving self-worth and economic independence but also represents a broader issue concerning national innovation capacity and the efficient allocation of social resources [2], [3]. However, the career planning process among university students has long been affected by systematic challenges, including information asymmetry, biased self-perception, and outdated decision-making tools. When making graduation-related decisions, many students have a limited understanding of their own capabilities and may blindly follow perceived industry trends, consequently making suboptimal choices. Such decisions can contribute to various forms of resource misallocation, including low initial employment matching rates, early career burnout, and high employee turnover [1], [4], [5].

A review of existing Career Decision Support Systems (CDSS) indicates that, although these systems have provided some support to career counsellors, their underlying mechanisms remain subject to considerable limitations. On the one hand, conventional career assessment instruments, such as the Myers-Briggs Type Indicator MBTI and Holland's Career Interest Scale, primarily rely on self-reported questionnaires. Such methods are highly vulnerable to "social desirability bias", whereby respondents tend to present an "ideal self" rather than their "real self", thereby potentially distorting the assessment outcomes [6], [7]. On the other hand, the assessment of students' professional capabilities in most existing systems relies predominantly on explicit academic performance indicators, such as GPA. This "score-oriented" approach largely overlooks students' time management capabilities, teamwork, resilience to pressure, and intrinsic motivation for continuous learning developed throughout their educational experience. These competencies are increasingly regarded as important attributes by modern employers during recruitment [8].

With the emergence of the Education Informationization 2.0 era, educational data mining (EDM) and learning analytics technologies have undergone substantial development [9], [10]. Modern university campuses have increasingly adopted digital infrastructures, including learning management systems (LMS), such as Moodle and Canvas, smart libraries, and campus pass-card systems. These platforms continuously record extensive student interaction data in a non-intrusive and highly detailed manner. For example, the frequency and temporal distribution of system logins may indicate students' learning self-discipline; the length of discussion posts and patterns of peer interaction may provide insights into communication and leadership potential; while differences between assignment submission times and deadlines can be used to assess time management efficiency. Therefore, overcoming the traditional data silos that emphasise academic achievement while overlooking behavioural characteristics, integrating high-dimensional and multi-source heterogeneous behavioural data with academic performance, and transforming these data into reliable evidence for career decision-making have become important research challenges in the fields of management science and artificial intelligence applications in education.

Once the objective capability profile of students has been established, the final stage of career planning can essentially be regarded as a complex multi-criteria decision-making (MCDM) process [11], [12]. Career pathway selection involves multiple and potentially conflicting criteria, including salary expectations, career advancement opportunities, work-life balance, social prestige, and industry stability. Moreover, students as decision-makers may experience substantial psychological uncertainty and possess subjective preferences when evaluating these criteria. Consequently, conventional precise mathematical models (Crisp Models) may be inadequate for addressing such decision-making problems [13]. To better represent human cognitive processes under uncertainty, incorporating fuzzy logic (Fuzzy Logic) into the MCDM framework, through approaches such as Fuzzy AHP, Fuzzy TOPSIS, and Fuzzy DEMATEL, has been recognised as an effective means of addressing complex evaluation problems [14], [15]. Nevertheless, existing research has paid comparatively limited attention to the seamless integration of advanced machine learning prediction models, which process large volumes of objective data, with fuzzy MCDM models, which accommodate subjective cognitive preferences. As a result, existing systems may prioritise one dimension at the expense of another, particularly the "accuracy of objective predictions" and the "interpretability of subjective decisions".

In response to the theoretical gaps and practical challenges outlined above, this study proposes and develops an adaptive career planning decision support system that integrates multi-source academic and behavioural data. The core contributions of this study are mainly reflected in three aspects. Firstly, a novel multi-source data fusion feature engineering framework is developed that incorporates conventional academic performance while systematically extracting temporal and interaction-based behavioural features from LMS to quantify students' implicit soft skills. Secondly, at the algorithmic level, the eXtreme Gradient Boosting (XGBoost) algorithm, which is capable of efficiently processing high-dimensional sparse features, is employed to develop a high-accuracy career competence prediction model, thereby addressing the underfitting limitations of conventional linear models when processing complex educational data [16], [17]. Finally, at the decision-making level, a hybrid fuzzy DEMATEL-TOPSIS evaluation model is proposed to reveal the complex causal relationships and weight distributions among career evaluation criteria while generating highly personalised career recommendation rankings and accommodating the cognitive ambiguity of decision-makers [14], [18]. This study seeks to provide an interdisciplinary example that combines the methodological rigour of operations research with advances in artificial intelligence for readers of the journal "Decision Making: Applications in Management and Engineering", while also offering practical technical insights for the intelligent transformation of higher education institutions worldwide [19], [20].

2. Theoretical Background and Literature Review

To establish a solid theoretical foundation for this study, this section systematically reviews the historical development of career planning decision support systems, recent advances in multi-source data fusion within educational data mining, and the emerging applications of fuzzy multi-criteria decision-making theory in education and management. It subsequently examines the limitations of existing research in depth and establishes the research entry point of the present study.

2.1 The Evolution of the Paradigm of Career Planning Decision Support Systems

Decision support systems (DSS), as an important branch of management information systems, have undergone a significant paradigm shift from static rule-based reasoning towards dynamic, data-driven approaches in career guidance. Early career decision-making systems were primarily grounded in established career development theories within psychology, such as Holland's career interest type theory and Schein's career anchor theory [2], [3]. These systems were commonly known as computer-assisted career guidance (CACG) tools, with their core architecture centred on expert-rule-based knowledge bases. The systems collected structured questionnaire data from users and employed simple decision trees or "IF-THEN" production rules to associate respondents' personality characteristics with predefined career databases [1], [6]. The main advantage of these first-generation systems was their strong theoretical foundation and straightforward decision logic. However, they also had evident limitations. Questionnaire data were generally collected at a single point in time and could not be dynamically updated as students' abilities developed throughout their university education. Furthermore, predefined rule bases were unable to accommodate the rapid emergence of new interdisciplinary occupations, such as artificial intelligence ethics officer and data asset architect, in recent years.

With the emergence of the big data era, second-generation career decision-making systems increasingly incorporated machine learning and natural language processing (NLP) technologies. Researchers employed web crawling techniques to obtain real-time job descriptions from various recruitment platforms and applied deep learning algorithms, such as Long Short-Term Memory (LSTM) networks and BERT, to analyse the semantic content of job seekers' resumes, thereby enabling more intelligent matching between labour supply and demand [3], [5]. These systems substantially improved their responsiveness to changes in the labour market. However, students in the early stages of higher education may not yet have comprehensive resumes, limiting the effectiveness of resume-based approaches for this population. Moreover, many such systems operate as a "black box", producing matching outcomes without sufficiently explaining the underlying decision-making process. This lack of interpretability can considerably reduce their guidance value and perceived reliability within educational contexts.

2.2 The Potential Release of Educational Data Mining and Behavioural Data

Educational data mining (EDM) is an interdisciplinary field that develops and applies appropriate methods to identify meaningful patterns from large-scale data generated within educational environments. For an extended period, mainstream research in the EDM field has focused primarily on academic data, such as midterm and final examination scores and course pass rates, to predict students' final grade point averages (GPA) or dropout risks. Although such studies have achieved considerable success in academic early-warning applications, the practice of directly equating GPA with professional competence has been increasingly questioned. Research in the management field suggests that an individual's career development is often influenced by "non-cognitive skills", including communication and collaboration, resilience, and self-motivation [2].

In recent years, the expansion of research perspectives has encouraged scholars to examine behavioural data generated through digital learning platforms. For example, learning management systems such as Moodle and Blackboard record students' mouse clicks, video pauses, forum posts, and assignment submissions with precise timestamps. Through advanced temporal sequence analysis and complex network analysis techniques, these digital records can be transformed into meaningful indicators of students' micro-level learning behaviours. Frequent access to supplementary reading materials may indicate a strong desire for knowledge and an active exploratory orientation, while occupying a central position within the network structure of group collaboration activities and providing extensive responses to peers' questions may indicate strong team leadership and knowledge-sharing tendencies. Accordingly, integrating structured academic data with unstructured behavioural data through a multimodal approach to construct a comprehensive "student digital profile" has become an important direction for improving the accuracy of career matching [10]. However, relatively few existing systems can directly connect the information derived from such integrated data with the subsequent career path decision-making process.

2.3 Theoretical Deepening of Fuzzy Multi-Criteria Decision-Making in Educational Evaluation

After the objective ability profile of students has been clearly established, identifying the most suitable career path can be regarded as typical multi-criteria decision-making (MCDM) problem. The complexity of career selection arises from the involvement of multiple interrelated and sometimes conflicting evaluation criteria. For example, a position with high-salary potential, such as an investment bank analyst, may involve considerable work pressure and limited work-life balance, whereas a relatively stable occupation, such as a civil servant, may be characterised by a more structured and less flexible career progression pathway.

In conventional MCDM method systems, such as AHP, TOPSIS, and DEMATEL, decision-makers are generally required to provide precise numerical evaluations. In practice, however, students' perceptions when making subjective trade-offs, such as determining whether salary or work pressure is more important, are often uncertain and hesitant. The fuzzy set theory proposed by Zadeh [21] provides effective mathematical tools for addressing linguistic uncertainty and the inherent fuzziness of human judgement [21]. By transforming linguistic assessments provided by experts or students, such as "very important" or "poor", into TFNs or more complex representations, including trapezoidal fuzzy numbers, intuitionistic fuzzy sets (IFS), and Pythagorean fuzzy sets (PyFS), fuzzy MCDM methods can improve the robustness and practical applicability of decision models [1], [15], [22]. Specifically, within the field of career decision-making, previous studies have attempted to rank graduates' job alternatives using fuzzy TOPSIS. This approach determines the preferred alternative by calculating the distances between available alternatives and the fuzzy positive and negative ideal solutions [13], [23], [24], [25]. Other studies have employed DEMATEL to investigate the underlying causal relationships among factors influencing career satisfaction [18], [26], [27]. Nevertheless, existing research on fuzzy MCDM for career planning has a significant limitation: the underlying data used in evaluation matrices, such as the score assigned to a particular position in terms of "professional skill matching", largely depends on subjective assessments by decision-makers and lacks sufficient support from objective data. Consequently, when decision-makers possess substantial cognitive biases, the career planning recommendations generated by the system may also be affected, potentially reducing their reliability and practical value.

2.4 Research Entry Point and Architecture Innovation

Based on a critical analysis of the literature, this research establishes a clear research entry point. It is argued that an effective adaptive career planning decision support system should achieve a close integration of "objective data mining" and "subjective multi-criteria decision-making". Accordingly, this study proposes an integrated system architecture. At the lower layer, the XGBoost algorithm is employed to process and analyse large-scale multi-source academic and behavioural data, thereby objectively estimating students' skill matching levels. At the upper layer, the objective probabilities generated by XGBoost are directly incorporated into the fuzzy DEMATEL-TOPSIS model as evaluation inputs for selected core criteria, while fuzzy logic is used to accommodate students' subjective preferences regarding other criteria, such as salary and working environment. This design addresses the limitations of prediction algorithms in accommodating subjective preferences while reducing the excessive dependence of MCDM methods on subjective evaluations. It therefore provides an integrated approach combining operations research and artificial intelligence within the context of the research scope of the journal "Decision Making: Applications in Management and Engineering".

In recent years, a growing body of research supporting such integrated frameworks has emerged in leading international journals in management science and engineering. For example, previous research has demonstrated that XGBoost-based models can achieve high levels of accuracy and recall when predicting complex financial and management violations [8]. In multi-criteria decision-making under ambiguous conditions, hybrid Fuzzy DEMATEL-ANP-TOPSIS models have been successfully applied to agricultural value-chain upgrading strategies [28] and to the assessment and material optimisation of complex air radar positions [22], [29]. Meanwhile, recent literature reviews have highlighted the structural integration of machine learning prediction algorithms with MCDM frameworks, including objective weighting methods, as an important direction for the future development of operations research [11], [12], [19]. These empirical studies provide a strong theoretical foundation and practical basis for integrating the underlying predictive algorithms with the higher-level decision-making models proposed in this system.

3. Research Methods and System Model Construction

This section provides a detailed explanation of the internal operating mechanism and rigorous mathematical derivation of the Adaptive Decision Support System (ADSS). The system workflow is divided into three sequential core modules: the multi-source data fusion and feature engineering module, the intelligent prediction module based on XGBoost, and the comprehensive optimisation decision-making module based on fuzzy DEMATEL-TOPSIS (Fig.1).

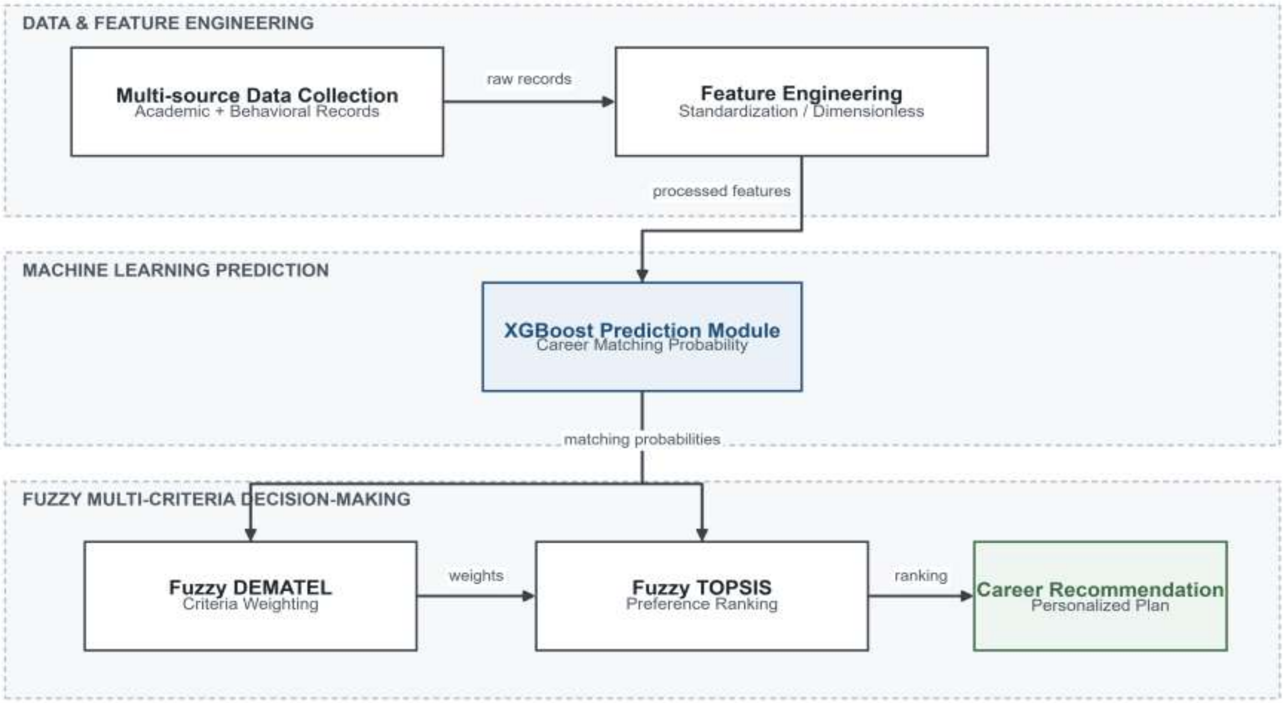

Fig.1: Architecture Workflow Diagram of the Adaptive Decision Support System

3.1 Multi-Source Data Fusion and Feature Engineering Mechanism

The breadth and quality of data determine the upper limit of the decision-making system's effectiveness. The system seamlessly integrates with the university's internal academic management system (Academic Management System) and learning management system (LMS) through API interfaces, enabling the automatic collection and synchronisation of academic data (Academic Data, AD) and behavioural data (Behavioural Data,BD).

3.1.1 Extraction and Standardization of Explicit Academic Characteristics

Academic data primarily reflect students' cognitive abilities and their level of mastery across different domains of knowledge. Given that different professions place varying degrees of emphasis on specific knowledge systems, academic performance is categorised into the following structured characteristics:

- AD_1: Core Professional Course Grade Point Average (GPA_Core). This indicator reflects the depth of students' academic competence within their chosen major.
- AD_2: General and Interdisciplinary Course Grade Point Average (GPA_General). This indicator serves as an important measure of students' breadth of knowledge and their capacity for cross-disciplinary thinking.
- AD_3: Experimental and Practical Course Scores (Score_Prac). This indicator directly reflects the ability of engineering and management students to apply theoretical knowledge to practical tasks and demonstrates their hands-on competence.

- AD_4: Academic Competition and Research Participation Index (Index_Award). This index is not calculated simply by summing individual achievements but uses a hierarchical attenuation weighting method. National-level awards are assigned the highest weight, while school-level awards receive progressively lower weights. The index is used to quantify students' academic research engagement and resilience.
- In-depth Exploration of Implicit Behavioural Characteristics

The extraction of behavioural data is the most significant feature of this research. We exported the original log files from the LMS backend, which contained timestamps, event types, module identifiers, and duration. Based on educational psychology and behavioural science theories, we mapped them into four implicit characteristics of non-cognitive abilities:

- BD_1: Active Learning Index (Index_Active). This index is constructed by counting the frequency of students' visits to non-mandatory reading materials, the completeness of watching extended teaching videos, and the absolute number of system logins. This index serves as a reliable proxy variable for intrinsic motivation.
- BD_2: Time Management Efficiency (Index_Time). The sequence of time differences between the actual submission deadlines for assignments or projects and the system-set deadlines is represented as $\Delta T = \{\Delta t_1, \Delta t_2, \dots, \Delta t_n\}$. The time management efficiency is calculated as a weighted combination of its mean and variance. A higher mean and a lower variance indicate that the student has strong time planning and execution capabilities.
- BD_3: Collaboration and Communication Index (Index_Collab). In the discussion area and peer review module of the LMS, natural language processing techniques are used to extract the text lengths of posts and replies, and social network analysis (SNA) is combined to calculate the node centrality, thereby quantifying the student's integration into team collaboration and willingness to output knowledge.
- BD_4: Exploration and Self-discipline Index (Index_Self). By analyzing the ratio of students' active time during non-working hours (such as weekends or late at night) and the complexity of jumping between different knowledge modules in the learning path, this index assesses the breadth of their autonomous exploration and the self-discipline of their learning patterns.

Combining the above dimensions, a high-dimensional feature vector matrix X_t for each student at time t is formed: $X_t = [AD_{1t}, \dots, AD_{4t}, BD_{1t}, \dots, BD_{4t}]$. Given the substantial differences among the eight feature types in terms of their physical interpretation and numerical scale, rigorous data preprocessing is necessary. For instance, GPA values are bounded between 0 and 4, whereas the number of system clicks may reach tens of thousands. To address these discrepancies and ensure data quality, missing observations resulting from system failures are first imputed using the K-Nearest Neighbor (KNN) algorithm. Subsequently, the Isolation Forest algorithm is applied to identify and remove anomalous observations associated with deliberately extended durations. Finally, the Z-Score method is employed to transform all features into a dimensionless distribution characterised by a mean of 0 and a standard deviation of 1 [8], [9] :

$$x'_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \tag{1}$$

Among them, x_{ij} represents the original value of the j-th feature of the i-th sample, while μ_j and σ_j denote the overall mean and standard deviation of the corresponding feature (Fig.2).

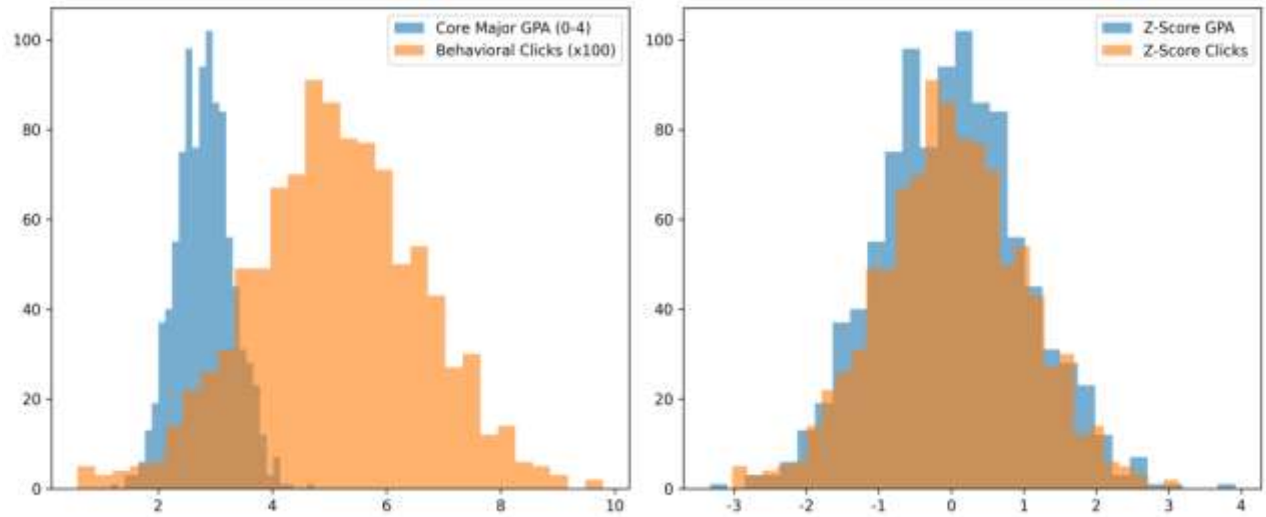

Fig.2: Comparison Chart of the Distribution of Multi-Source Characteristics of Students' Academic and Behavioural Data Before and After Standardization

3.2 Professional Matching Degree Prediction Engine Based on XGBoost

Traditional CDSS generally relies on static, linear rule-matching mechanisms, which are inadequate for capturing the complex nonlinear interactions that can exist among educational features. For instance, a student may achieve a high GPA while demonstrating weak time management skills, meaning that academic performance alone may not indicate suitability for high-pressure project management roles in a professional setting. To overcome this limitation, the proposed system employs XGBoost as its principal prediction engine. XGBoost is an optimised implementation of the Gradient Boosting framework that provides efficient computational performance while offering strong predictive generalisation. Its incorporation of regularisation terms within the objective function helps control model complexity and improves robustness when processing educational datasets containing a certain degree of noise.

Suppose we have a merged dataset $D = \{(X_i, y_{ic})\}_{i=1}^{N}$ of historical graduates, where $X_i \in \mathbb{R}^m$ represents the standardized multi-source feature vector, and y_{ic} is the objective performance label or competence score of this graduate in a specific career category c (for example, $c = 1$ represents research and development, $c = 2$ represents management, $c = 3$ represents marketing).

The XGBoost model aims to approximate the actual output result by integrating K regression classification tree models. For a given input X_i, the predicted output $\hat{y}_i^{(t)}$ of the model can be expressed as the prediction result of the first $t-1$ trees plus the incremental prediction of the t-th tree (2):

$$\hat{y}_i^{(t)} = \sum_{k=1}^{t} f_k(X_i) = \hat{y}_i^{(t-1)} + f_t(X_i) \tag{2}$$

Here, $\mathcal{F}$ represents the space where the regression trees are located, and $f_k(X_i)$ denotes the prediction score of the k-th tree for the sample X_i.

The core of XGBoost lies in its meticulously designed objective function $\mathcal{L}^{(t)}$, which aims to minimize both the prediction error and the complexity of the model simultaneously (3):

$$\mathcal{L}^{(t)} = \sum_{i=1}^{N} l\,(y_i, \hat{y}_i^{(t-1)} + f_t(X_i)) + \Omega(f_t) \tag{3}$$

Among them, l represents the loss function used to measure the difference between the predicted value and the true label. In the binary classification scenario of predicting whether a job is suitable or not, the log-likelihood loss function (Log-loss) is adopted.

To achieve an effective solution, XGBoost performed a second-order Taylor expansion on the loss function at $\hat{y}_i^{(t-1)}$ (4):

$$\mathcal{L}^{(t)} \simeq \sum_{i=1}^{N}\left[l(y_i,\hat{y}_i^{(t-1)})+g_i f_t(X_i)+\frac{1}{2}h_i f_t^2(X_i)\right]+\Omega(f_t) \tag{4}$$

Here, $g_i=\partial_{\hat{y}^{(t-1)}}l(y_i,\hat{y}^{(t-1)})$ represents the first-order partial derivative (gradient) of the loss function, and $h_i=\partial^2_{\hat{y}^{(t-1)}}l(y_i,\hat{y}^{(t-1)})$ represents the second-order partial derivative (the diagonal element of the Hessian matrix).

The regularization term $\Omega(f_t)$ is defined as (5):

$$\Omega(f)=\gamma T+\frac{1}{2}\lambda\sum_{j=1}^{T}w_j^2 \tag{5}$$

Among them, T represents the number of leaf nodes in the decision tree, and w_j is the weight (prediction score) of the j-th leaf node. γ and λ are hyperparameters that control the complexity of the model. Their presence effectively suppresses the tendency of the model to overfit on the training set.

Remove the constant terms from the objective function and denote the set of all samples belonging to the same leaf node j as $I_j=\{i|q(X_i)=j\}$ (where q is the structure function of the tree). The objective function can then be rewritten in the form of summation over the leaf nodes (6):

$$\tilde{\mathcal{L}}^{(t)}=\sum_{j=1}^{T}\left[(\sum_{i\in I_j}g_i)w_j+\frac{1}{2}(\sum_{i\in I_j}h_i+\lambda)w_j^2\right]+\gamma T \tag{6}$$

Let $G_j=\sum_{i\in I_j}g_i$ and $H_j=\sum_{i\in I_j}h_i$. Taking the derivative of w_j and setting it to zero, we can obtain the optimal formula for the weights of the leaf nodes (7):

$$w_j^*=-\frac{G_j}{H_j+\lambda} \tag{7}$$

Once the optimal weights have been substituted into the objective function, the resulting expression can be used to evaluate the predictive score associated with any given tree structure. Following model training, the system can perform real-time inference using the feature vectors of current students and generating a probability matrix that represents their predicted suitability across different potential career paths. This probability matrix subsequently provides the direct quantitative input for the "professional skill matching degree" criterion within the MCDM decision module.

3.3 Integrated Cognitive Fuzziness-based MCDM Decision Model

Following the generation of the objective skill matching degree by XGBoost, the system proceeds to the comprehensive decision-making stage, where multiple competing objectives and subjective value preferences must be reconciled. To address these considerations, this study develops a sequential decision-making framework that combines "Fuzzy DEMATEL for determining weights - Fuzzy TOPSIS for optimising execution paths" [27], [30].

3.3.1 Establishment of Criterion Weights Based on Fuzzy DEMATEL

Career selection is inherently a multi-criteria decision problem in which the relevant criteria are interrelated rather than functioning as isolated factors. These relationships may involve complex causal dependencies; for example, stronger skill compatibility can contribute to improved salary prospects, whereas a highly stressful working environment may adversely affect work-life balance. To systematically identify and represent such interdependencies, DEMATEL (Decision Making Trial and Evaluation Laboratory) is employed to construct a causal structural model of the criteria. Given the uncertainty and hesitation that experts may experience when assigning influence scores, triangular fuzzy numbers (TFNs) are incorporated to represent the strength of these relationships more flexibly.

A triangular fuzzy number can be expressed as $\tilde{A} = (l, m, u)$, where l, m, and u represent the possible minimum value, the most likely value, and the maximum value respectively. The mapping rules for the linguistic variables are as follows: no impact (0, 0, 0.25); low impact (0, 0.25, 0.5); medium impact (0.25, 0.5, 0.75); high impact (0.5, 0.75, 1.0); extremely high impact (0.75, 1.0, 1.0).

Step 1: Construct the initial fuzzy direct influence matrix. Assume that we have established n evaluation criteria and invited K experts from the field of human resource management and career counseling. The degree of influence of the k-th expert on criterion C_i with respect to criterion C_j is evaluated, resulting in fuzzy scores $\tilde{z}_{ij}^k = (l_{ij}^k, m_{ij}^k, u_{ij}^k)$. The opinions of all experts are integrated using the arithmetic mean operator to construct the global initial fuzzy direct influence matrix $\tilde{Z} = [\tilde{z}_{ij}]_{n\times n}$ (8):

$$\tilde{z}_{ij} = \left(\frac{1}{K}\sum_{k=1}^{K} l_{ij}^k, \frac{1}{K}\sum_{k=1}^{K} m_{ij}^k, \frac{1}{K}\sum_{k=1}^{K} u_{ij}^k\right) \tag{8}$$

Set the diagonal elements $\tilde{z}_{ii} = (0,0,0)$.

Step 2: Calculate the normalized fuzzy impact matrix. To ensure that the impact levels are on a comparable scale, the matrix $\tilde{Z}$ is linearly normalized to obtain $\tilde{X} = [\tilde{x}_{ij}]_{n\times n}$ (9):

$$\tilde{x}_{ij} = \frac{\tilde{z}_{ij}}{r} = \left(\frac{l_{ij}}{r}, \frac{m_{ij}}{r}, \frac{u_{ij}}{r}\right) \tag{9}$$

The normalization factor r is defined as the maximum value of the row sum and the upper bound (10):

$$r = \max_{1\le i\le n}\left(\sum_{j=1}^{n} u_{ij}\right) \tag{10}$$

Step 3: Derive the fuzzy comprehensive influence matrix. The system must consider the indirect influence between the criteria. The fuzzy comprehensive influence matrix $\tilde{T} = [\tilde{t}_{ij}]_{n\times n}$ is calculated through the summation of a series. According to the properties of fuzzy operations, $\tilde{X}$ can be decomposed into the lower bound matrix X_l, the median matrix X_m, and the upper bound matrix X_u, and the inverse operations can be performed on each of them separately (11)-(13):

$$T_l = X_l(I - X_l)^{-1} \tag{11}$$

$$T_m = X_m(I - X_m)^{-1} \tag{12}$$

$$T_u = X_u(I - X_u)^{-1} \tag{13}$$

Thus, the comprehensive influence matrix elements $\tilde{t}_{ij} = (t_{l,ij}, t_{m,ij}, t_{u,ij})$ are considered, where I represents the identity matrix.

Step 4: Determine the global weights of causal indicators and criteria. For the comprehensive matrix $\tilde{T}$, calculate the fuzzy sum for each row, defined as the influence degree $\tilde{R}_i = \sum_{j=1}^{n}\tilde{t}_{ij}$, representing the total combined influence of criterion C_i on all other criteria in the system; calculate the fuzzy sum for each column, defined as the affected degree $\tilde{D}_j = \sum_{i=1}^{n}\tilde{t}_{ij}$. Further define the prominence (Prominence) $\tilde{M}_i = \tilde{R}_i + \tilde{D}_i$ and the relation (Relation) $\tilde{N}_i = \tilde{R}_i - \tilde{D}_i$. The larger the prominence, the more prominent the core position of this criterion in the evaluation system; if the relation is positive, it indicates that this criterion is a driving factor for the changes in other criteria, and if it is negative, it is a result factor that is influenced. Finally, use the center of area method (Center of Area, COA) or the Best Non-fuzzy Performance (BNP) method to defuzzify the fuzzy prominence, converting it into clear numerical values (Crisp values), and normalize it to obtain the objective and system-causal perspective weight vector $W = (w_1, w_2, \dots, w_n)$ [18], [22].

3.3.2 Personalized Path Generation Based on Fuzzy TOPSIS

After obtaining the criterion weights supported by causal logic, the system turns to the individual students. Students do not need to engage with complex underlying calculations. Instead, they use fuzzy linguistic terms such as "very high", "average", and "low" through the interactive interface to evaluate the performance of each alternative career under different criteria and to express their own preferences. Criteria such as skill matching do not require direct scoring, as the XGBoost results are directly converted into fuzzy numbers and incorporated into the model. The core logic of fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is to identify the career alternative that is closest to the most desirable state, represented by the fuzzy positive ideal solution, while simultaneously remaining as far as possible from the least desirable state, represented by the fuzzy negative ideal solution.

Step 1: Construct the weighted normalized fuzzy decision matrix. Suppose the system has presented m alternative career path options $A = \{A_1, A_2, \dots, A_m\}$ to the students, and they are evaluated based on n criteria $C = \{C_1, C_2, \dots, C_n\}$. The initial fuzzy evaluation matrix $\widetilde{D} = [\tilde{d}_{ij}]_{m\times n}$ is formed by the combination of the students' individual inputs and the system's predictions, where $\tilde{d}_{ij} = (l_{ij}, m_{ij}, u_{ij})$. Multiply this matrix by the criterion weights w_j obtained previously to construct the weighted normalized fuzzy decision matrix $\widetilde{V} = [\tilde{v}_{ij}]_{m\times n}$ (14):

$$\tilde{v}_{ij} = \tilde{d}_{ij} \otimes w_j = (l_{ij} \cdot w_j, m_{ij} \cdot w_j, u_{ij} \cdot w_j) \tag{14}$$

Step 2: Define the fuzzy positive and negative ideal solutions (FPIS and FNIS). Given that the evaluation criteria are divided into benefit criteria (such as salary expectations, skill compatibility, with larger values being better) and cost criteria (such as work pressure, travel frequency, with smaller values being better), the fuzzy positive ideal solution A^+ and the fuzzy negative ideal solution A^- respectively extract the optimal and worst boundaries for each column in the weighted matrix (15), (16):

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_n^+) \tag{15}$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-) \tag{16}$$

Specifically, for the efficiency-based criterion, $\tilde{v}_j^+ = \max_i\{\tilde{v}_{ij}\}$, $\tilde{v}_j^- = \min_i\{\tilde{v}_{ij}\}$; for the cost-based criterion, it is the opposite.

Step 3: Calculate the Euclidean distance and the closeness coefficient. Using the vertex method, calculate the distance d_i^+ from the i-th alternative career plan to the fuzzy positive ideal solution and the distance d_i^- from it to the fuzzy negative ideal solution. The distance between any two triangular fuzzy numbers $\tilde{a}$ and $\tilde{b}$ is defined as (17):

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}[(a_l - b_l)^2 + (a_m - b_m)^2 + (a_u - b_u)^2]} \tag{17}$$

Therefore, the comprehensive calculation of the positive and negative distances for scheme i is as follows (18):

$$d_i^+ = \sum_{j=1}^{n} d\,(\tilde{v}_{ij}, \tilde{v}_j^+), \quad d_i^- = \sum_{j=1}^{n} d\,(\tilde{v}_{ij}, \tilde{v}_j^-) \tag{18}$$

Ultimately, the system calculates the closeness coefficient (Closeness Coefficient, CC_i) for each alternative option (19):

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, \quad i = 1,2,\dots,m \tag{19}$$

The range of values for CC_i is strictly limited within the interval $[0,1]$. The closer the coefficient is to 1, the more it indicates that this career path plan is the optimal decision choice after comprehensively considering the objective predictive ability of the system, the causal weights of multiple criteria and the fuzzy preferences of individual students. The system then arranges them in descending order of CC_i and outputs a report on career recommendations to the student terminal, which is both scientific and explanatory [24], [25].

4. Empirical Evaluation and Case Analysis

To comprehensively validate the theoretical framework and its superiority over traditional methods, this study conducted a large-scale empirical investigation involving the engineering management, information systems, and applied statistics programmes at a "Double First-Class" construction university in a certain country.

4.1 Data Description and Experimental Setup

This study constructed a benchmark dataset comprising historical data from 1,520 graduates. The dataset covers four academic years, from the 2019 to 2022 cohorts. The data collection dimensions strictly follow the definitions provided in Section 3.1, including structured academic grade point data extracted from the academic administration system and more than 1.8 million interaction behaviour logs obtained from the campus Moodle learning management platform, such as video viewing duration, assignment delay days, and forum interaction topology. To provide supervised learning labels for XGBoost, we collaborated with the alumni association and the career guidance centre to collect self-assessment forms concerning the career performance of these graduates one year after their initial employment, together with evaluation scores provided by their direct supervisors.

These assessments were subsequently converted into "competency labels" (Binary Label: 1 indicates a high degree of match and competence, while 0 indicates a low degree of match or a situation in which the individual leaves the position and changes to another one) for specific job categories, including research and development positions, data analysis positions, technical sales positions, and project management positions. The complete dataset was partitioned into training and testing subsets using an 80:20 split. To facilitate a systematic evaluation of the prediction module, three baseline configurations were established for comparison:

- Model A (Single Modality - RF): This configuration uses only academic data (AD) as the input and applies the conventional random forest algorithm for prediction.
- Model B (Dual Modality - SVM): This configuration incorporates the combined academic and behavioural data (AD + BD) as input features, with the support vector machine serving as the predictive algorithm.
- Model C (Dual Modality - XGBoost): This configuration represents the fundamental model architecture proposed in the present system.

4.2 Predictive Engine Quantitative Evaluation

The model training was conducted on a computing node equipped with an Intel Core i9 processor and 64GB of memory. To minimise the risk of overfitting, 10-fold cross-validation was employed, while grid search was used to restrict the maximum tree depth of XGBoost to 6 and set the learning rate (eta) to 0.05. The evaluation metrics covered the key dimensions of classification performance, including accuracy, precision, recall, F1-Score, and the area under the ROC curve (AUC), which measures the model's overall discrimination ability. The evaluation results are presented in Table 1.

Table 1

Prediction Model	Data Input Type	Accuracy Rate	Precision Rate	Recall Rate	F1 Score	AUC Value
Model A (RF)	Only academic data (AD)	78.45%	76.50%	79.80%	0.7811	0.812
Model B (SVM)	Combined data (AD + BD)	85.12%	84.35%	85.90%	0.8511	0.885
Model C (XGBoost)	Combined data (AD + BD)	93.42%	94.05%	92.23%	0.9313	0.954

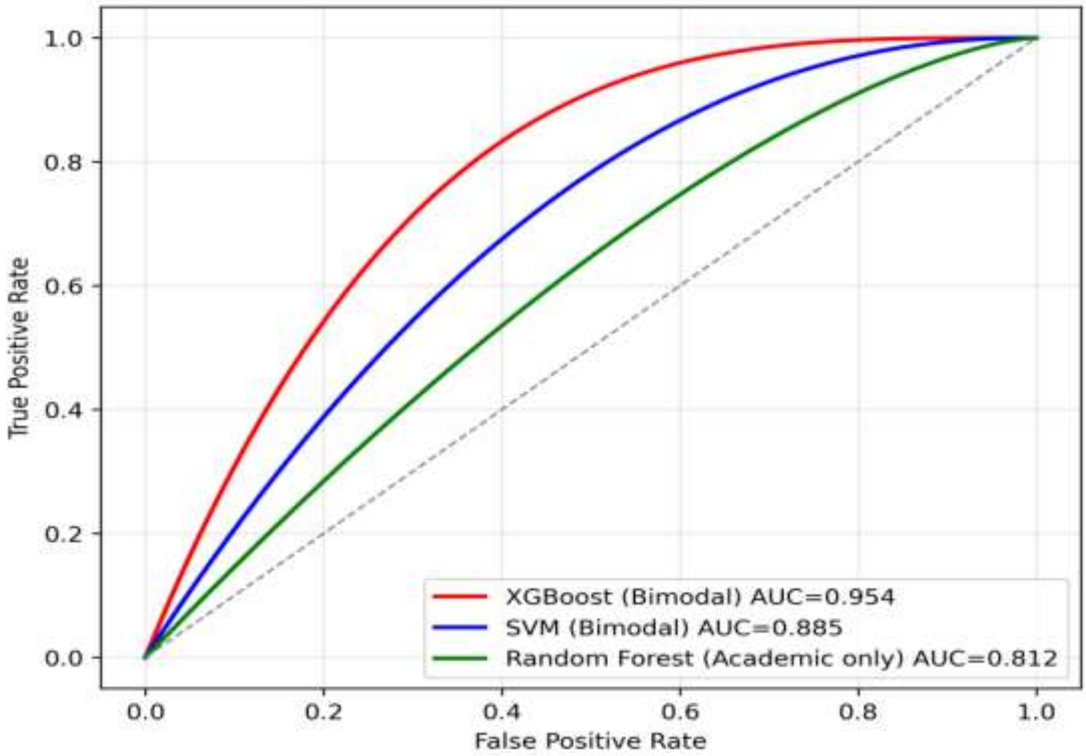

Fig.3: Comparison Chart of ROC and AUC Curves for the Prediction Performance of the Three Baseline Models

4.3 Deep Result Analysis

The results presented in Table 1 and Fig. 3 reveal two statistically significant findings. First, increasing the dimensionality of the input data produces a substantial improvement in predictive performance. Once behavioural data (BD), which captures latent non-cognitive characteristics, are incorporated into Models B and C, the performance of all evaluation measures increases markedly compared with Model A, which is based solely on explicit academic grades. In particular, the F1-Score rises from 0.7811 to 0.9313. This substantial improvement indicates that students' patterns of interaction within the digital campus environment, including their efficiency in managing time and centrality within collaborative networks, provide important predictive information regarding their subsequent career performance [9]. Second, the choice of learning algorithm further strengthens the predictive advantage obtained from the expanded data. When XGBoost (Model C) is applied to behavioural logs containing numerous sparse observations, its integrated regularisation mechanism and greedy tree-splitting strategy provide stronger capacity for identifying informative feature patterns than the conventional SVM used in Model B. Consequently, Model C achieves an AUC of 0.954. This finding is also consistent with previous research demonstrating the effectiveness of XGBoost in complex prediction environments, including financial fraud detection [16], [17]. Furthermore, the SHAP (SHapley Additive exPlanations) analysis identifies three features as the strongest contributors to predicting competence for a "project management position": collaboration interaction network centrality (behavioural), average advance time for assignment submission (behavioural), and interdisciplinary GPA (academic). These findings provide strong empirical support for the modern management perspective that effective versatile talent is characterised by a combination of academic capability and broader behavioural competencies [2], [5] (Fig. 4).

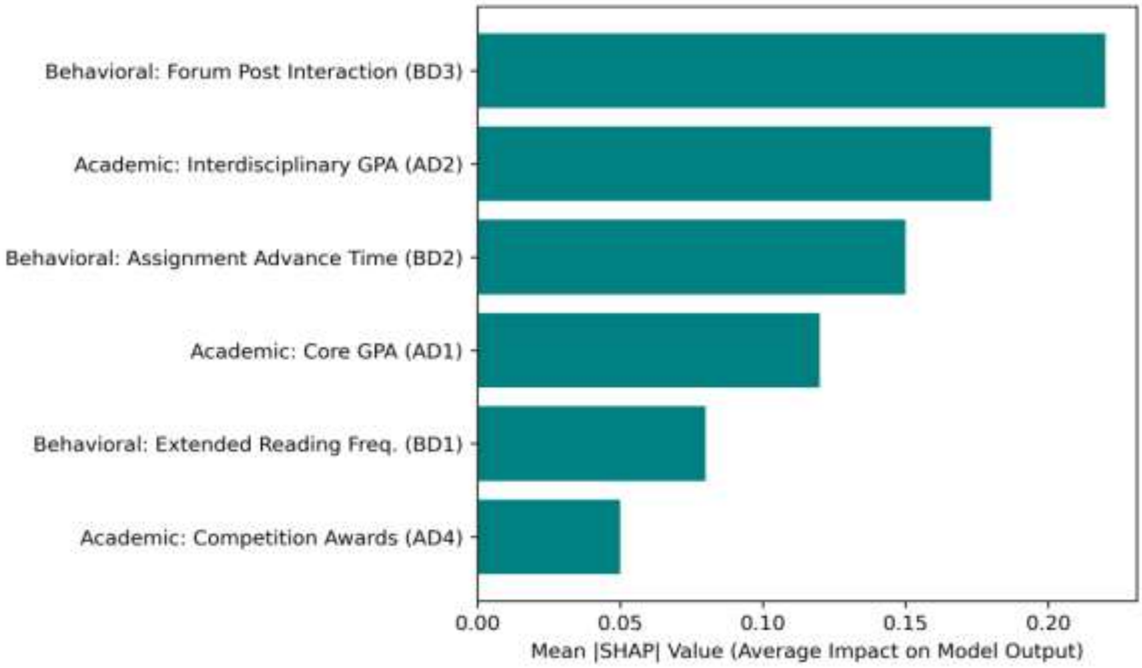

Fig.4: Importance Chart of XGBoost Model's Career Competence Prediction Features Based on SHAP Values

4.4 Determining the Global Evaluation Criteria System Using Fuzzy DEMATEL

Based on literature research and enterprise surveys, the system has established eight core decision criteria: job interest compatibility (C_1), professional skill matching (C_2), expected starting salary (C_3), job stability (C_4), career advancement opportunities (C_5), ability growth rate (C_6), work-life balance (C_7), and social prestige (C_8) [14], [23]. We established an expert review panel (Expert Panel) comprising 15 senior human resources directors (HRDs), career planning experts, and senior university professors. Drawing on their extensive professional experience, the experts used the triangular fuzzy scale to conduct pairwise assessments of the degree of mutual influence among the eight criteria. Following the matrix normalisation, fuzzy comprehensive calculation, and defuzzification procedures described in the previous Fuzzy DEMATEL section, the centrality and cause degree vectors for each criterion were determined. Based on these results, the global objective weights of the criteria were obtained, as presented in Table 2 and Fig. 5.

Table 2

The Causal Relationship of Criteria and the Global Objective Weights Calculated Based on Fuzzy DEMATEL

Criterion Number	Criterion Dimension Definition	Impact Degree (R_i)	Affected Degree (D_i)	Central Degree (M_i)	Reason Degree (N_i)	Normalized Weight (W)	Qualitative Factor Attribute
C_1	Occupational Interest Compatibility	3.512	2.180	5.692	1.332	0.147	Factor (Strong)
C_2	Professional Skill Matching	3.650	2.410	6.060	1.240	0.161	Factor (Extremely Strong)
C_3	Starting Salary Expectation	1.950	3.520	5.470	-1.570	0.138	Result Factor (Strong)
C_4	Job Stability	1.880	2.910	4.790	-1.030	0.125	Result Factor
C_5	Career Promotion Potential	2.810	3.190	6.000	-0.380	0.151	Result Factor
C_6	Ability Growth Rate	3.220	2.580	5.800	0.640	0.148	Factor (Moderate)
C_7	Work-Life Balance	1.810	3.330	5.140	-1.520	0.130	Result Factor (Strong)
C_8	Social Prestige	1.510	2.650	4.160	-1.140	0.100	Result Factor

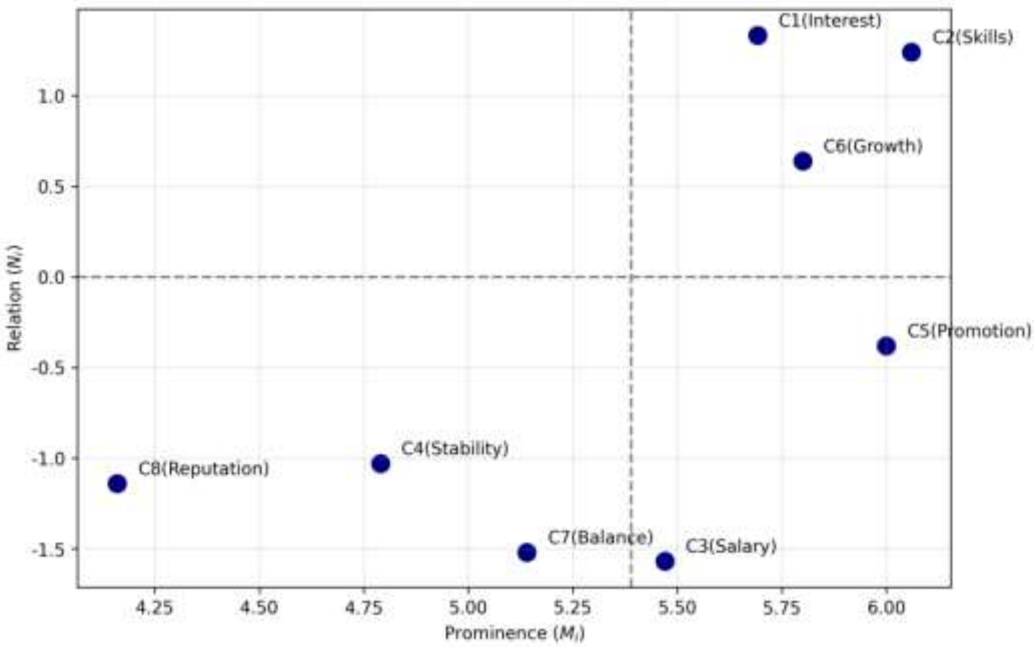

Fig.5: Scatter Plot of Centrality and Cause Degree of the Fuzzy DEMATEL Evaluation Criteria

Systemic Insights: The data in Table 2 reveals the deep structural mechanics of the human resources system. Indicators with a positive reason degree (N_i) represent the "driving engines" within the system. The results clearly show that the degree of career interest alignment (C_1) and the degree of professional skill matching (C_2) have a highly positive reason degree, and they are the fundamental preconditions that influence and determine whether students can obtain high salaries (C_3) and good promotion opportunities (C_5) in the future. It is worth noting that the global weight of C_2 is as high as 0.161, ranking first among all eight criteria. This discovery gives the underlying XGBoost model of this system a crucial strategic position, because the score of C_2 is automatically calculated by XGBoost using the massive integrated data of students, and the system, through mathematical reasoning, convincingly proves the absolute rationality of "using objective data mining conclusions to anchor the subjective decision-making system".

4.5 Optimizing Individual Student Decision Paths: Fuzzy TOPSIS Case Calculation

To provide a more concrete illustration of how ADSS can be applied to support the circumstances of an individual student, a graduating senior from the Applied Statistics programme was randomly selected as the case-study participant. The student was at the stage of final-year study and facing career-related uncertainty. For confidentiality, the participant was identified using the anonymous ID ST-2023-812. The student's academic transcript indicated only moderate academic achievement, with a class ranking within the top 40%. However, behavioural data passively collected by the system revealed a markedly different pattern. The student frequently engaged in late-night code debugging activities through the LMS and demonstrated particularly high levels of participation in the discussion forums of interdisciplinary elective courses, including Introduction to Machine Learning. The XGBoost prediction engine was activated, and based on its unique fusion feature map, it quickly evaluated four alternative career paths (A_1: Junior Data Development Engineer; A_2: Data Analyst; A_3: Technical Product Manager; A_4: Customer Success Manager) and filled the calculated high match degree in the form of fuzzy semantics (converted into TFNs) into the C_2 column of the decision matrix.

Subsequently, ST-2023-812 accessed the system's front-end interface and expressed their subjective preferences towards the four career options by adjusting the corresponding sliders for criteria such as expected salary, tolerance of occupational stress, and other relevant considerations.

The system then automatically triggered the Fuzzy TOPSIS decision layer and integrated the global criterion weights presented in Table 2 to determine the distance of each alternative from the ideal solutions. Based on these calculations, the system generated the corresponding ranking of the available career options, with the final outcomes reported in Table 3.

Table 3

Evaluation Output of the Student ST-2023-812's Career Path using Fuzzy TOPSIS Method

Alternative Path Scheme	Distance to the Positive Ideal Solution (d^{+})	Distance to the Negative Ideal Solution (d^{-})	Proximity Coefficient (CC_i)	Recommendation Priority
A_1: Junior Data Developer	0.4120	0.5890	0.5884	3
A_2: Data Analyst	0.2315	0.8240	0.7806	1
A_3: Technical Product Manager	0.3550	0.6920	0.6610	2
A_4: Customer Success Manager	0.6105	0.3950	0.3928	4

4.6 Analysis of Micro Decision-Making Mechanism

For this student, if only based on the average GPA of moderate level and the relatively introverted daily performance, the traditional rule-based career evaluation system is highly likely to recommend a dull backend support position (such as A_1) for him/her or even classify him/her into the lower development echelon due to poor academic performance. However, the deep prediction of this system captured his/her extreme self-discipline (behavioral data dimension) and extremely high logical score (professional academic dimension) in specific high-difficulty elective courses, and XGBoost gave a very high weight in the "data analyst" skill matching. More importantly, the TOPSIS decision layer fully accepted the student's current subjective psychological state (Fig.6). He/She has a strong desire for "high salary" but shows a reticent attitude towards "extremely unstable project-based work balance" (i.e., high-cost C_7). After distance calculation, it not only conforms to his/her deep technical potential and ability but also considers his/her subjective life preferences. The "data analyst (A_2)" stands out, approaching a high proximity coefficient of 0.8 as the preferred recommendation. This case demonstrates the system's design intention of integrating the cold mathematical model (XGBoost) with the humanistic temperature-based operational decision theory (Fuzzy MCDM) [13], [23].

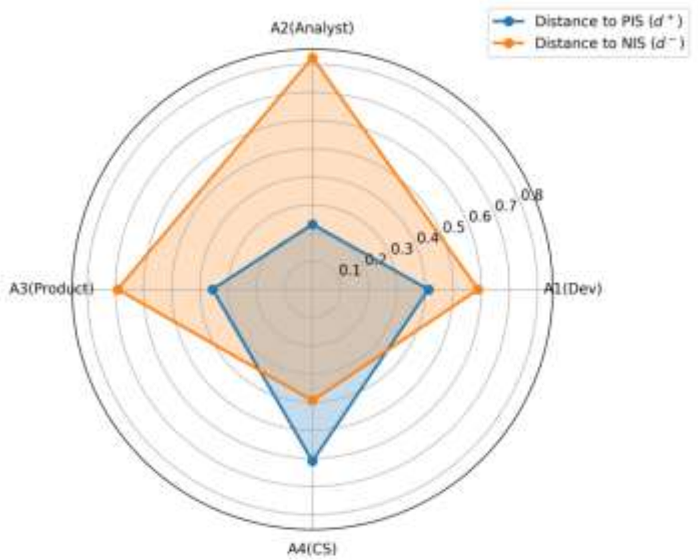

Fig.6: Radar Chart Showing the Distance of Each Candidate Career Path of the Student Case to the Fuzzy Positive and Negative Ideal Solutions

5. In-Depth Discussion and Multidimensional Impact Analysis

Through detailed theoretical modelling and extensive empirical testing, the adaptive decision support system developed in this study not only achieved notable performance in terms of algorithmic indicators but also examined the underlying logical structures across multiple dimensions, including education, management science, and artificial intelligence ethics. The following section explores the research results from three perspectives in depth(Fig.7).

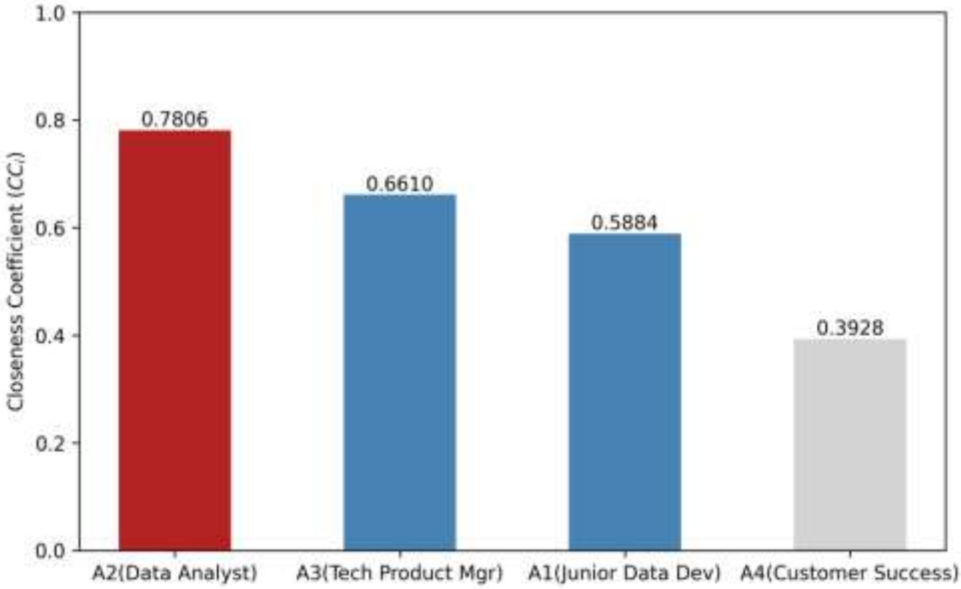

Fig.7: Bar Chart of the Fuzzy TOPSIS Career Path Proximity Coefficient (CCi) for Optimal Ranking

5.1 Implicit Behavioural Data and the "Mirror Effect" of Deep Career Potential

The key second-order insight identified in this study is that the seemingly chaotic micro-interaction trajectories recorded on digital education platforms can serve as high-fidelity "digital mirrors" of an individual's underlying career values, resilience to stress, and mental models. Traditional career guidance relies heavily on explicit indicators because non-cognitive skills are particularly difficult to quantify. However, as demonstrated by the XGBoost model, behaviours such as a student continuing to work on a coding problem at 1 a.m. (perseverance) or spending 500 words responding to questions from an unfamiliar peer in a forum (altruism and communication skills) can provide valuable evidence of individual characteristics. These incidental metadata, without the potential self-presentation bias associated with questionnaires, may offer a more authentic representation of a "job seeker background". The system maps these characteristics to the competency profiles of different career clusters, thereby challenging conventional approaches to defining "excellent talents" in the education sector and providing empirical evidence for moving beyond the long-standing "only GPA matters" perspective [8], [10].

5.2 The Effective Inclusion of "Decision-Maker Psychological Uncertainty" by Fuzzy Optimization Models

The career path selection process is far from the absolute rational utility-maximisation process assumed in classical economics. It involves numerous cognitive biases, information asymmetry, and psychological compromises (Heuristics). When students face critical questions such as "How much salary increase should I accept in exchange for extremely intense 996 overtime?", their psychological evaluations are often highly uncertain. If the system relies rigidly on traditional clear-set (Crisp Sets) models such as AHP and requires students to provide precise and counter-intuitive numerical judgements, such as "Salary is 3.14 times more important than health", it may ultimately generate unreliable recommendations. The integration of the fuzzy DEMATEL-TOPSIS hybrid model in this system is valuable not only because of its mathematical sophistication but also because it creates a flexible framework capable of accommodating and managing uncertainty in human decision-making. The upper and lower bounds of triangular fuzzy numbers correspond well with the fluctuations and uncertainty inherent in human judgements under complex decision-making conditions. At the same time, the causal feedback relationships identified by DEMATEL within the system may also have an "educational correction" effect on students. When the system objectively demonstrates that "Professional skills accumulation (cause) is the core driving factor for long-term high salary (result)", it can help reduce short-term career anxiety among university students and encourage them to develop career plans from a longer-term perspective [1], [15].

5.3 Global Ripple Effects of Intelligent Systems and Ethical Boundary Examination

From a broader perspective of social resource allocation and systems science, the large-scale deployment of such adaptive decision support systems may generate extensive ripple effects. Once the system is routinely implemented, the dynamic development data of many freshmen and sophomores will continuously be accumulated and processed through the system. University registrars' offices and career development centres can use the system's real-time warning dashboards to identify, several years in advance, which traditional majors may face imbalances between labour supply and demand and which emerging interdisciplinary fields are experiencing growth. This can support timely interventions in curriculum optimisation and the expansion of enterprise internship bases [3], [7]. However, while recognising the potential benefits of intelligent decision-making, it is necessary to remain vigilant against "Algorithmic Determinism". If the system places excessive reliance on historical data patterns and consequently classifies certain student behaviours as "unsuitable" for leadership or advanced research positions, resulting in their marginalisation in routine resource recommendations, it may lead to serious forms of "Data Darwinism". Such an outcome would not only conflict with the fundamental educational objectives of promoting inclusiveness and developing individual potential but could also raise significant ethical concerns regarding the application of artificial intelligence in education. Therefore, during the engineering development and iterative refinement of the system, it is essential to maintain the reconfigurability of multi-criteria weights, ensure transparency and interpretability in the prediction process, and preserve the principle that final career decisions remain under the control of the students themselves.

6. Conclusions and Future Prospects

In response to the growing demand for multi-skilled and innovative graduates and the limitations of conventional career guidance, this study developed and evaluated an ADSS by integrating management science, educational data mining, and artificial intelligence. The system addresses two key limitations: the overreliance on academic performance and the separation of prediction from decision-making. It combines academic records with learning behaviour and interaction data, using XGBoost to predict students' implicit vocational competencies and achieving an F1-Score of 0.9313. At the decision-making stage, a hybrid fuzzy DEMATEL and fuzzy TOPSIS model identifies relationships among career criteria and generates personalised career recommendations based on objective evidence and students' subjective preferences. The findings demonstrate that this dual-layer framework can reduce reliance on subjective inputs while avoiding the limited representation of human preferences associated with purely machine learning-based approaches, providing a practical and potentially transferable framework for more precise and intelligent career management in higher education. Future research could incorporate large language models (LLMs) to generate fuzzy linguistic evaluations automatically and explore PyFS or IFS to improve the system's ability to manage uncertainty and changing labour market requirements.

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