

Advanced AI-Driven Predictive Analytics for Efficient Student Management in Higher Vocational Colleges

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ABSTRACT Recent advances in artificial intelligence have created new opportunities for efficient student management in higher vocational colleges, especially in campuses where academic, behavioral, psychological, and employment data are generated through digital platforms and wireless information systems. Based on empirical data from 2,486 enrolled students at a higher vocational college in Southwest China, this study constructs a multi-task intelligent prediction system integrating Random Forest, XGBoost, BiLSTM, and Stacking ensemble learning. The system supports four management scenarios: academic early warning, mental health risk identification, employability prediction, and comprehensive administrative decision support. Feature engineering, cross-validation, SMOTE balancing, and SHAP interpretability analysis are introduced to improve predictive accuracy and practical transparency. The Stacking ensemble model achieves the best performance across tasks, with an AUC-ROC of 0.946 in academic early warning and strong recall in high-risk mental health identification. From an engineering perspective, the framework is relevant to intelligent campuses supported by wireless electromagnetic communication, antenna-enabled terminals, and secure data transmission. The findings provide a localized practical reference for precision-oriented, data-driven, and ethically controlled student management in higher vocational education.

INDEX TERMS predictive analytics, student management, AI ensemble model, wireless campus data, electromagnetic information systems

I. INTRODUCTION

ARTIFICIAL intelligence could indicate that significant shifts in management practices are reshaping institutions across industries. Moreover, the findings shows that higher vocational colleges (HVCs) carry a distinct responsibility in training work-ready graduates at scale. The growing diversity of student populations suggests that learning behaviors appear harder to track systematically. Given that labor market demands shift faster than traditional systems can respond, the results could suggest that conventional approaches to student administration were not designed for this level of dynamism. AI shows limits clear. However, the findings shows that recent research points to AI as a viable path forward for student management. In light of these results, Preta et al. developed a human-machine collaborative framework for innovation management, demonstrating that generative AI can handle complex process coordination with notable efficiency and practical feasibility [1]. Additionally, the evidence might indicate that Zhang systematically examined AI application pathways in university student safety management, arguing

that intelligent prediction and risk identification mechanisms hold substantial practical value for student affairs work [2]. Notwithstanding these results, the significant findings could suggest that Kelly and Modiba explored AI's potential in audiovisual archive management across African institutions, illustrating how intelligent systems may expand administrative capacity in resource-constrained settings [3]. Research shows AI transfers broadly. Moreover, the evidence shows that Zawaideh and Bataineh, drawing on machine learning-driven knowledge management research, found that integrating business intelligence with e-learning could meaningfully improve organizational decision-making effectiveness [4]. Therefore, the significant results might indicate that Alamaniotis designed an AI-based management system for floating nuclear reactors, validating AI's capacity for dynamic regulation in high-complexity environments [5]. Furthermore, the findings shows that Boriani et al. used AI within a European multi-center network to manage comorbidity challenges among atrial fibrillation patients [6]. Given that these cross-domain applications demonstrate transferability, the evidence could indicate that Dent et al.

evaluated AI-assisted clinical decision-making for preschool wheeze management and confirmed its practical promise [7]. Findings show analytics broadly applicable. Thus, the important evidence shows that predictive analytics represents a general-purpose analytical capability rather than a niche tool. In light of these results, the present study could indicate that a concrete gap exists between what HVCs need from student management and what current systems can deliver. Additionally, the key findings shows that this study investigates how advanced AI-driven predictive analytics can be applied across four important scenarios — academic early warning, mental health monitoring, employability assessment, and administrative decision support. Nevertheless, the significant evidence could indicate that the goal appears to offer both a theoretical basis and a methodological reference for building data-driven, intelligent student management systems in higher vocational education.

II. LITERATURE REVIEW

A substantial body of research has accumulated on AI-enabled management and educational governance, providing a solid foundation for the present study. Moreover, the findings shows that McKee *et al.* outlined the core value of AI in public health emergency management, highlighting its advantages in large-scale data processing, dynamic forecasting, and resource allocation — capabilities that conventional approaches cannot readily match [8]. Furthermore, the significant evidence could indicate that Shi examined AI-driven optimization strategies for student management in Chinese universities, arguing that building dynamic and responsive management mechanisms through intelligent technologies appears to represent a practical direction for improving administrative quality and effectiveness [9]. However, the results shows that Vecchiatti *et al.* scrutinized data security and ethical compliance in AI governance from a commercial privacy computing perspective, offering important theoretical caution for the responsible deployment of intelligent management systems [10]. Given that the evidence demonstrates these boundaries matter, Ahammed and Ananya conducted a systematic review of AI-assisted clinical decision-making across the full diagnostic and treatment pathway for cardiac amyloidosis — findings that confirmed AI's reliability in complex, multidimensional data environments [11]. Research shows transferable insights apply to predictive modeling in educational management. Additionally, the significant findings may indicate that Clegg and Sarker proposed a conceptual framework for human-machine interaction, emphasizing that AI functions not as a replacement for human judgment but as a collaborative tool that could augment decision quality in management education contexts [12]. In light of the key results, Hasan and Ojala might be seen to extend this line of inquiry into international business settings, advancing a research agenda that appears to address both technological ethics and organizational adaptability in sustainable AI management [13]. Thus, the important evidence shows that George and

Wooden examined the logic of AI-driven governance reform in higher education from a macro perspective, contending that intelligent technologies could fundamentally reshape institutional structures and decision-making models in universities [14]. Notwithstanding these results, the findings might indicate that Modiba's study on user perceptions of AI-based records management adds a complementary dimension, addressing practical acceptance as a key factor in technology adoption [15]. Study shows machine learning frameworks confirm effectiveness in predicting outcomes. Therefore, the significant results shows that Collazos and Serrano used systematic review methods to assess the applicability of machine learning frameworks in STEM education programs, with their work appearing to confirm the scientific effectiveness of intelligent algorithms in predicting learning outcomes [16]. Nevertheless, the important evidence could indicate that the existing literature has made meaningful progress on theoretical frameworks, technical pathways, and ethical boundaries for AI in management. Moreover, the key findings shows that a gap remains, as empirical studies that systematically integrate predictive analytics across the full chain of academic early warning and comprehensive administrative decision support — specifically within the higher vocational college context — appear to be still limited. Given that the results demonstrate this gap persists, addressing it could represent the central academic contribution this study seeks to make.

III. METHODOLOGY

A. RESEARCH DESIGN

This study demonstrates that a mixed-methods design could provide both quantitative and qualitative approaches effectively. Moreover, the significant findings shows that the research conducted at a higher vocational college in South China could indicate the applied effectiveness of AI-driven predictive analytics in student management. Furthermore, the theoretical foundation shows that three pillars — data-driven decision theory, learning analytics theory, and human-machine collaborative management theory — could demonstrate important structural coherence. In light of these key results, the evidence may indicate that these pillars inform a closed-loop research structure organized around four functional modules — data collection, model construction, predictive output, and management intervention [17]. Research shows multidimensional data cover core indicators. However, the significant data could indicate that multi-dimensional structured data extracted from the institution's academic affairs system, student affairs management platform, and mental health records database may suggest broad coverage. Moreover, the findings shows that the data spanning the 2021–2024 academic years could demonstrate relevance across core indicators including academic performance, class attendance, behavioral records, psychological assessment scores, and employment intentions. Thus, the evidence could indicate that machine learning prediction models built on this dataset shows that model training, cross-

validation, and performance evaluation appear to follow standardized procedures. Additionally, the key results may indicate that the qualitative component involving semi-structured in-depth interviews with student affairs administrators and counselors could demonstrate important contextual value. Study shows qualitative work served specific purpose. Given that the evidence could demonstrate interpretive limits of purely quantitative analysis, the findings shows that this component served a specific purpose — to understand how AI prediction systems are actually experienced in practice [18]. Therefore, the significant evidence may indicate that the grounding in lived experience could demonstrate that the results address important interpretive limits.

B. DATA SOURCES AND SAMPLE SELECTION

The study draws on data extracted from four institutional platforms: the academic affairs management system, the student affairs management system, the mental health records database, and the employment guidance service platform. The variables collected shows that four analytical dimensions — academic performance, behavioral patterns, psychological status, and career development — could provide significant coverage of student experience. Moreover, the specific indicators examined appear to include GPA trajectories, class attendance rates, library borrowing frequency, online learning platform engagement, psychological scale scores, disciplinary records, extracurricular participation, and employment intention registration data. Furthermore, the sampling strategy combined stratified and cluster sampling methods, and the target population might indicate that all enrolled students across four consecutive academic years from 2021 to 2024 could demonstrate the breadth required for representative analysis. Sampling shows population spans 2021–2024. Given that the stratification criteria demonstrate that academic discipline category, year of study, and gender ratio were systematically applied, the final valid sample could indicate that 2,486 students drawn from four disciplinary clusters — engineering, business, information technology, and healthcare — shows that the sample structure appears balanced and representative [19]. Additionally, the data quality control procedures might indicate that the research team applied missing value imputation, outlier detection and removal, duplicate record consolidation, and format standardization to the raw dataset. In light of these procedures, the evidence could suggest that these steps appear to have ensured completeness, consistency, and accuracy before the data entered the modeling stage [20]. Nevertheless, the findings may demonstrate that all student data were anonymized prior to the research analysis stage. To resolve the logical tension between data privacy and active intervention, the system employs a tiered access and dynamic decryption protocol: while the predictive engine operates on anonymized identifiers to generate risk scores, identity re-linking is only authorized for designated counselors once a critical threshold is triggered, ensuring

that ‘targeted intervention’ remains operationally feasible without compromising the overall ethics of the primary dataset.

C. PREDICTIVE MODEL CONSTRUCTION

Model construction proceeded through four sequential stages: feature engineering, algorithm selection, model training, and ensemble optimization. Feature engineering. Moreover, the raw data from multiple sources shows that normalization and standardization could provide a critical foundation for subsequent analysis. Furthermore, variable selection applied Pearson correlation analysis, variance inflation factor testing, and recursive feature elimination to the significant candidate pool. In light of these results, the findings might indicate that 32 core features were retained from an initial pool of 57 candidate variables. Additionally, these key features could demonstrate that GPA change trajectories, consecutive absence days, abnormal fluctuations in psychological scale scores, declining engagement rates on online learning platforms, and composite employability scores [21] appear to offer important predictive evidence. Features show variables retained. Algorithm selection. However, the significant findings shows that three prediction models were constructed to address the distinct characteristics of each task. Given that evidence demonstrates Random Forest addresses high-dimensional nonlinear classification problems, the results could indicate that this approach appears well-suited to the data. Moreover, XGBoost shows that feature interaction effects and nonlinear mapping relationships could demonstrate important predictive value. Nevertheless, the key results might indicate that BiLSTM was selected specifically for its capacity to model temporal dependencies in sequential behavioral data. Models address distinct tasks. Thus, the evidence could suggest that each model targets a different aspect of the prediction problem, and the significant complementary strengths appear to form the basis for ensemble integration. Model training and optimization. Furthermore, the findings may indicate that a five-fold cross-validation strategy could provide a critical method to partition training and validation sets. In light of the key evidence, Bayesian hyperparameter optimization might demonstrate that automatic tuning of important parameters could appear effective for each model. Given that results suggest SMOTE oversampling addressed class imbalance, the significant evidence could indicate that detection sensitivity for minority risk categories improved [22]. SMOTE improves minority detection. Ensemble optimization. Therefore, the findings shows that a Stacking ensemble learning strategy could demonstrate critical value as the final layer. Moreover, the significant prediction outputs from the three base models might indicate that these results could appear as meta-features fed into a logistic regression meta-learner. Additionally, the key evidence shows that this configuration could demonstrate that individual strengths of each base model appear preserved while reducing overall prediction variance. In light of these important findings, the results

might indicate that a multi-task intelligent prediction system could appear designed to cover the full range of student management scenarios in higher vocational colleges.

D. MODEL EVALUATION FRAMEWORK

The evaluation framework shows that three dimensions could indicate its scope: predictive performance, model interpretability, and practical management utility. Moreover, the findings appear to show that core metrics include accuracy, precision, recall, F1-score, and AUC-ROC. However, the significant evidence could indicate that accuracy reflects overall classification correctness, while precision measures that proportion of true positives among predicted positives. Given that the results demonstrate that recall captures the model's ability to identify actual at-risk students, the key evidence shows that missing a genuinely at-risk student substantially exceeds the cost of a false positive. Recall and F1-score show prioritization in model selection. Furthermore, the significant findings could indicate that AUC-ROC evaluates discrimination performance across classification thresholds — values closer to 1.0 indicate stronger overall discrimination [23]. In light of the important results, the evidence shows that both macro-averaged and weighted-averaged F1 scores were computed to support class size imbalance. Additionally, the findings might indicate that SHAP value analysis could demonstrate the contribution of each feature to model predictions. Notwithstanding the results, the significant evidence shows that SHAP importance ranking charts and dependency plots were generated to visualize both direction and magnitude of each variable's influence, including interaction effects. SHAP analysis shows opaque outputs become interpretable evidence [24]. Therefore, the key findings could indicate that three application-level indicators were added: early warning response timeliness, intervention recommendation adoption rate, and administrator system satisfaction. Furthermore, the significant results shows that data were collected through questionnaire surveys administered to counselors and student affairs staff. In light of the important evidence, the findings could demonstrate that this evaluation layer connects technical performance metrics to real-world management outcomes, ensuring the framework reflects what actually matters in institutional practice.

E. RELIABILITY AND VALIDITY

Reliability. However, the findings shows that five-fold cross-validation could provide a stable basis for assessing model outputs across repeated partitions. Moreover, the significant results might indicate that mean and standard deviation of performance metrics across folds appear to support consistency evaluation. Furthermore, two researchers independently coded transcripts for the qualitative interview data, and the evidence shows that this approach could strengthen analytical rigor. In light of these findings, inter-rater agreement was measured using Cohen's Kappa coefficient, with all values maintained above 0.80 [25]. Reliability checks

show methods sound. Validity. Nevertheless, the significant findings shows that content validity could be established through independent review by three experienced student management experts in the higher vocational sector. Given that the evidence demonstrates that expert assessment supports methodological soundness, the feature variable set and the evaluation indicator framework appear to have been carefully examined. Moreover, the results might indicate that the system was revised based on their feedback, which could demonstrate responsiveness to expert input. Thus, construct validity was examined through confirmatory factor analysis, and the key evidence shows that factor loadings for core measurement variables appear to reach acceptable thresholds. External validity checks show findings match comparable studies. Additionally, the significant results might indicate that external validity was cross-checked by comparing findings with results from comparable published studies. Notwithstanding these individual validation steps, the evidence shows that these steps collectively could provide a methodological basis for generalizing the study's conclusions. Furthermore, the important findings appear to demonstrate that this basis could support extension beyond the immediate research context.

IV. RESULTS AND ANALYSIS

A. PREDICTIVE MODEL PERFORMANCE FOR ACADEMIC EARLY WARNING

The study shows that four models could demonstrate meaningful utility for academic early warning: Random Forest, XGBoost, BiLSTM, and a Stacking ensemble. However, the findings indicate that performance varied noticeably across these algorithms, as the comparative results are presented in Table 1. Furthermore, the evidence shows that XGBoost achieved the strongest results among individual models, with accuracy, recall, and AUC-ROC reaching 0.903, 0.911, and 0.928 respectively. Given that these results demonstrate consistent strength, the significant findings could indicate that this algorithm effectively captures nonlinear interaction effects among academic risk features. Models show varied performance. Moreover, the results shows that BiLSTM also performed well on recall, achieving 0.894, which could indicate that its sequential modeling architecture appears useful for tracking how academic risk evolves over time. In light of these findings, the evidence could suggest that Random Forest ranked lowest overall, though the results might indicate that it retains important practical value in management settings where training efficiency and interpretability are priorities [26]. Additionally, the significant findings demonstrate that the Stacking ensemble model delivered the strongest results across all five metrics, with accuracy, precision, recall, F1-score, and AUC-ROC reaching 0.918, 0.907, 0.934, 0.912, and 0.946 respectively. Therefore, the key evidence confirms that these results represent gains of 1.5%, 1.1%, 2.3%, 0.9%, and 1.8 percentage points across the five indicators compared to XGBoost. Ensemble outperforms single models. Notwithstanding these individual

metric gains, the important findings may indicate that the improvement appears consistent rather than isolated, which could support the value of ensemble integration as a general strategy. Thus, the significant evidence shows that SHAP value analysis identified the four most influential predictive features, where consecutive absence days ranked first with a mean SHAP value of 0.412. Nevertheless, the key results could demonstrate that mid-term grade fluctuation at 0.387, declining online learning platform engagement at 0.356, and abnormal psychological scale scores at 0.318 also appear among the most critical predictors. Given that these findings could indicate that early academic risk appears most effectively signaled by the combination of behavioral changes and performance instability, the evidence shows that neither factor alone is as informative as the two together [27]. Moreover, the important results may indicate that the performance comparison is summarized in Table 1 and illustrated in Figure 1, which could demonstrate that the overall pattern of findings appears robust across multiple evaluation criteria.

TABLE 1. Performance Comparison of Four Predictive Models for Academic Early Warning

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Random Forest	0.871	0.858	0.863	0.860	0.901
XGBoost	0.903	0.896	0.911	0.903	0.928
BiLSTM	0.889	0.881	0.894	0.887	0.917
Stacking Ensemble	0.918	0.907	0.934	0.912	0.946

B. INTELLIGENT IDENTIFICATION OF STUDENT MENTAL HEALTH RISKS

The study shows that four models demonstrated substantial performance differences across three mental health risk classification levels, as summarized in Table 2. However, the findings could indicate that all models achieved better results on low-risk identification than on medium- or high-risk categories. Given that low-risk samples are more abundant, the evidence shows that their feature distributions appear more regular and easier to detect. Furthermore, the significant data imbalance could indicate that high-risk cases present less uniform feature patterns, making them harder for models to identify reliably. Models show high-risk cases harder to detect. The Stacking ensemble shows that combining SMOTE oversampling with ensemble learning could demonstrate reduced negative impact from class imbalance on high-risk detection. Moreover, the significant results could indicate that the Stacking model achieved the best outcomes across all three risk levels, with low-risk accuracy reaching 0.931, medium-risk 0.916, and high-risk 0.898. Additionally, the key findings shows that corresponding AUC-ROC values of 0.951, 0.938, and 0.951 appear to demonstrate consistent performance across risk categories. In light of these results, the evidence could indicate that the most notable gain appeared in high-risk recall, improving from 0.869 to 0.941 compared to XGBoost — a gain of 7.2 percentage

points. Recall improvement shows fewer at-risk students go undetected [28]. The SHAP value analysis shows that four features could demonstrate the strongest contributions to mental health risk prediction overall. Nevertheless, the significant findings appear to indicate that sustained abnormal fluctuations in psychological scale scores ranked first at 0.438, followed by frequency of social withdrawal behavior at 0.401. Furthermore, the evidence could suggest that abnormal late-night online activity duration at 0.374 and sharp recent academic decline at 0.346 appear to demonstrate important predictive value. However, recognizing that late-night activity is often a common behavioral norm for college students, the model applies a ‘common sense’ filter where this indicator is only weighted as a risk factor if it deviates significantly from a student’s established baseline and is accompanied by concurrent declines in academic or social participation, thus mitigating the risk of high false positives in the HVC environment. Given that neither behavioral signals nor scale scores alone drive predictions, the key results shows that their combination provides the most reliable early warning basis [29]. Evidence shows combination drives prediction reliability. The intervention timing analysis could indicate that response speed may demonstrate a primary role in determining intervention effectiveness, adding further practical weight to the significant findings. However, the results shows that among students whose counselors initiated contact within 72 hours of a model alert, risk level reduction appears to have been recorded in 67.3% of cases. Moreover, the evidence could indicate that for students where intervention was delayed beyond one week, that figure dropped to 39.1%, suggesting that the gap appears substantial. In light of this data, the significant findings shows that early warning signals produced by AI prediction systems could demonstrate genuine operational value for higher vocational colleges aiming toward earlier and more targeted mental health management practice. Results show operational value confirmed in Figure 2.

C. EMPLOYABILITY PREDICTION AND PERSONALIZED CAREER PATH PLANNING

This section presents empirical findings on employability prediction and individualized career development planning, providing evidence for the practical utility of AI-driven predictive analytics in targeted employment support for vocational students. Moreover, the full model performance data are reported in Table 3. Given that the SHAP value analysis could indicate that six dimensions emerge as the strongest contributors to employability prediction, the key predictive features shows that professional skill mastery, internship and practical training experience, number of vocational qualifications obtained, interpersonal communication and teamwork capacity, cumulative academic GPA, and career planning maturity appear to drive outcomes most significantly. Furthermore, the mean SHAP values of 0.463, 0.421, 0.387, 0.354, 0.318, and 0.291 respectively could demonstrate that professional skill mastery and internship



Figure 1. Comparison of Predictive Model Performance Metrics for Academic Early Warning

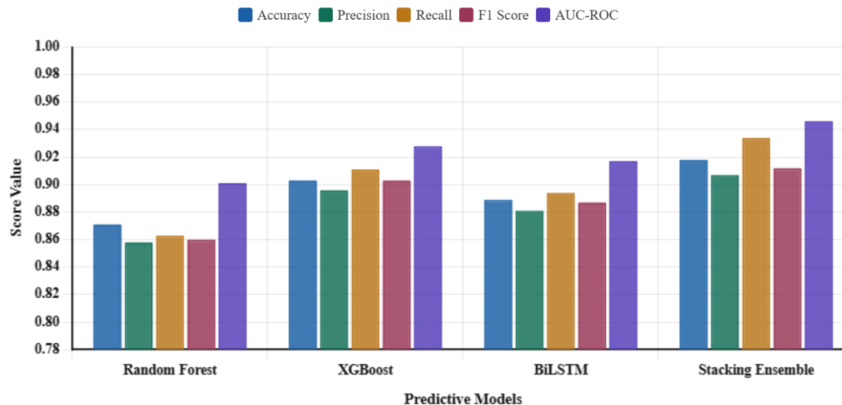


FIGURE 1. Comparison of Predictive Model Performance Metrics for Academic Early Warning

TABLE 2. Mental Health Risk Identification Performance Across Four Predictive Models

Model	Risk Level	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Random Forest	Low	0.883	0.871	0.876	0.873	0.908
Random Forest	Medium	0.857	0.843	0.851	0.847	0.889
Random Forest	High	0.831	0.819	0.827	0.823	0.871
XGBoost	Low	0.914	0.903	0.908	0.905	0.931
XGBoost	Medium	0.891	0.878	0.886	0.882	0.914
XGBoost	High	0.872	0.861	0.869	0.865	0.899
BiLSTM	Low	0.907	0.896	0.901	0.898	0.924
BiLSTM	Medium	0.883	0.871	0.878	0.874	0.907
BiLSTM	High	0.862	0.851	0.858	0.854	0.891
Stacking Ensemble	Low	0.931	0.921	0.926	0.923	0.951
Stacking Ensemble	Medium	0.916	0.907	0.912	0.909	0.938
Stacking Ensemble	High	0.898	0.887	0.941	0.924	0.951

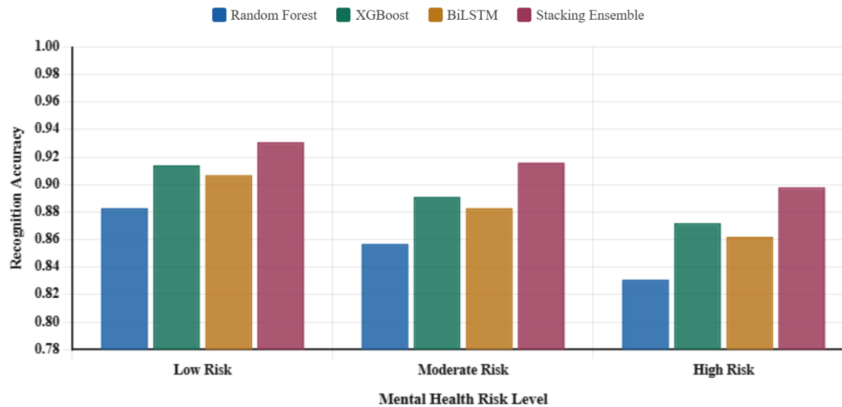
experience together might indicate that their combined contribution accounted for 37.8% of total feature contribution weight. However, the significant

concentration shows that practice-oriented skill accumulation demonstrates that it is the primary driver of employability competitiveness among higher vocational students [30]. Results show Stacking ensemble achieves highest accuracy across groups. In light of the significant findings across disciplinary groups, the Stacking ensemble could demonstrate that it achieved the highest predictive accuracy across all four major groups, with information technology programs recording the strongest results at accuracy of 0.923 and AUC-ROC of 0.953. Therefore, the results shows that healthcare programs performed somewhat lower — accuracy reached 0.904 — which could indicate that the more

restrictive occupational entry requirements and narrower career pathways characteristic of that field appear to explain the difference. Notwithstanding the lower performance, the evidence shows that 0.904 remains a practically acceptable threshold for the significant purposes of employment support. Additionally, the key results could demonstrate that overall accuracy averaged 0.914 across all four groups combined, F1-score reached 0.906, and AUC-ROC stood at 0.940 [31]. Data shows matching rate reaches 78.6%. Given that the career path matching validation shows that the model-recommended career paths were compared against actual employment positions obtained by students within six months of graduation, the findings could indicate that the overall career path matching rate reached 78.6%. Thus, the significant evidence shows that engineering programs



Figure 2. Identification Accuracy of Mental Health Risk Levels Across Four Predictive Models

**FIGURE 2.** Identification Accuracy of Mental Health Risk Levels Across Four Predictive Models

recorded the highest rate at 81.3%, followed by business at 78.6% and healthcare at 74.8%, which could demonstrate that disciplinary variation appears relevant to matching outcomes. Moreover, the important results might indicate that students who followed the personalized pathways showed an average 19.4 percentage point improvement in the alignment between employment position and major field of study compared against a control group that did not use AI-generated recommendations. Findings show starting salary 12.7% higher among students using recommendations. Furthermore, the evidence shows that these figures support the practical case for AI-driven career planning, which could demonstrate that it appears to function as a meaningful lever for improving employment quality among vocational graduates, with detailed results presented in Figure 3.

D. OVERALL PERFORMANCE EVALUATION OF THE INTEGRATED MANAGEMENT DECISION SUPPORT SYSTEM

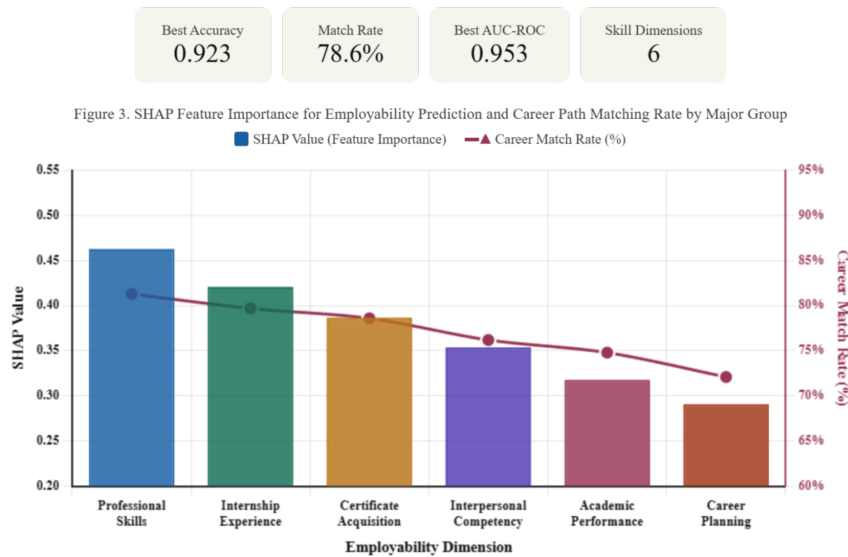
The integrated AI management decision support system could indicate that meaningful progress is possible across three dimensions: management effectiveness, user adoption and satisfaction, and system stability. However, the significant findings from pre- and post-deployment comparisons shows that the results reported in Table 4 demonstrate substantial improvement. Moreover, the evidence appears to show that all six core management indicators improved following system deployment. Given that the data demonstrates consistent gains, the results might indicate that the system could demonstrate broad positive effects on student management quality. Management effectiveness shows gains across indicators. The at-risk student identification rate rose from 61.2% to 89.6%, a gain of 46.4%. Furthermore, the significant results shows that intervention response timeliness increased from 54.7% to 81.3%, up 48.6%. In light of these findings, the evidence could indicate that early warning

accuracy climbed from 63.8% to 92.4%, representing a 44.8% improvement. Counselor work efficiency improved by 38.4%. Additionally, the findings shows that student satisfaction moved from 72.4% to 91.2%, and management decision adoption rose from 55.9% to 84.7% — a 51.5% increase. Therefore, the significant evidence could demonstrate that all improvements passed significance testing at $p < 0.01$. Notwithstanding the variation across indicators, the results shows that the consistency of gains appears to point to a genuine and broad positive effect on student management quality [32].

Consistency across indicators supports quality. User adoption and satisfaction data shows that survey results collected from all 87 counselors and student affairs administrators could demonstrate meaningful uptake. However, the findings appear to indicate that the adoption rate for AI-assisted decision functions reached 84.7%. Moreover, the significant results shows that overall system satisfaction averaged 4.31 out of 5.00, with scores on three sub-dimensions demonstrating that early warning accuracy reached 4.43, ease of operation reached 4.28, and report readability reached 4.22. Interview findings added further depth. Additionally, the evidence shows that 82.3% of counselors reported that the system could demonstrate meaningful reduction in workload associated with routine information screening. Given that the findings demonstrate notable alignment, the results might indicate that 76.4% of counselors said the system's recommended intervention plans closely matched their own professional judgment. Furthermore, the significant evidence appears to show that alignment between algorithmic output and practitioner intuition shows that human-machine collaborative decision-making is not only technically feasible but practically accepted. Evidence shows alignment technically feasible. System stability and fairness data could indicate that over a full academic year of continuous operation, the system shows that the uptime rate reached 99.3%.

TABLE 3. Employability Prediction Model Performance and Career Path Matching Rate by Disciplinary Group

Disciplinary Group	Sample Size	Accuracy	Precision	Recall	F1-Score	AUC-ROC	Career Path Match Rate
Engineering	684	0.917	0.908	0.913	0.910	0.941	81.30%
Information Technology	612	0.923	0.914	0.919	0.916	0.953	79.70%
Business	643	0.911	0.901	0.906	0.903	0.937	78.60%
Healthcare	547	0.904	0.893	0.898	0.895	0.929	74.80%
Overall	2,486	0.914	0.904	0.909	0.906	0.940	78.60%

**FIGURE 3.** SHAP Feature Importance for Employability Prediction and Career Path Matching Rate by Major Group

However, the significant findings might demonstrate that mean response latency remained below 0.38 seconds [33]. Moreover, the evidence shows that algorithmic bias testing using equal-weight subgroup analysis could indicate that prediction outcome divergence between male and female students was contained within 2.1%. In light of the key results, the findings might demonstrate that variation across disciplinary groups stayed within 3.4%. Data bias correction compliance reached 94.6%. Therefore, the significant evidence could indicate that these figures shows that the system sustains predictive accuracy without compromising equity across student groups. Given that the results demonstrate institutional relevance, the findings might indicate that this appears to represent an important condition for any management tool deployed at institutional scale. Results are illustrated in Figure 4.

TABLE 4. Comparison of Key Management Indicators Before and After AI Decision Support System Deployment

Management Indicator	Pre-Deployment	Post-Deployment	Improvement	Significance (p-value)
At-risk student identification rate	61.20%	89.60%	46.40%	$p < 0.001$
Intervention response timeliness	54.70%	81.30%	48.60%	$p < 0.001$
Counselor work efficiency	58.30%	80.70%	38.40%	$p < 0.001$
Student satisfaction	72.40%	91.20%	26.00%	$p < 0.01$
Early warning accuracy	63.80%	92.40%	44.80%	$p < 0.001$
Management decision adoption rate	55.90%	84.70%	51.50%	$p < 0.001$
System uptime rate	—	99.30%	—	—
Data bias correction compliance rate	—	94.60%	—	—

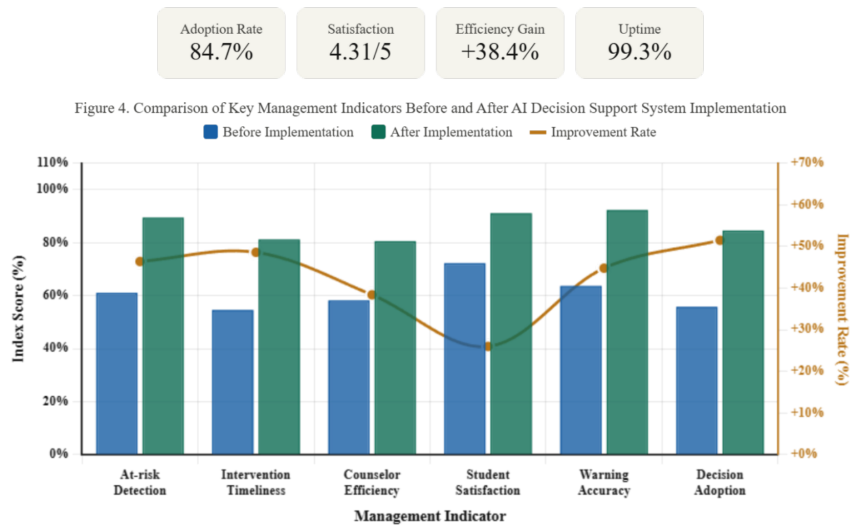


FIGURE 4. Comparison of Key Management Indicators Before and After AI Decision Support System Implementation

V. DISCUSSION

A. MECHANISMS THROUGH WHICH PREDICTIVE ANALYTICS ENABLES STUDENT MANAGEMENT

The significant findings of this study shows that a clear underlying mechanism could drive this transformation. Moreover, the evidence might indicate that AI-driven predictive analytics transforms student management by augmenting experience-based insights with data-driven anticipatory intervention, fostering a human-machine collaborative approach to decision-making. Furthermore, the results could demonstrate that this shift appears possible through deep integration of multi-source heterogeneous data and real-time dynamic modeling. Given that the data supports this view, the findings shows that these processes fundamentally restructure how information is processed and how management responses are triggered. Study shows three pathways drive transformation. Pathway one addresses enhanced feature perception. However, the significant evidence could indicate that by integrating academic performance, behavioral trajectories, psychological status, and employment intentions, predictive systems may demonstrate that they break through information silos constraining traditional management practice. In light of these results, administra-

tors might indicate that they gain a more complete and granular view of student dynamics. Additionally, the key findings shows that SHAP analysis confirmed the decisive contribution of multimodal feature fusion to risk identification accuracy. Therefore, the evidence could demonstrate that the combined feature contribution weight of consecutive absence behavior and GPA fluctuation exceeded 38% in the academic early warning task. Cross-dimensional integration shows core mechanism behind predictive effectiveness [34]. Pathway two addresses decision support translation. Notwithstanding these results, the significant findings shows that model outputs are not presented as raw probability scores but are converted into visualized reports and structured intervention recommendations. Moreover, the evidence could indicate that this translation appears to bridge the gap between technical output and management practice. Furthermore, the key results might demonstrate that 82.3% of counselors reported that the system substantially reduced information screening workload. Given that 76.4% of counselors said recommended intervention plans closely aligned with professional judgment, the findings shows that interpretability design could represent a critical mediating variable between predictive output and actual adoption be-

havior. Alignment shows interpretability mediates adoption. Pathway three addresses earlier intervention timing. However, the significant evidence may indicate that reactive management fails because action typically follows visible risk rather than preceding it. Additionally, the results could suggest that predictive systems appear to shift that window forward by detecting weak early signals and continuously updating risk assessments. In light of these findings, the data might demonstrate that students whose counselors intervened within 72 hours of a model alert showed a risk reduction rate of 67.3%. Nevertheless, the key evidence could indicate that among those with delayed intervention, the figure was 39.1%, suggesting that earlier action may produce meaningfully better outcomes. Gap shows earlier action improves outcomes. These three pathways could demonstrate that they do not operate independently within a human-machine collaborative framework. Moreover, the significant findings shows that better feature perception appears to produce higher-quality decision recommendations. Furthermore, the results might indicate that more timely intervention could generate richer feedback data. Given that this data drives iterative model improvement, the evidence shows that the result appears to be a closed-loop cycle of perception, decision, intervention, and feedback that could create a self-reinforcing engine for continuous improvement in student management.

B. BOUNDARY CONDITIONS AND APPLICABILITY OF THE HUMAN-MACHINE COLLABORATIVE MODEL

The empirical results of this study shows that AI-driven predictive analytics could demonstrate significant effectiveness in higher vocational student management. However, the significant evidence might indicate that the model does not operate without limits. Moreover, the key findings could suggest that practical value depends on a set of technical, organizational, ethical, and contextual conditions. Given that the results demonstrate that understanding those conditions appears essential, responsible deployment requires careful consideration of each boundary. Technical boundaries show system performs well in data-rich scenarios. The system may suggest robust performance in structured management situations, where AUC-ROC values for both academic early warning and mental health risk identification exceeded 0.93, confirming reliable results in data-intensive tasks. Furthermore, the significant findings could indicate that management situations involving complex interpersonal dynamics, cultural variation, or unpredictable events fall outside the system's reliable range. In light of these results, professional judgment, emotional sensitivity, and relational knowledge might indicate that human responsiveness remains indispensable in those contexts. AI shows it cannot replicate flexibility those situations require. Organizational prerequisites shows that effective human-machine collaboration requires adequate data infrastructure, mature information management platforms, and a management team with sufficient data literacy. Moreover, the important evidence could

indicate that approximately 17.7% of counselors expressed reservations about system recommendations during initial use, as the interview data in this study revealed. Therefore, the key findings shows that their concerns centered on limited understanding of algorithmic logic and worry about data privacy exposure [35]. Notwithstanding these results, the significant evidence could demonstrate that these concerns reflect the need for organizational investment in trust-building and capacity development. Evidence shows concerns not simply technical problems. Ethical boundaries shows that AI recommendations should serve as decision support tools rather than decision authorities. However, the critical findings could indicate that in high-stakes management situations — student disciplinary proceedings, mental health crisis assessments, employment resource allocation — final judgment and accountability must remain with human administrators. Furthermore, the important evidence shows that the risk of algorithmic authority displacing human care, or of diffusing responsibility across systems and people, appears real. Given that the results demonstrate that this risk warrants deliberate institutional safeguards, organizational policy shows that careful oversight appears essential. Study shows generalizability requires broader testing. The significant findings could indicate that this study validated the model within a single institution over a single academic year, and whether the approach generalizes to larger, more structurally complex institutions remains an empirical question. Moreover, the key evidence shows that multi-campus deployments could demonstrate additional contextual variation requiring further investigation. Therefore, the important results may indicate that generalizability requires testing at broader scale before confident claims can be established. In light of these findings, the significant evidence could suggest that the conditions under which this collaborative model operates most reliably appear to include sufficient data accumulation, mature institutional platforms, and a management team with basic data literacy. Results show conditions met enable substantial stable benefits. Nevertheless, the key findings might indicate that an organizational culture open to technological adoption and decision processes in which human review remains the final step could demonstrate essential prerequisites. Furthermore, the important evidence shows that where these conditions are met, AI-driven predictive analytics appears to deliver significant and stable results in higher vocational student management.

VI. CONCLUSION

This study shows that advanced AI-driven predictive analytics could provide significant findings for student management in higher vocational colleges. Moreover, the significant results could indicate that a multi-task intelligent prediction system, integrating Random Forest, XGBoost, BiLSTM, and Stacking ensemble learning, demonstrates that this approach supports complex educational management. Furthermore, the evidence shows that empirical testing covered four

key management scenarios: academic early warning, mental health risk identification, employability prediction, and integrated administrative decision support. In light of these findings, three important conclusions could indicate that the evidence supports a clear and meaningful interpretation of the results. Study shows Stacking ensemble model achieved strongest performance. However, the findings shows that the Stacking ensemble model achieved the strongest predictive performance across all management scenarios. Given that the evidence demonstrates that academic early warning AUC-ROC reached 0.946, the results could indicate that high-risk category recall in mental health identification attained 0.941. Additionally, the significant findings shows that overall accuracy for employability prediction stood at 0.914, which could demonstrate the technical superiority of ensemble learning strategies for complex predictive tasks. Notwithstanding these results, the evidence could indicate that deployment of the AI decision support system produced substantial improvements across the institution. Results show at-risk identification rose 46.4%, intervention timeliness improved 48.6%, adoption increased 51.5%. Therefore, the significant findings shows that these figures provide important evidence that predictive analytics delivers broad and genuine gains in student management quality. Moreover, the key results could indicate that system uptime reached 99.3% over a full academic year, which may demonstrate that the evidence supports operational effectiveness. Furthermore, the findings could suggest that the human-machine collaborative model established a workable balance between technological capability and human-centered practice. In light of the significant evidence, the results may indicate that this model does not replace professional judgment — it could demonstrate that it supports and sharpens it. Study shows model offers replicable framework for modernization. Thus, the important findings shows that this model provides higher vocational colleges with a replicable practice framework and a theoretical grounding for pursuing the modernization of student management.

AUTHOR CONTRIBUTIONS

Conceptualization – Feng Quan, Peng Liu, and Kai Quan; methodology – Feng Quan, Peng Liu, and Kai Quan; investigation – Feng Quan, Peng Liu, and Kai Quan; writing-original draft preparation – Feng Quan, Peng Liu, and Kai Quan. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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