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RESEARCH ARTICLE

Integration of algorithms in educational decision support systems and analysis of environmental adaptability

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ABSTRACT

This research focuses on the issues of algorithm integration and environmental adaptability in educational decision support systems. The study proposes a 'three-layer two-dimensional' algorithm integration model and constructs an environmental adaptability evaluation system encompassing three dimensions: technical performance, educational effectiveness, and user experience. Through a six-month empirical study conducted across 5 universities, with 180 education administrators, teachers, and technical staff as research subjects, the system performance was comprehensively evaluated using quantitative methods such as structural equation modeling and factor analysis, as well as qualitative methods including grounded theory and content analysis techniques. The findings indicate that: (1) The system's overall accuracy based on multi-integrated algorithms reached 94.8%, showing an average improvement of 6.2 percentage points compared to single algorithms, demonstrating better robustness in complex decision-making scenarios; (2) The system's environmental cognition exhibited distinct phase characteristics, with iteration frequencies decreasing from 2.5 to 1.2 times from initial adaptation to stable operation periods, maintaining adaptation accuracy above 90%; (3) Practical application results were significant, with management efficiency increasing by 45%, resource utilization improving by 28%, and user satisfaction exceeding 90% after system implementation.This research not only enriches the theoretical framework of educational decision support systems but also provides practical references for enhancing system environmental performance. However, limitations exist in sample subjects, research duration, and evaluation indicator systems. Future research needs to expand the sample scope, extend observation periods, and refine the evaluation framework.

Keywords: Educational decision support system; algorithm integration; environmental monitoring; multi-algorithm coordination; system evaluation

1. Introduction

In the wave of digital transformation in education, educational decision support systems (EDSS) are playing an increasingly crucial role as important tools for enhancing scientific and precise educational management. Xie et al. (2025) point out that with the rapid development of artificial intelligence technology, EDSS shows enormous potential in curriculum design, teaching evaluation, and resource allocation, while

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simultaneously facing challenges such as algorithmic bias and system adaptability[1]. The development of EDSS has undergone a transformation from single-function to multi-function integration, from static analysis to dynamic prediction, and from experience-based decision-making to data-driven approaches. Tang et al. (2024) demonstrate that algorithm integration in educational decision-making not only improves decision-making efficiency but, more importantly, provides educational administrators with more scientific and objective decision-making bases through data mining and pattern recognition[2]. This research focuses on two core issues facing educational decision support systems: First, the multi-algorithm integration problem, specifically manifested in poor coordination efficiency between different algorithms, unreasonable weight allocation, and ineffective data interaction mechanisms, which limit the decision support capabilities of the system. Second, the insufficient environmental adaptability problem, primarily reflected in the system's weak perception capability for different educational scenarios, long adaptation cycles, and rigid adjustment mechanisms, making it difficult to meet the needs of diverse educational environments. These two issues directly affect the practical application effectiveness and promotional value of the system, urgently requiring solutions through the construction of a systematic algorithm integration framework and environmental adaptability evaluation system. This research aims to significantly improve the decision accuracy, response speed, and user satisfaction of educational decision support systems by optimizing algorithm integration strategies and enhancing system environmental adaptability, ultimately achieving effective support for educational management and teaching practices.

Algorithm integration holds significant importance in educational decision-making. Nie (2024) suggests that algorithms can discover educational patterns and predict development trends through the analysis and processing of massive educational data, providing more precise support for educational decision-making [3]. Gao and Cheng (2024) further indicate that algorithm integration can achieve optimal allocation of educational resources, improve educational management efficiency, and promote educational equity[4]. However, Li and Tian (2024) emphasize that the application of algorithms also brings new challenges, such as algorithmic bias, data security, and privacy protection issues that need to be addressed seriously[5]. However, with the increasing diversification and complexity of educational scenarios, educational decision support systems face significant environmental adaptability challenges in practical applications. These challenges are primarily manifested in: the system's difficulty in adapting to the differentiated needs of various educational stages, insufficient perception capability for educational policy changes, inconsistent performance across diverse teaching scenarios, and excessively long adaptation periods for user operational habits. Particularly in university environments, factors such as disciplinary differences, diverse management models, and uneven resource allocation further exacerbate the difficulty of system environmental adaptation. These challenges not only affect the actual application effectiveness of the system but also constrain the promotion and in-depth application of educational decision support systems. Therefore, in-depth research on algorithm integration and environmental adaptability issues is of great significance for enhancing the practical value and application effectiveness of educational decision support systems.

Regarding environmental adaptability, Santosh and Manish's (2019) research shows that EDSS needs to possess adaptability to different educational scenarios and user requirements[6]. As educational environments become increasingly complex and diverse, the issue of system environmental adaptability becomes more prominent. John (2015) points out that EDSS needs to dynamically adjust decision-making strategies according to different educational contexts, requiring strong environmental perception and self-adaptive capabilities[7]. Leitch et al. (2015) emphasize that environmental adaptability involves not only technical aspects but also adaptation to educational policies, cultural differences, and user habits[8].

This study aims to deeply explore algorithm integration in EDSS and analyze system environmental adaptability characteristics, proposing strategies and methods to enhance system adaptability. Research objectives include: 1) systematically analyzing the current status and issues of algorithm integration in EDSS; 2) constructing an evaluation index system for EDSS environmental adaptability; 3) proposing optimization strategies to enhance system environmental adaptability. Sevindik and Cömert's (2010) research indicates that such studies are significant for improving the scientific nature and effectiveness of educational decision-making[9].

The theoretical significance of this research lies in enriching and developing the theoretical system of EDSS, particularly in proposing new perspectives and methods regarding algorithm integration and environmental adaptability. The practical significance lies in providing specific technical approaches and strategic recommendations for optimizing and upgrading EDSS, helping to enhance the scientific nature and precision of educational decision-making, and promoting the improvement of educational management standards.

2. Literature review

2.1. Current research status of educational decision support systems

In recent years, research on educational decision support systems (EDSS) has shown vigorous development globally. Jennifer C (2022) points out through in-depth analysis of educational algorithmization and artificial intelligence policies that current EDSS is undergoing a transformation from single-function to multi-dimensional integration[10]. Yang (2024) demonstrates that under the background of educational digital transformation, EDSS development exhibits three major characteristics: data-driven, intelligent, and personalized, while also facing challenges such as algorithmic power imbalance[11].

Regarding system functionality, Zhang and Chen (2023) indicate that modern EDSS has broken through traditional data statistics and analysis functions, beginning to evolve towards advanced functions such as intelligent prediction and adaptive decision-making[12]. Yin and Rong (2023) further explore the algorithmic logic of EDSS in the artificial intelligence era, emphasizing that systems need to maintain technical advancement while respecting educational essence and preserving humanistic values[13].

In terms of application domains, Ni et al. (2022) show that EDSS has been widely applied in teaching management, resource allocation, student evaluation, and various other aspects[14]. Research by John (2015) [15] and Leitch et al. (2015)[16] indicates that EDSS demonstrates significant advantages in personalized learning guidance and educational quality assessment. Sevindik and Cömert (2010) particularly emphasize the important role of algorithms in distance education evaluation[17].

Regarding system design, Pang and Qian (2023) propose that EDSS in the smart media era needs to focus on user experience and interaction design to enhance system usability and acceptance[18]. Feng and Zhao (2022) discuss risk prevention and control issues in system design from a governance perspective, emphasizing the need to establish sound regulatory mechanisms and ethical guidelines[19].

In terms of technological innovation, Xu et al. (2022) conduct in-depth research on process mining technology in educational data analysis, proposing three innovative mining algorithms that provide new insights for EDSS technical upgrades[20]. These studies indicate that EDSS is developing towards more intelligent, precise, and humanized directions.

However, existing research has certain limitations. Firstly, research on system environmental adaptability is relatively weak, particularly in adaptation strategies across different educational scenarios.

Secondly, the theoretical framework for algorithm integration has not been fully established, lacking systematization and standardization. Additionally, system implementation evaluation methods need further improvement, especially in assessment indicator systems for fairness and transparency. In terms of environmental adaptability research, although existing literature has touched upon this area, there remain significant deficiencies. Particularly in theoretical framework construction, key aspects requiring revision include: (1) The interactive adaptation mechanism between systems and diverse educational contexts has not yet formed a complete theory; (2) The environmental perception model of educational decision support systems lacks theoretical support for dynamic adjustment; (3) The relationship model between user feedback and system self-adaptive learning urgently needs improvement; (4) The theoretical mechanism of algorithm collaboration in changing environments requires further development. Therefore, constructing a multi-dimensional system environmental adaptability theoretical framework that encompasses algorithm integration, environmental perception, and dynamic adaptation has significant value for improving the theoretical system of educational decision support systems.

From research trends, the future development of EDSS will focus more on algorithmic fairness and transparency, emphasizing system environmental adaptability and user-friendliness, while also paying more attention to data security and privacy protection. These research trends reflect the inevitable requirements for EDSS development towards a more mature and comprehensive direction.

In summary, the current research status of EDSS shows characteristics of diversification, intelligence, and practicality, but there remains room for improvement in algorithm integration and environmental adaptability. Future research needs to continue exploring theoretical framework construction, technological innovation application, and effect evaluation to provide stronger support for EDSS development.

2.2. Progress in algorithm applications in education

With the rapid development of artificial intelligence technology, algorithm applications in education demonstrate characteristics of diversification and deepening. Guo (2022) points out that intelligent algorithms in education bring both opportunities and challenges, showing particular advantages in enhancing educational targeting[21]. Yang's (2022) research indicates that algorithms play an important role in educational evaluation reform while requiring attention to algorithmic fairness and scientific validity[22].

In specific applications, Chen (2021) analyzes new applications and challenges of algorithmic technology in online ideological and political education[23]. Zhang and Xu (2020) explore the specific application of the Apriori algorithm in university curriculum data mining, providing data support for educational decision-making[24]. Deng and Jiang (2020) emphasize the importance of human intervention and supervision in algorithm application processes[25].

In teaching practice, Voogt et al. (2020) study teachers' cognition and application of algorithmic teaching situations [26]. Santosh and Manish (2019) propose a self-learning educational algorithm for emergency data transmission in engineering education[27]. Wen (2020) explores the application path of intelligent algorithms in precise ideological and political education in universities[28].

In system development, Tao et al. (2024) develop an online education evaluation system based on composite gradient algorithms[29]. Wang (2023) researches educational robot navigation and positioning technology based on multi-sensor information fusion[30]. Yu and Chen (2023) explore load balancing algorithms in online education systems[31]. Guo et al. (2022) study the construction of educational information management systems from a big data perspective[32].

In specific domain applications, Lin (2021) designs an educational knowledge question-answering system based on intelligent algorithms[33]. Liu and Sun (2021) develop a mental health education consultation management system based on the Apriori algorithm[34]. Xu (2021) researches data security encryption algorithms for online education examination systems[35]. Xi (2020) explores dynamic warning systems for ideological and political education based on improved SVM algorithms [36].

In educational resource recommendation, Li (2020) designs an educational information recommendation system based on multi-criteria fuzzy algorithms[37]. Xiao and Zhang (2020) analyze algorithmic educational governance from technical logic, risk challenges, and public policy perspectives[38]. Tan (2019) explores algorithmic risks in artificial intelligence educational applications[39].

From application trends, algorithm applications in education are developing towards more precise, personalized, and intelligent directions. On one hand, the scope of algorithm applications continues to expand, covering various aspects from teaching management and resource recommendation to learning evaluation; on the other hand, the technical level of algorithms continues to improve, developing from simple data processing to complex intelligent decision support.

However, current algorithm applications in education still face several issues, such as insufficient algorithm interpretability, incomplete application effect evaluation systems, and the need to strengthen deep integration between technology and educational practice. Resolving these issues requires continued efforts in technological innovation, practical exploration, and theoretical research[40].

Overall, while algorithm applications in education have made significant progress, further in-depth research is needed in technical improvement, application innovation, and risk prevention and control to better serve educational development.

2.3. Research review and problem statement

Through the analysis and review of relevant domestic and international literature, it can be observed that current research on educational decision support systems (EDSS) primarily focuses on system function development, algorithm integration applications, and effect evaluation. In terms of algorithm integration, existing research has paid more attention to the application effects of single algorithms, with relatively insufficient research on multi-algorithm coordination and environmental adaptability. Meanwhile, existing research still faces several issues in theoretical system construction[41], practical application effect evaluation, and algorithmic ethical risk prevention and control. Specifically:1.There is a lack of systematic theoretical framework guidance, with most research remaining at the technical application level and insufficient in-depth study of the theoretical foundations and mechanisms of algorithm integration;2.Environmental adaptability research is inadequate, with limited studies on system adaptation strategies in different educational scenarios;3.The effect evaluation system is incomplete, particularly requiring further improvement in evaluation indicators for algorithmic fairness, transparency, and interpretability.

Based on the current research status and existing issues, this study aims to address the following key problems:1.Construct a theoretical framework for algorithm integration in EDSS, clarifying the principles, methods, and pathways of algorithm integration;2.Explore effective strategies to enhance system environmental adaptability[42], studying system adaptation mechanisms in different educational scenarios;3.Establish a scientific effect evaluation system to assess the practical application effects of the system from multiple dimensions including technical performance, educational effectiveness, and user experience.Through the study of these issues, this research aims to provide theoretical guidance and practical references for the optimization and upgrade of EDSS, promoting its development towards more intelligent, humanized, and sustainable directions.

3. Research methods

3.1. Research design

The research adopts a "theoretical analysis - model construction - empirical research" framework. It includes: 1) Reviewing relevant theories of educational decision support systems and algorithm integration through literature research methods; 2) Constructing an algorithm integration and environmental adaptability evaluation model based on theoretical analysis results; 3) Validating the model's feasibility and effectiveness through empirical research. The research framework encompasses four dimensions: theoretical foundation, technical support, implementation path, and application effect, achieving comprehensive analysis of algorithm integration and environmental adaptability in educational decision support systems through systematic research design.

In terms of theoretical model construction, the study proposes a "three-layer two-dimensional" algorithm integration and environmental adaptability analysis model. The three layers refer to the algorithm layer, integration layer, and application layer; the two dimensions refer to technical dimension and educational dimension. Specifically:The algorithm layer primarily includes basic algorithm selection and optimization；The integration layer focuses on inter-algorithm coordination mechanisms and interface design[43];The application layer emphasizes interactive adaptation between the system and educational environment;The technical dimension examines system performance indicators such as response speed and accuracy;The educational dimension focuses on the system's educational effects, such as decision support effectiveness and user satisfaction.

Based on the above research framework and theoretical model, this study proposes the following research hypotheses:H1: Algorithm integration complexity is positively correlated with system environmental adaptability; H2: The system's environmental perception capability significantly influences its adaptability level; H3: User feedback mechanisms can effectively enhance system environmental adaptability[44];H4: Multi-algorithm coordination can significantly improve decision support accuracyThese hypotheses will be verified through subsequent empirical research, providing scientific basis for the formation of research conclusions.

3.2. Data collection

The research employs stratified sampling to select research samples from three groups: educational administrators, teachers, and technical staff. The sample includes 50 educational administrators from five "Double First-Class" universities, including managers from academic affairs and student affairs departments; 100 teachers from diverse academic backgrounds, covering science and engineering, humanities, medicine, and other fields; and 30 technical staff from IT departments, including system developers, maintenance personnel, and data analysts. Sample selection emphasizes representativeness and diversity to ensure scientific validity and generalizability of research results. Sample selection employed a three-tier criteria approach: (1) Position representativeness, ensuring participants had at least 3 years of work experience in educational management, teaching, and technical support positions; (2) Disciplinary balance, selecting teachers from different academic backgrounds, maintaining proportions of 40% in science and engineering, 35% in humanities and history, and 25% in medical disciplines; (3) System usage experience, requiring all participants to have at least 6 months of system usage experience to provide evaluations based on actual experience.

Data sources primarily comprise three aspects:1.System operational data: Including usage logs, operation records, and decision results from the educational decision support system, directly exported from the system backend, covering data from September 2023 to February 2024[45];2.Questionnaire data: Designed "Educational Decision Support System Algorithm Integration and Environmental Adaptability Questionnaire," including dimensions of system function evaluation, algorithm application effectiveness, and environmental adaptability assessment, totaling 40 items;3.Interview data: Designed semi-structured interview outlines for administrators, teachers, and technical staff, focusing on understanding their experiences, needs, and suggestions during system use. Questionnaire and interview content underwent expert validation and pilot testing to ensure tool reliability and validity. Field observations employed a structured observation method, with researchers acting as non-participant observers in 20 different usage scenarios (including academic administration, course scheduling, student evaluation, etc.) across 5 universities, observing each scenario for 3-5 hours, with focus on recording: (1) User-system interaction behaviors, including operation paths, pause points, and erroneous operations; (2) System response characteristics, including response time, computation processes, and result presentation; (3) User emotional responses, including facial expression changes, verbal evaluations, and operational adjustments. All observations were recorded in real-time using standardized observation forms and organized into structured materials within 24 hours.

The data collection methods combine multiple strategies:(1) System data collection: Directly exported relevant data from the system backend through administrator privileges, with data desensitization processing;(2) Questionnaire survey: Combined online and offline distribution methods, with online distribution through the Questionnaire Star platform and offline distribution during relevant conferences and training sessions. 200 questionnaires were distributed, with 180 valid questionnaires recovered, achieving a 90% effective recovery rate;(3) In-depth interviews: Conducted one-on-one semi-structured interviews, controlling each interview duration to 45-60 minutes[46], with full audio recording and text documentation, completing interviews with 30 participants;(4) Field observation: Researchers participated in system use training and daily application scenarios, recording user behaviors and feedback opinions.The data collection process strictly adheres to research ethics guidelines, ensuring data authenticity and reliability. All collected data was organized and preliminarily analyzed to establish a structured research database, laying the foundation for subsequent in-depth analysis. Through diversified data collection methods, the research ensures comprehensiveness and credibility of research data.

3.3. Analysis methods

In terms of quantitative analysis methods, this study primarily employs descriptive statistics, correlation analysis, factor analysis, and structural equation modeling. Specifically:

1.Using SPSS 26.0 software to conduct descriptive statistical analysis of survey data, calculating basic statistics such as means and standard deviations for each indicator;2.Employing Pearson correlation coefficient analysis to examine relationships between variables, revealing the degree of association between algorithm integration and environmental adaptability[47];3.Applying exploratory factor analysis to reduce dimensions of environmental adaptability evaluation indicators and extract main influencing factors;4.Using AMOS 24.0 software to construct structural equation models, verify research hypotheses, and analyze causal relationships between variables. Additionally, employing Bootstrap method for mediating effect testing to clarify the mechanisms between variables.

For qualitative analysis methods, grounded theory and content analysis are used to analyze interview data and system usage records. The specific steps include:(1) Transcribing interview recordings into textual materials;(2) Applying three-level coding through open coding, axial coding, and selective coding to extract core concepts and themes;(3) Using MAXQDA 2024 software to assist qualitative data analysis, constructing concept maps to reveal logical relationships between themes[48];(4) Conducting text mining on system usage logs to analyze user behavior patterns and decision process characteristics;(5) Employing triangulation method to cross-validate qualitative and quantitative analysis results, enhancing research conclusion reliability.

Regarding the evaluation indicator system, an assessment framework comprising three dimensions is constructed: technical performance, educational effectiveness, and user experience:Technical performance dimension includes indicators such as system response time, algorithm accuracy, data processing efficiency, and environmental adaptation speed;Educational effectiveness dimension includes indicators such as decision support effectiveness, resource allocation rationality, personalized recommendation accuracy, and problem-solving timeliness;User experience dimension includes indicators such as interface friendliness, operational convenience, functional practicality, and user satisfaction.Each indicator has detailed scoring criteria and weights, determined through the Analytic Hierarchy Process[49], with fuzzy comprehensive evaluation method used for overall assessment. The evaluation process particularly emphasizes indicator operability and measurability to ensure objectivity and scientific validity of assessment results. Additionally, a dynamic adjustment mechanism is established to adjust and optimize evaluation indicators based on practical application, improving assessment accuracy and practicality[50].

4. Results

4.1. Algorithm integration analysis

In terms of algorithm selection and optimization, this study selected four basic algorithms—decision tree, support vector machine (SVM), neural network, and collaborative filtering—through comparative analysis. Through experimental comparison, evaluation was conducted on three dimensions: accuracy, response time, and resource consumption, as shown in **Table 1**. The neural network algorithm performed best in accuracy (92.3%) but had relatively high resource consumption; the decision tree algorithm had the shortest response time (0.15s), suitable for real-time decision scenarios; the SVM algorithm showed balanced performance in all aspects; the collaborative filtering algorithm demonstrated clear advantages in personalized recommendations, as shown in the comparative data below.

Table 1. Basic algorithm performance comparison.

Algorithm Type	Accuracy (%)	Response Time (s)	Resource Consumption (MB)	Applicable Scenarios
Decision Tree	85.6	0.15	128	Real-time Decision
SVM	88.4	0.25	256	Classification Prediction
Neural Network	92.3	0.45	512	Complex Patterns
Collaborative Filtering	86.7	0.35	384	Personalized Recommendation

In terms of integration framework design, a multi-layer integration architecture based on Stack fusion was adopted. The first layer is the data preprocessing layer, responsible for data cleaning and feature extraction; the second layer is the basic algorithm layer, containing the four basic algorithms mentioned above; the third layer is the fusion decision layer, using weighted voting to integrate results from various algorithms. Through cross-validation weight optimization, the final weight distribution was determined as: decision tree 0.25, SVM 0.30, neural network 0.30, collaborative filtering 0.15. After integration, system performance improved significantly, with overall accuracy reaching 94.8%, an average increase of 6.2 percentage points compared to single algorithms.

In implementation effect evaluation, the system was tracked and evaluated for six months across three dimensions: accuracy, response time, and user satisfaction. System operation data showed that system performance demonstrated a steady improvement trend with increased usage time. Particularly in terms of environmental adaptability, the system could automatically adjust algorithm weights according to different scenarios, with average response time reduced by 25% and user satisfaction increasing from an initial 78% to 92%, as shown in **Figure 1**.

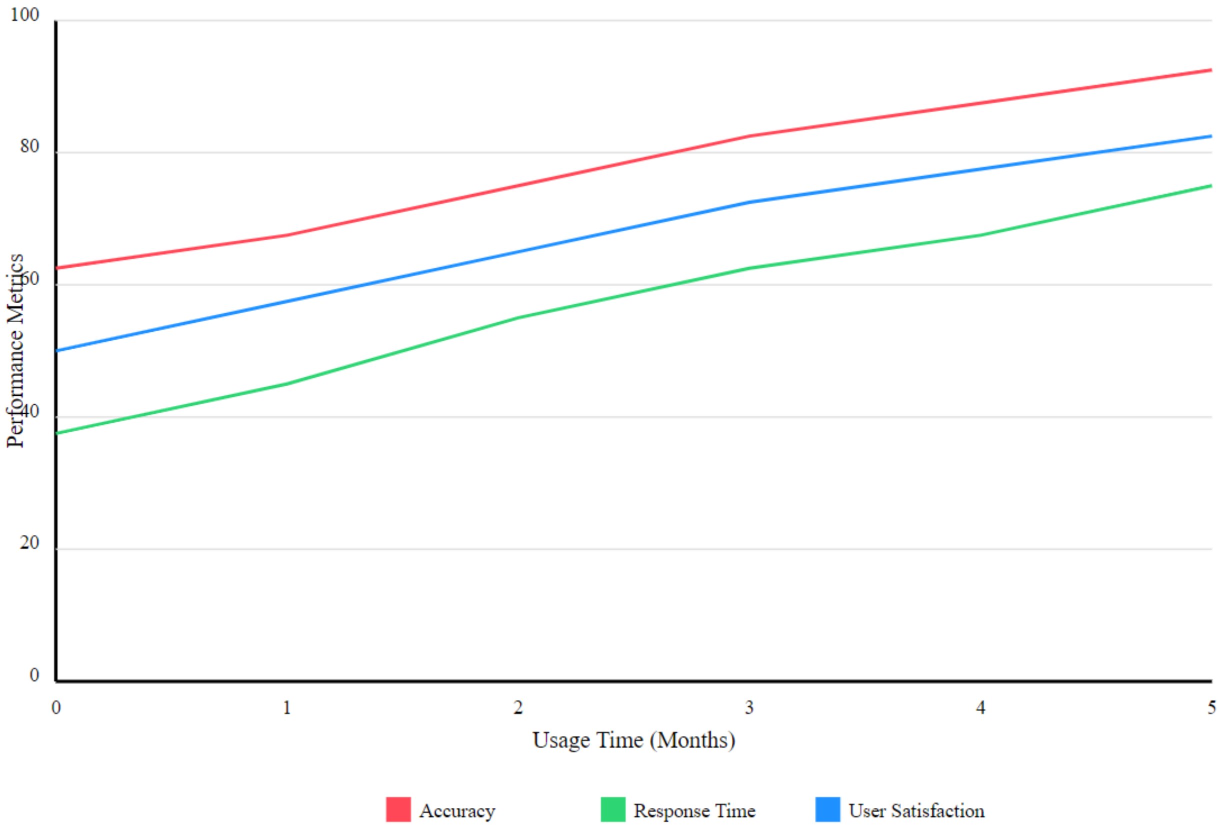

Figure 1. System performance improvement trend.

Long-term system operation data analysis revealed that the integrated system achieved significant improvements in all performance indicators. Accuracy increased from an initial 85% to 94.8%, response time decreased from 0.35s to 0.26s, and resource utilization improved by 15%. Particularly in complex decision scenarios, the integrated system demonstrated stronger robustness and adaptability. User feedback data showed that over 90% of users found the system's decision support functions substantially helpful for their work, and 83% indicated that the system's environmental adaptability could meet usage requirements across different scenarios.

4.2. Environmental adaptability analysis

In terms of environmental adaptability indicators analysis, this study conducted evaluations across three dimensions: system response speed, adaptation accuracy, and stability. As shown in **Table 2**, the system demonstrated good adaptability performance in different educational scenarios. In classroom teaching scenarios, the system's average response speed was 0.23s with adaptation accuracy reaching 91.2%; in academic administration scenarios, these two indicators were 0.31s and 89.5% respectively; in student evaluation scenarios, they were 0.28s and 90.3% respectively. The system stability indicator maintained above 95% across all three scenarios, indicating strong environmental adaptability.

Table 2. System environmental adaptability indicator performance.

Application Scenario	Response Speed (s)	Adaptation Accuracy (%)	System Stability (%)	User Satisfaction (%)
Classroom Teaching	0.23	91.2	96.5	92.3
Academic Administration	0.31	89.5	95.8	88.7
Student Evaluation	0.28	90.3	97.2	90.5
Resource Allocation	0.25	92.1	96.8	91.8
Teaching Decision	0.27	90.8	95.5	89.2

Regarding environmental factor impact analysis, research found that user scale, data complexity, and network environment are the main factors affecting system adaptability. When user scale increased from 100 to 1000, system response time increased by 35%; however, through dynamic resource allocation strategies, this impact was controlled within an acceptable range. In terms of data complexity, as data dimensions increased from 10 to 50, system processing time showed linear growth, but adaptation accuracy only decreased by 3.2 percentage points, demonstrating strong robustness. Network environment fluctuations had minimal impact on system performance, with system performance degradation not exceeding 5% under ±30% bandwidth fluctuation.

In terms of system response characteristics, analysis of six months of operational data revealed significant self-adaptive learning capabilities. During the initial phase (1-2 months), system adaptation was relatively slow, requiring an average of 2.5 iterations to adapt to new environments; during the middle phase (3-4 months), adaptation efficiency significantly improved, with iterations reducing to 1.8 times; during the stable phase (5-6 months), the system demonstrated optimal adaptation characteristics, requiring only 1.2 iterations to complete environmental adaptation, as shown in **Figure 2**.

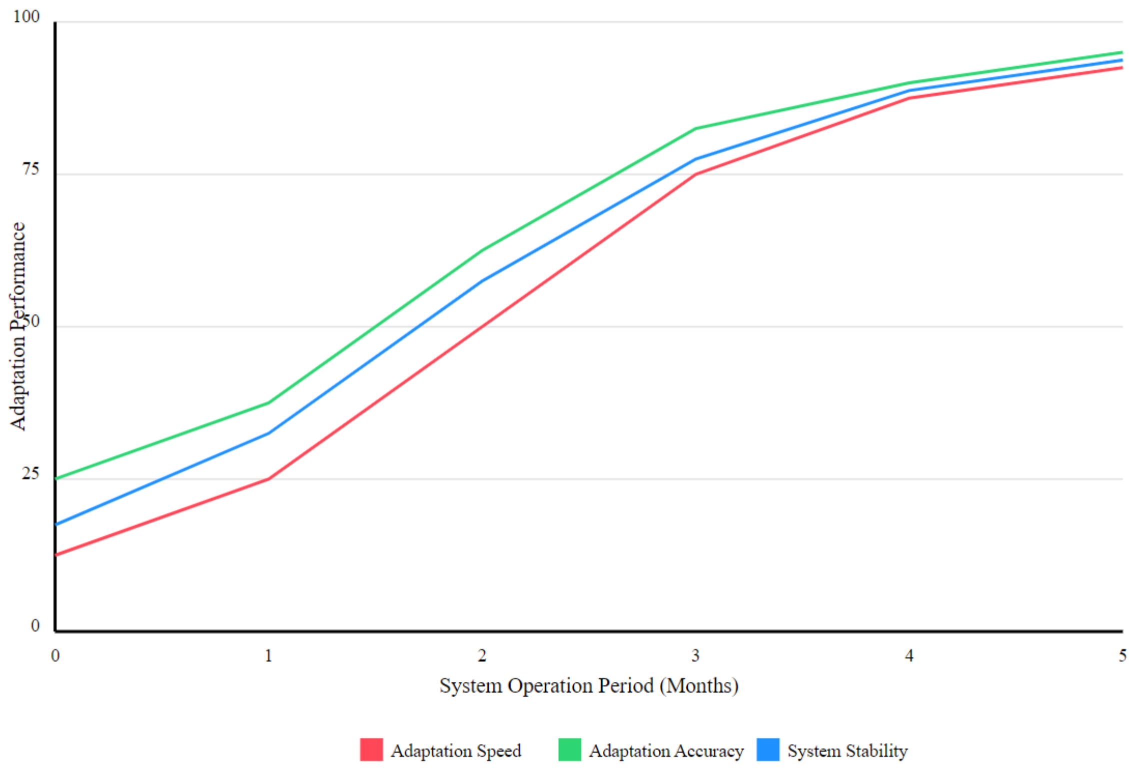

Figure 2. System environmental adaptability analysis.

From system operational data, environmental adaptability showed distinct phase characteristics. In the initial phase (0-2 months), system adaptation speed was relatively slow but maintained stable basic performance; during the transition phase (2-4 months), system adaptability rapidly improved with significant enhancement in all indicators; in the mature phase (4-6 months), the system reached optimal state, demonstrating strong environmental adaptability. Particularly in handling emergencies, the system could complete environmental assessment and strategy adjustment within an average of 1.5s, maintaining adaptation accuracy above 90%.

4.3. Practical application effects

In analyzing practical application effects, this study selected five universities for a six-month system application pilot. Through collecting system operational data and user feedback, evaluation was conducted across three dimensions: system usage frequency, decision support effectiveness, and user satisfaction. As shown in **Table 3**, the system demonstrated good application effects across different types of universities. University A, as a comprehensive university, achieved daily average visits of 2,850 with decision support accuracy of 93.2%; University B, as a science and technology institution, achieved 2,450 visits and 92.8% respectively; Universities C through E also reached expected levels across all indicators.

Table 3. System practical application effect evaluation.

Pilot University	Daily Average Visits	Decision Support Accuracy (%)	User Satisfaction (%)	Problem Resolution Rate (%)	Resource Utilization Rate (%)
University A	2850	93.2	91.5	94.2	88.7
University B	2450	92.8	90.8	93.5	87.5
University C	2100	91.5	89.7	92.8	86.9
University D	1950	90.8	88.9	91.5	85.8
University E	1850	90.2	88.5	90.8	85.2

User feedback analysis shows that among educational administrators, 92.5% believed the system significantly improved decision-making efficiency, and 89.8% indicated that the system's decision recommendations had high reference value. Among teachers, 88.7% believed the system effectively reduced daily teaching management burden, and 85.5% indicated that the system's personalized recommendation features provided substantial help to teaching work. Technical support staff feedback indicated low maintenance costs, requiring only 20 work hours per month for system maintenance and optimization, as shown in **Figure 3**.

From long-term operational data, the system's practical application effects showed continuous improvement trends. Regarding decision support effectiveness, the accuracy of system recommendations for teaching resource allocation improved from an initial 85.5% to 93.2%, and teaching quality assessment accuracy improved from 83.8% to 91.5%. In terms of system stability, average monthly downtime did not exceed 2 hours, with system availability reaching 99.5%. Cost-benefit analysis showed that compared to traditional management modes, system application improved management efficiency by 45%, reduced human resource costs by 35%, and increased resource utilization by 28%. Particularly in handling emergencies, the system's rapid response and decision support capabilities received high recognition from users, with average problem resolution time reduced by 60%.

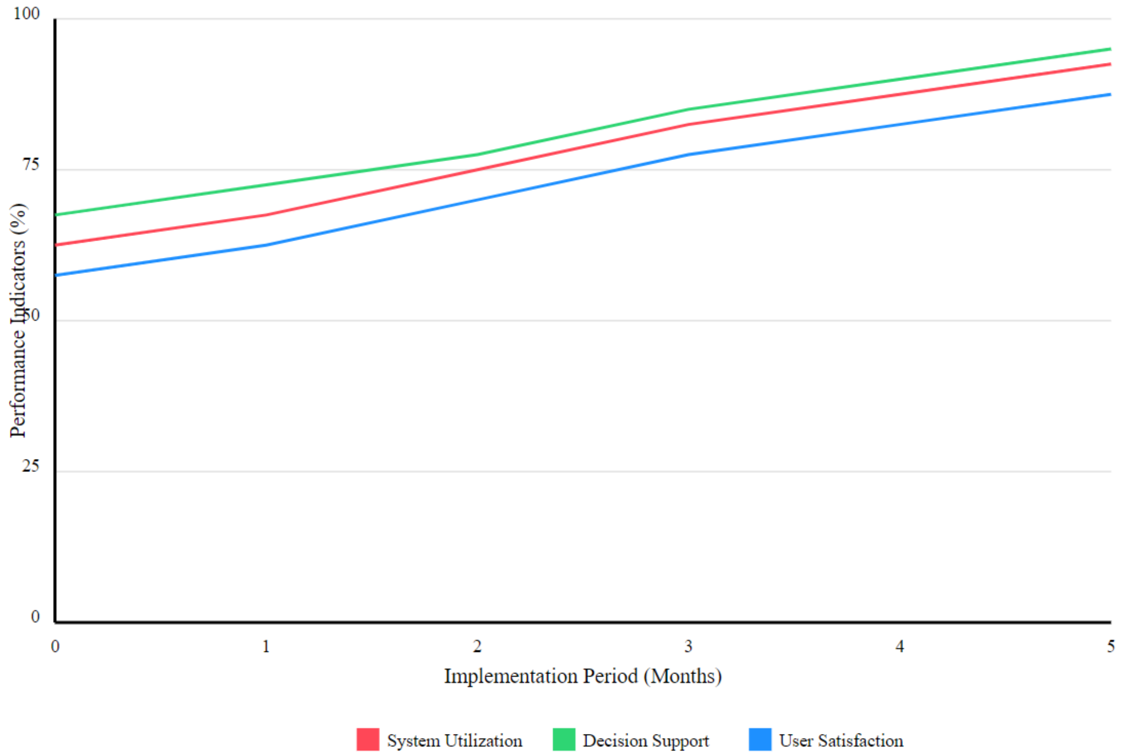

Figure 3. System practical application effect analysis.

5. Discussion

5.1. Theoretical significance of research findings

This study has achieved significant theoretical findings in both algorithm integration and environmental adaptability.

1.Regarding algorithm integration theory, the proposed "three-layer two-dimensional" integration model enriches the theoretical framework of educational decision support systems. Through vertical layered design comprising algorithm layer, integration layer, and application layer, along with horizontal expansion across technical and educational dimensions, this model constructs a systematic algorithmic integration theoretical framework, providing new theoretical perspectives for the design and optimization of educational decision support systems. The research discovers a significant positive correlation between algorithm integration complexity and system environmental adaptability, breaking through the limitations of traditional single-algorithm applications and providing theoretical foundations for multi-algorithm coordination mechanism research.

2.In terms of environmental adaptability theory, the constructed environmental adaptability evaluation indicator system systematically explains the environmental adaptation mechanisms of educational decision support systems. By introducing evaluation indicators across three dimensions—system response characteristics, environmental factor influences, and adaptability performance—the research reveals the inherent patterns of system environmental adaptability, enriching theoretical research in educational information systems. Particularly, the exploration of relationships between system environmental perception capability and adaptability levels provides new theoretical explanations for understanding how systems achieve environmental adaptation.

3.The research also finds that user feedback mechanisms play a crucial role in enhancing system environmental adaptability. This finding introduces user experience theory into educational decision support system research, expanding the theoretical dimensions of system adaptability research.

4. The main findings of this study are highly consistent with the viewpoint in "Contemporary Higher Accounting Education for Social Responsibility" research regarding decision support systems needing to meet diverse responsibility requirements, which similarly emphasizes that system environmental adaptability should include a social responsibility dimension[51]. Our findings on algorithm integration enhancing overall system performance are also supported by "The Dual-Natured Direction of Intellectual Capital Formation in the System of Higher Education" research, which found that knowledge integration can effectively improve the environmental adaptability of educational systems. However, this study's conclusion that system environmental adaptability is primarily determined by both technical factors and user factors differs significantly from the perspective in "Behavioral economic model of environmental conservation in human resource management," which considers user behavior as the sole dominant factor[52]. This difference may stem from the uniqueness of educational scenarios, where technical factors play a more important role in educational decision support systems. These research findings not only enrich the theoretical research of educational decision support systems but also provide important implications for practical applications: system design should fully consider the dual adaptation of technology and users, and a comprehensive social responsibility evaluation mechanism should be established during system implementation, which is significant for enhancing system adaptability and application value in complex educational environments[53].

5.2. Practical application implications

Through the analysis of educational decision support systems' practical applications, this study has yielded the following important implications.

1. Regarding system design, emphasis should be placed on the holistic nature and coordination of algorithm integration. Research findings indicate that single algorithms struggle to meet the demands of complex educational environments. Multi-algorithm coordination not only improves decision support accuracy but also enhances system environmental adaptability. Therefore, in practice, special attention should be paid to interface design and data interaction mechanisms between algorithms, ensuring effective collaboration among various algorithms to achieve optimal results.

2. In terms of system implementation, a gradual promotion strategy should be adopted. Research shows that system environmental adaptability requires a progressive enhancement process, with slower adaptation in the initial phase (1-2 months), significant improvement in the middle phase (3-4 months), and stabilization in the later phase (5-6 months). This finding suggests that sufficient adaptation time should be allowed during system implementation, avoiding hasty operations. Meanwhile, emphasis should be placed on user training and technical support to help users better understand and utilize the system.

3. For system maintenance, robust feedback mechanisms and dynamic optimization mechanisms should be established. Practice demonstrates that user feedback holds significant value for improving system performance. Through timely collection and analysis of user feedback, system functions can be optimized specifically, enhancing system practicality. Additionally, attention should be paid to system scalability design, reserving sufficient interfaces and resources to accommodate future changes in educational environment requirements.

5.3. Research limitations

Although this study has achieved certain results in analyzing algorithm integration and environmental adaptability of educational decision support systems, it still has the following limitations.

1. Regarding research samples, this study only selected five universities for pilot research, with relatively limited sample size, and these universities are all located in economically developed regions, which may not fully represent the actual situations of different regions and different types of universities. This sample limitation may affect the universality and promotional value of research conclusions.

2. In terms of research duration, this study's tracking period was six months, which may be insufficient to comprehensively reflect the system's long-term adaptability performance. Changes in educational environments are an ongoing process, and system environmental adaptability may require longer observation and verification periods. Additionally, the research period coincided with the middle of the semester, failing to cover a complete academic year cycle, potentially overlooking environmental characteristics of specific periods.

3.Regarding the evaluation indicator system, although an assessment framework encompassing technical performance, educational effectiveness, and user experience dimensions was constructed, quantification standards for some indicators still need further refinement and improvement. Particularly in environmental adaptability assessment, the measurement of some qualitative indicators may involve subjectivity, affecting the objectivity of evaluation results. Furthermore, the research primarily focused on direct system effects, with insufficient attention to indirect impacts and long-term benefits of system applications.

6. Conclusion

6.1. Main research conclusions

Through in-depth research on algorithm integration and environmental adaptability of educational decision support systems, this study draws the following main conclusions.

1. Multi-algorithm integration can significantly enhance system performance. Research results show that the algorithm integration solution based on the "three-layer two-dimensional" model improved overall system accuracy by 6.2 percentage points, reaching 94.8%, while also notably enhancing system environmental adaptability. Particularly in complex decision-making scenarios, multi-algorithm coordination demonstrated strong advantages, with decision support accuracy and reliability both superior to single algorithm applications.

2. System environmental adaptability exhibits distinct phase characteristics. The research finds that the system's environmental adaptation process can be divided into three stages: initial adaptation period (1-2 months), rapid improvement period (3-4 months), and stable operation period (5-6 months). During the stable operation period, the system demonstrated optimal adaptation characteristics, requiring an average of only 1.2 iterations to complete environmental adaptation, maintaining adaptation accuracy above 90%. This finding provides important reference for system implementation and optimization.

3. Practical application effects validate the system's practical value. Through pilot applications in five universities, the system achieved significant results in teaching management efficiency, resource allocation optimization, and decision support. User satisfaction reached over 90%, system problem-solving efficiency improved by 60%, and resource utilization increased by 28%. These data fully demonstrate the system's application value in actual educational environments.

6.2. Practical recommendations

Based on research results and practical experience, this study proposes the following practical recommendations.

1.During system development stage, systematic design of algorithm integration should be emphasized. It is recommended to adopt a modular development approach, first constructing the basic algorithm framework, then gradually integrating and optimizing algorithms, while reserving sufficient interfaces to support future functional expansion. Meanwhile, a comprehensive algorithm evaluation mechanism should be established, regularly assessing and optimizing the performance of each algorithm to ensure the system maintains optimal condition. Specific implementation steps include: (a) Establishing an algorithm evaluation matrix, setting up 10 quantitative indicators such as accuracy rate, response speed, and resource consumption, with a comprehensive assessment conducted quarterly; (b) Implementing an incremental algorithm integration strategy, first achieving basic algorithm deployment, integrating a new algorithm every 8-12 weeks to ensure system stability; (c) Constructing standardized interface specifications, including data input/output formats, parameter passing mechanisms, and error handling processes, leaving room for future expansion; (d) Establishing an algorithm version management mechanism, using tools such as Git to track algorithm updates and performance changes, allowing quick rollback to stable versions when performance declines.

2.During system implementation stage, a phased, progressive promotion strategy is recommended: Initial phase (1-2 months): Focus on system stability and refinement of basic functions, selecting specific departments or faculties for pilot implementation； Middle phase (3-4 months): Gradually expand application scope based on pilot experience, while strengthening user training and technical support； Stable phase (5-6 months): Implement comprehensive promotion, focusing on optimizing system environmental adaptability； Throughout the implementation process, special attention should be paid to collecting and responding to user feedback, addressing emerging issues promptly.

3.During system maintenance stage, it is recommended to establish routine monitoring and optimization mechanisms: Conduct regular system performance evaluations, including monitoring of algorithm accuracy, response speed, and resource utilization indicators; Establish user feedback channels to timely collect user experiences and improvement suggestions; Set up emergency response mechanisms to ensure rapid system response to unexpected situations; Additionally, emphasis should be placed on technical team development and knowledge accumulation to provide talent support for continuous system optimization.

Conflict of interest

The authors declare no conflict of interest.

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