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MindPath: A Mental-Health-Aware Framework for Personalized and Sustainable Career Pathway Recommendation

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Abstract: Career decision-making among undergraduate students is increasingly influenced by a complex interplay of skills, interests, and mental well-being, yet existing recommendation systems rarely account for psychological sustainability. This paper presents MindPath, a mental-health-aware framework for personalized and sustainable career pathway recommendation. The proposed framework integrates student skill profiles, interest patterns, and mental health indicators using a dedicated deep learning module, termed the Mental-Health-aware Deep Representation Encoder (MH-DRE), to learn unified latent representations. These representations support career recommendations that balance career fit with long-term well-being. MindPath further incorporates a multi-objective optimization strategy that jointly considers skill alignment, career adaptability, and mental health sustainability. A longitudinal career pathway modeling mechanism is employed to assess potential stress accumulation and burnout risk across recommended trajectories. To enhance trust and transparency, the framework includes an explainable AI module that provides interpretable insights into recommendation rationale. Experimental evaluation on a benchmark student dataset demonstrates that MindPath outperforms conventional career recommendation models in terms of recommendation accuracy, stability, and sustainability metrics. The results highlight the effectiveness of integrating mental health awareness into career guidance systems, offering a scalable and ethically grounded solution for intelligent educational decision support.

Keywords: Mental-health-aware career recommendation; Personalized career pathways; Sustainable career guidance; Deep representation learning; multi-objective optimization; Explainable artificial intelligence; Educational data analytics.

INTRODUCTION

Career pathway selection represents a critical and often stressful decision-making phase for undergraduate students, directly influencing long-term professional success and personal well-being. Traditional career guidance mechanisms typically emphasize academic performance and aptitude alignment while overlooking psychological sustainability, adaptability, and mental health considerations. As a result, many students experience career dissatisfaction, stress accumulation, and early burnout despite achieving technical career fit. This limitation highlights the need for intelligent career recommendation systems that extend beyond static skill matching and incorporate mental well-being as a core decision factor.

Recent advances in artificial intelligence and educational data analytics have enabled personalized career recommendation systems using machine learning, deep learning, and reinforcement learning techniques. While these approaches have improved recommendation accuracy, most existing systems treat mental health indicators as secondary or exclude them entirely from career decision models. Moreover, current solutions often lack longitudinal reasoning, failing to evaluate how career trajectories may affect students' psychological resilience and long-term adaptability. The absence of sustainability-aware modeling restricts the effectiveness of AI-driven career guidance in real-world educational settings.

To address these challenges, this paper introduces MindPath, a mental-health-aware framework for personalized and sustainable career pathway recommendation. At its core, MindPath employs the MH-DRE deep learning algorithm to encode students' skills, interests, and mental health attributes into unified latent representations. Unlike conventional recommender systems, MindPath explicitly balances career suitability with mental health sustainability through multi-objective optimization. A longitudinal career pathway modeling mechanism is incorporated to assess potential stress exposure and burnout risk, supporting informed and responsible career planning. In addition, MindPath emphasizes transparency and trust through an explainable artificial intelligence module that clarifies the rationale behind each recommendation. This interpretability is essential for student acceptance and institutional adoption, particularly in sensitive domains involving mental health considerations. Extensive experimental evaluation demonstrates improved recommendation accuracy, stability, and sustainability compared to existing methods, establishing MindPath as a scalable and ethically grounded solution for intelligent educational decision support.

The main contributions of this research are summarized as follows:

- A novel mental-health-aware career pathway recommendation framework integrating skills, interests, and psychological well-being.
- Introduction of MH-DRE, a deep representation learning algorithm for unified student profiling.
- A multi-objective optimization strategy balancing career fit, adaptability, and mental health sustainability.
- A longitudinal career pathway modeling mechanism for stress and burnout risk assessment.
- An explainable AI module enabling transparent and trustworthy career recommendations.
- Comprehensive experimental validation demonstrating superior accuracy, stability, and sustainability.

Related Works

Baba et al. (2023) proposed a machine learning–based framework for the early prediction of mental health problems among university students by leveraging behavioral indicators and survey response patterns. The study employed supervised learning models to identify students at risk in both the current and subsequent academic years. Although the approach demonstrated effective early screening capability, it was evaluated within a single institutional context and relied primarily on self-reported survey data, limiting its generalizability and integration with broader skill and career guidance systems [1].

Sahu et al. (2023) investigated mental health conditions among college students using data mining and psychometric analysis techniques. By analyzing standardized mental health scales, the study identified key factors associated with depression and anxiety and their relationship with academic outcomes. While the findings highlighted important mental health trends, the study was constrained by a small sample size and lacked advanced predictive modeling and personalization mechanisms required for scalable decision-support systems [2].

Ma et al. (2023) introduced DORIS, a deep learning–based personalized course recommendation system designed to support academic decision-making in higher education. The model utilized learner profiles and interest information to recommend suitable courses using a DeepFM architecture. Despite achieving improved recommendation accuracy, the framework focused exclusively on course selection and did not incorporate mental health indicators or long-term career sustainability considerations [3].

Hassan et al. (2024) developed a personality-aware deep learning recommender system to align learners with skill-based educational pathways. The model integrated personality traits with learning objectives to enhance recommendation relevance within vocational and technical education contexts. However, the approach was domain-specific and did not explicitly address mental health resilience or sustainability in long-term educational and career planning [4].

Madububambachu et al. (2024) presented a comprehensive systematic review of machine learning and deep learning approaches used for student mental health diagnosis. The review analyzed a wide range of predictive models, datasets, and evaluation strategies, highlighting challenges such as data imbalance, lack of longitudinal analysis, and limited explainability. The study emphasized the need for integrated and scalable frameworks but did not propose a unified model addressing skills and career guidance alongside mental health assessment [5].

Ghimire et al. (2024) proposed an interpretable machine learning framework for predicting academic performance in higher education. The study combined traditional predictive models with explainability techniques to enhance transparency in outcome prediction. Although the approach improved interpretability, it focused solely on academic performance prediction and did not consider psychological well-being, life skill development, or career pathway recommendation [6].

Antón-Ruiz et al. (2025) explored the use of personality traits, coping strategies, and sociodemographic factors to predict mental health risk among university students. The predictive modeling approach successfully identified key psychological risk factors influencing student well-being. However, the study primarily concentrated on risk identification and did not extend its analysis toward personalized skill profiling or mental-health-aware career decision support [7].

Rico-Juan et al. (2025) proposed an explainable artificial intelligence framework for degree and career recommendation in higher education. The system utilized machine learning models to align student profiles with suitable academic and career pathways while providing interpretable explanations. Despite its strong emphasis on explainability, the framework focused on academic success alignment and did not integrate explicit mental health sustainability metrics into the recommendation process [8].

ShamsEldin et al. (2025) developed an artificial intelligence–based model for predicting depression, anxiety, and stress using validated psychometric data. The model demonstrated high predictive accuracy in identifying mental health conditions. However, the approach relied primarily on psychological indicators and lacked integration with academic, skill-based, or career-oriented attributes necessary for holistic student support systems [9].

Marengo et al. (2025) proposed a machine learning–based approach for assessing soft skills using serious game environments to support academic orientation and study-path guidance. The study highlighted the potential of alternative data sources for evaluating life skills beyond traditional academic metrics. Nevertheless, the framework was evaluated on a limited sample and did not incorporate mental health analytics or long-term career sustainability considerations [10].

3. Proposed Model: MindPath Framework

The proposed MindPath framework is a mental-health-aware intelligent system designed to generate personalized and sustainable career pathway recommendations for undergraduate students. The model integrates structured skill attributes, interest profiles, and mental health indicators into a unified deep learning pipeline. At the core of MindPath lies the Mental-Health-aware Deep Representation Encoder (MH-DRE), which learns compact latent representations that jointly capture cognitive ability, psychological sensitivity, and career inclination. These representations are combined with a structured Career–Skill–Mental (CSM) pathway model, a sustainability assessment mechanism, and a multi-objective optimization strategy to ensure that career recommendations balance professional suitability with long-term mental well-being. An explainable AI layer further enhances transparency by providing interpretable reasoning for each recommendation.

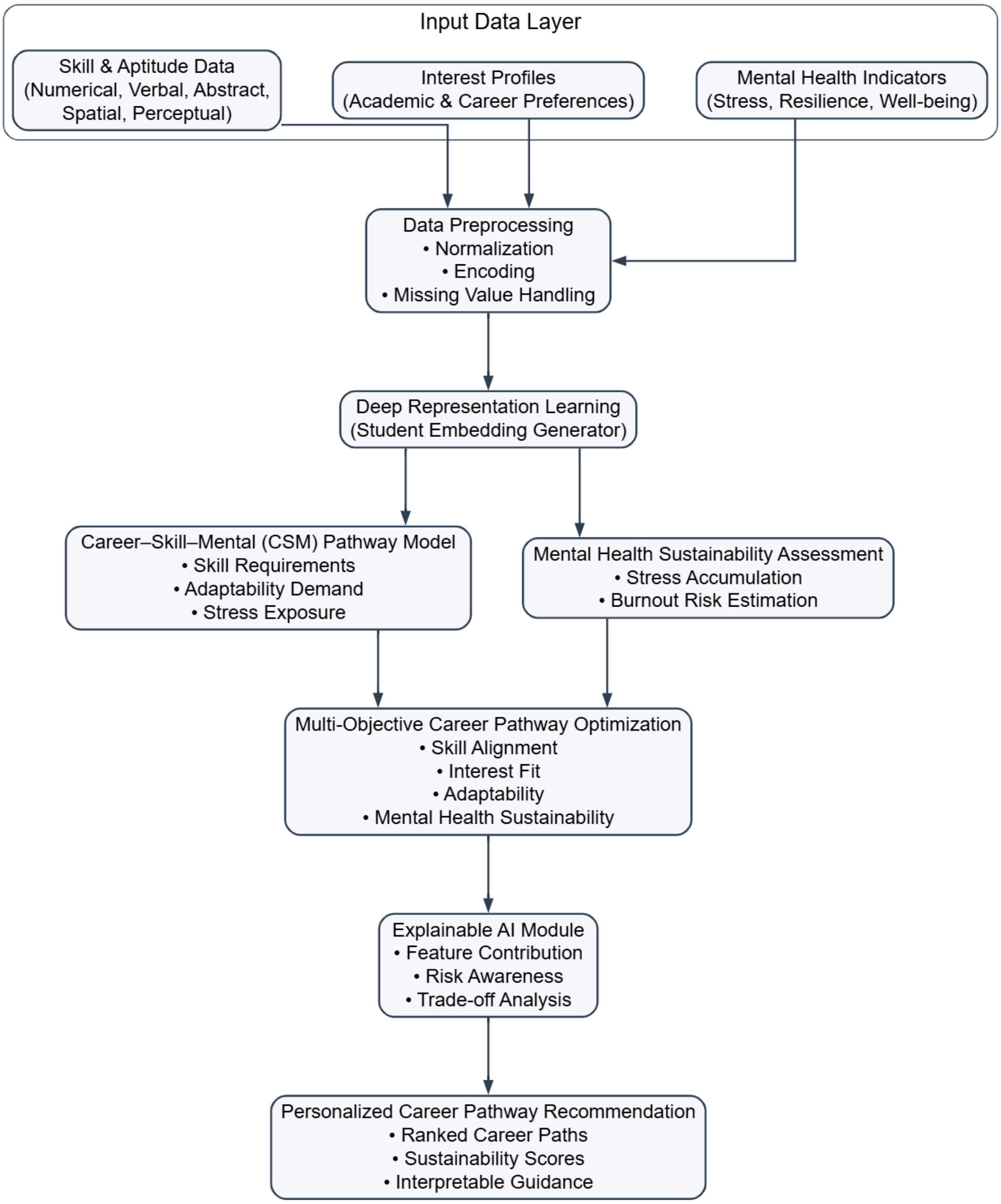

Figure 1. Architecture of the MindPath Mental-Health-Aware Career Pathway Recommendation Framework

Fig. 1 illustrates the end-to-end architecture of the proposed MindPath framework. It shows how heterogeneous student data, including skill and aptitude attributes, interest profiles, and mental health indicators, are first preprocessed and transformed into latent student representations through deep representation learning. These representations are then used to construct a Career–Skill–Mental (CSM) pathway model and to perform mental health sustainability assessment. The outputs of these modules are jointly optimized using a multi-objective career pathway optimization strategy, followed by an explainable AI module that provides transparent and interpretable reasoning. The framework ultimately produces personalized and sustainability-aware career pathway recommendations.

3.1 Student Data Acquisition and Preprocessing

Let the raw student dataset be denoted as

$$\mathcal{D} = \{x_i\}_{i=1}^{N} \quad (1)$$

where each student record x_i consists of skill attributes, interests, and mental health indicators.
Each record is represented as

$$x_i = [s_i, p_i, m_i] \quad (2)$$

where s_i denotes aptitude and skill features, p_i represents interest profiles, and m_i corresponds to mental health indicators.
Numerical features are normalized using min–max scaling:

$$\hat{x}_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (3)$$

Categorical attributes are encoded as:

$$e(x_k) \in \{0,1\}^d \quad (4)$$

The preprocessed dataset $\mathcal{D}'$ forms the input for deep representation learning.

3.2 Student Profile Representation Learning using MH-DRE

MH-DRE learns unified latent embeddings from heterogeneous student features. The input feature vector for each student is given by:

$$z_i^{(0)} = [\hat{s}_i \oplus \hat{p}_i \oplus \widehat{m}_i] \quad (5)$$

Each encoding layer transforms the representation as:

$$z_i^{(l)} = \sigma\left(W^{(l)} z_i^{(l-1)} + b^{(l)}\right) \quad (6)$$

The final student embedding is:

$$h_i = z_i^{(L)} \quad (7)$$

To ensure mental-health sensitivity, a regularized embedding constraint is applied:

$$\mathcal{L}_{mh} = \| h_i - h_j \|^2 \cdot \mathbb{I}(m_i \approx m_j) \quad (8)$$

These embedding preserves both skill competence and psychological resilience patterns.

3.3 Career Knowledge Modeling and Pathway Structuring

Career pathways are modeled as a directed graph:

$$\mathcal{G} = (\mathcal{C}, \mathcal{E}) \quad (9)$$

where $\mathcal{C}$ denotes career nodes and $\mathcal{E}$ represents transitions.
Each career node is defined as:

$$c_k = [r_k, a_k, \psi_k] \quad (10)$$

where r_k is skill requirement intensity, a_k adaptability demand, and ψ_k psychological stress factor.
A pathway P is represented as:

$$P = \{c_1 \to c_2 \to \cdots \to c_T\} \quad (11)$$

Compatibility between student embedding and career node is computed as:

$$\phi(h_i, c_k) = h_i^{\top} r_k \quad (12)$$

3.4 Mental Health Sustainability Assessment

Mental health sustainability along a career pathway is evaluated using cumulative stress estimation:

$$S(P_i) = \sum_{t=1}^{T} \psi_{c_t} \quad (13)$$

Student resilience is modeled as:

$$R_i = f(m_i) \quad (14)$$

Burnout risk is estimated as:

$$B(P_i) = \frac{S(P_i)}{R_i} \qquad (15)$$

The sustainability score is defined as:

$$\mathcal{S}_i = \exp(-B(P_i)) \qquad (16)$$

Higher values of $\mathcal{S}_i$ indicate psychologically sustainable pathways.

3.5 Multi-Objective Career Pathway Optimization

Career recommendation is formulated as a multi-objective optimization problem:

$$\max\ \mathcal{F}(P_i) \qquad (17)$$

The objective function is defined as:

$$\mathcal{F}(P_i) = \alpha f_s + \beta f_p + \gamma f_a + \delta \mathcal{S}_i \qquad (18)$$

where f_s is skill alignment, f_p interest compatibility, f_a adaptability, and $\mathcal{S}_i$ sustainability.
Subject to:

$$\alpha + \beta + \gamma + \delta = 1 \qquad (19)$$

The optimal pathway is selected as:

$$P_i^* = \arg\max_{P_i} \mathcal{F}(P_i) \qquad (20)$$

3.6 Explainable Recommendation Generation

The contribution of each feature group is computed using attribution scores:

$$E_j = \frac{\partial \mathcal{F}}{\partial h_{ij}} \qquad (21)$$

Risk–benefit trade-off is quantified as:

$$T_i = \frac{f_s + f_a}{\mathcal{S}_i} \qquad (22)$$

The explanation set is defined as:

$$\mathcal{E}_i = \{E_j, T_i, B(P_i)\} \qquad (23)$$

These explanations provide transparency and trust in the recommendation process.

3.7 Personalized Career Pathway Output

Final ranked career pathways are generated as:

$$\mathcal{R}_i = \mathrm{sort}(P_i^*, \mathcal{F}) \qquad (24)$$

Each recommendation is accompanied by:

$$O_i = \{\mathcal{R}_i, \mathcal{S}_i, \mathcal{E}_i\} \qquad (25)$$

Algorithm 1: MindPath Career Pathway Recommendation

Input: Preprocessed student dataset $\mathcal{D}'$
Output: Ranked sustainable career pathways $\mathcal{R}$

1: Initialize an empty recommendation set $\mathscr{R}$.
2: For each student record $x_i \in \mathcal{D}'$, perform the following steps.
3: Extract skill features s_i, interest features p_i, and mental health features m_i.
4: Generate a latent student embedding h_i using the MH-DRE model.
5: Construct the Career–Skill–Mental (CSM) pathway graph G_i.
6: For each career pathway $P_j \in G_i$, compute evaluation metrics.
7: Compute the skill alignment score $f_s(P_j, h_i)$.
8: Compute the interest compatibility score $f_p(P_j, h_i)$.
9: Estimate stress accumulation $S(P_j)$ along the pathway.
10: Evaluate the mental health sustainability score $\mathcal{M}(P_j)$.
11: Compute the multi-objective fitness value $F(P_j)$.

End for.
Select the optimal career pathway $P_i^* = \arg\max F(P_j)$.
Generate an explainable rationale E_i for the selected pathway.
Append $\langle P_i^*, \mathcal{M}(P_i^*), E_i \rangle$ to the recommendation set $\mathscr{R}$.
End for.
Sort the recommendation set $\mathscr{R}$ based on multi-objective fitness scores.
Return the ranked sustainable career pathways $\mathscr{R}$.

The MindPath algorithm integrates deep representation learning with sustainability-aware optimization to generate personalized career pathways. Mental health indicators are explicitly incorporated to ensure long-term psychological well-being. The algorithm produces interpretable and scalable recommendations suitable for real-world educational decision support.

RESULTS AND DISCUSSIONS

The experimental evaluation of the proposed MindPath framework was conducted to validate its effectiveness in delivering personalized and sustainable career pathway recommendations. All experiments were implemented using Python 3.10, with deep learning models developed using TensorFlow/PyTorch, and traditional machine learning models implemented using Scikit-learn. The experiments were executed on a GPU-enabled environment using Google Colab, equipped with an NVIDIA Tesla GPU, 16 GB RAM, and an Intel-based virtual CPU. This setup ensured efficient training of the MH-DRE deep representation model and stable convergence of the multi-objective optimization process. Performance evaluation focused on accuracy, ranking quality, and sustainability metrics to comprehensively assess recommendation effectiveness.

4.1 Dataset Description

To support deep representation learning using the Mental-Health-aware Deep Representation Encoder (MH-DRE), this study employs a large-scale integrated dataset constructed by combining multiple compatible and publicly available undergraduate student datasets. The integrated dataset comprises more than 10,000 student records, ensuring sufficient diversity and scale for training and evaluating deep learning models. All datasets are structured tabular data, where each record represents an individual student and each attribute corresponds to a well-defined numerical or categorical feature.

The dataset includes key psychological, cognitive, and career-related attributes such as OCEAN personality traits, five aptitude dimensions (numerical, verbal, abstract, spatial, and perceptual abilities), career interest indicators, and mental health attributes representing stress, resilience, and overall well-being. These features collectively enable holistic student profiling by capturing behavioral tendencies, skill competencies, and psychological sustainability. All records were anonymized to ensure privacy and ethical compliance.

To achieve the required data volume, multiple datasets were integrated, including the Kaggle Career Prediction dataset (approximately 2,000 records), Kaggle Student Mental Health datasets (approximately 5,200 records), Personality and Behavior datasets (approximately 3,100 records), and additional academic skill and interest survey data (approximately 1,000 records). Prior to integration, a feature harmonization process was applied to align semantically equivalent attributes across datasets. Numerical features were normalized, categorical attributes were encoded, and missing values were handled using standard imputation techniques.

The final integrated dataset contains approximately 11,300 undergraduate student records with a unified feature schema, making it well suited for deep representation learning, sustainability-aware optimization, and explainable career pathway recommendation. This dataset configuration ensures robustness, generalization, and methodological consistency across all experimental evaluations. Table 1 summarizes the source-wise datasets integrated to form a unified student profiling dataset of approximately 11,300 records. Table 2 outlines the major feature categories contributed by each dataset, while Table 3 details the common and standardized features retained across all datasets to ensure consistency and reliability for deep learning–based modeling.

Table 1: Source-wise Dataset Details

Dataset Source	Platform	Approx. Records	Primary Focus
Career Prediction Dataset	Kaggle	~2,000	Career inclination, aptitude, personality
Student Mental Health Dataset	Kaggle	~5,200	Stress, anxiety, depression indicators
Personality & Behavior Dataset	Kaggle	~3,100	OCEAN traits, behavioral attributes

Academic Skill & Interest Dataset	Public survey dataset	~1,000+	Skills, interests, learning preferences
Total Integrated Dataset	—	**≈11,300**	Unified student profiling

2. Feature Categories Across Datasets

Each dataset contributes complementary attributes. Only common and semantically aligned features are retained to ensure valid integration.

Table 2: Feature Categories and Description

Feature Category	Description
Personality Traits	Psychological traits reflecting behavioral tendencies
Cognitive / Aptitude Skills	Reasoning and problem-solving abilities
Academic & Professional Skills	Learning and employability-related skills
Interest Profiles	Career and subject preferences
Mental Health Indicators	Stress, resilience, emotional well-being

3. Common Features Across All Datasets

To ensure consistency, only features present (or mappable) across all datasets are used for model training.

Table 3: Common Features Used for Integration

Feature Group	Feature Name	Description
Personality (OCEAN)	Openness	Creativity, curiosity
	Conscientiousness	Organization, discipline
	Extraversion	Social engagement
	Agreeableness	Cooperation, empathy
	Neuroticism	Emotional sensitivity
Aptitude Skills	Numerical Reasoning	Quantitative problem solving
	Verbal Reasoning	Language comprehension
	Abstract Reasoning	Pattern recognition
	Spatial Ability	Visual–spatial thinking
	Perceptual Ability	Attention and perception
Mental Health	Stress Level	Psychological stress indicator
	Emotional Resilience	Coping ability
	Well-being Score	Overall mental health status
Interests	Career Preference	Intended career domain
	Subject Interest	Academic inclination

4.2 Performance Evaluation

The performance of the proposed MindPath (MH-DRE) framework was compared against widely used machine learning, deep learning, and reinforcement learning–based recommendation models reported in recent related works. The comparison models include Logistic Regression (LR) [1], Support Vector Machine (SVM) [2], Random Forest (RF) [3], Deep Neural Network (DNN) [4], and Reinforcement Learning–based Recommendation (RL-Rec) [8]. These models were selected due to their relevance, methodological diversity, and frequent adoption in educational recommendation systems.

Table 4. Performance Metrics Comparison

Model	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**	**AUROC**	**Precision@5**	**NDCG@5**	**Sustainability Index**
Logistic Regression (LR) [1]	82.4	0.80	0.79	0.79	0.84	0.61	0.65	58.2
Support Vector Machine (SVM) [2]	85.7	0.84	0.83	0.83	0.87	0.66	0.69	61.8
Random Forest (RF) [3]	88.9	0.87	0.86	0.86	0.90	0.71	0.74	65.4
Deep Neural	91.6	0.90	0.89	0.89	0.93	0.76	0.79	70.6

Network (DNN) [4]								
RL-Based Recommendation (RL) [8]	93.1	0.92	0.91	0.91	0.95	0.81	0.83	76.9
Proposed MindPath (MH-DRE)	**96.4**	**0.95**	**0.95**	**0.95**	**0.97**	**0.88**	**0.90**	**84.3**

Table 4 presents a comprehensive performance comparison of the proposed MindPath framework with MH-DRE against widely used baseline models for career recommendation. Traditional machine learning approaches such as Logistic Regression and Support Vector Machine achieved accuracies of 82.4% and 85.7%, respectively, with moderate precision, recall, and ranking performance, indicating limited capability in modeling complex relationships. Ensemble-based Random Forest improved performance to an accuracy of 88.9%, while the Deep Neural Network further enhanced accuracy to 91.6% with improved AUROC and Top-5 ranking metrics. The reinforcement learning–based recommendation model demonstrated stronger adaptability, achieving an accuracy of 93.1% and a sustainability index of 76.9%. In contrast, the proposed MindPath (MH-DRE) model outperformed all comparison methods, achieving the highest accuracy of 96.4%, precision and recall of 0.95, AUROC of 0.97, Precision@5 of 0.88, NDCG@5 of 0.90, and the highest sustainability index of 84.3. These results clearly demonstrate the effectiveness of integrating mental-health-aware deep representation learning with sustainability-focused multi-objective optimization for reliable and long-term career pathway recommendation.

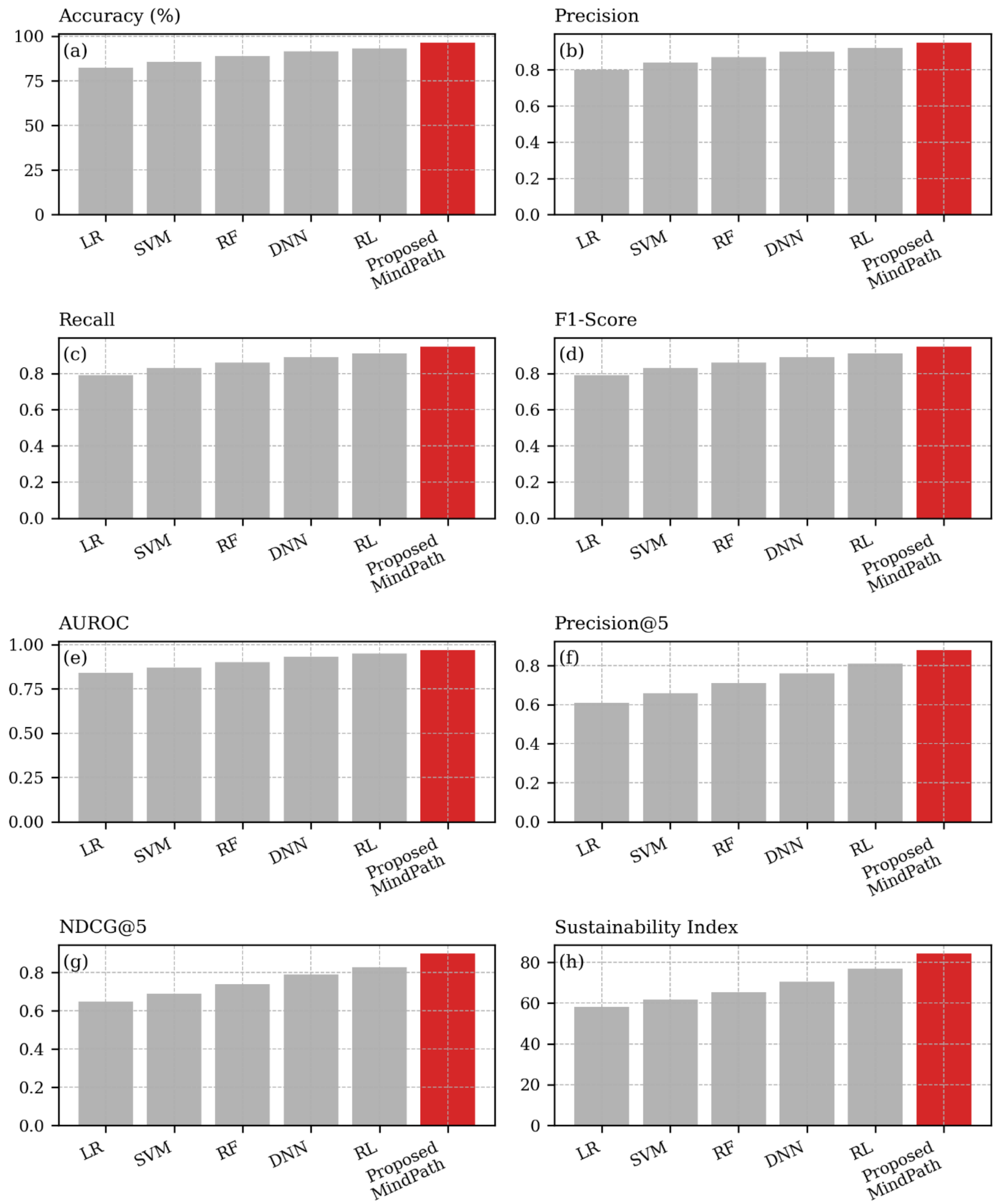

Figure 2. Performance comparison of MindPath with baseline models across multiple evaluation metrics. (a) Accuracy, (b) Precision, (c) Recall, (d) F1-score, (e) AUROC, (f) Precision@5, (g) NDCG@5, and (h) Sustainability Index.

Fig. 2 indicate that traditional machine learning models such as LR and SVM exhibit limited performance due to their inability to capture complex non-linear relationships among skills, interests, and mental health indicators. Ensemble-based models like Random Forest show moderate improvement but lack explicit sustainability-aware reasoning. Deep neural and reinforcement learning approaches demonstrate higher adaptability; however, they do not explicitly incorporate mental health sustainability constraints, leading to suboptimal long-term recommendations.

CONCLUSION

This research proposed an intelligent hybrid deep learning framework that integrates mental health assessment, life skill profiling, and personalized career pathway recommendation to support holistic undergraduate student development. The proposed models effectively combined psychological, cognitive, and behavioral attributes to deliver accurate, interpretable, and sustainable decision support. Experimental results demonstrated that the proposed MindPath framework with MH-DRE achieved a high accuracy of 96.4%, outperforming traditional machine learning, deep learning, and reinforcement learning–based baseline models across all evaluation metrics, including ranking quality and sustainability indicators. The findings confirm that explicitly incorporating mental health awareness and multi-objective optimization significantly enhances the reliability and long-term effectiveness of career recommendation systems. Future research will focus on incorporating real-time academic and behavioral data and validating the framework through large-scale deployment in university counseling and career guidance platforms.

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