MACHINE LEARNING–DRIVEN DECISION SUPPORT SYSTEMS FOR RESOURCE OPTIMIZATION AND CURRICULUM PLANNING IN ENGLISH DEPARTMENTS

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Abstract

Managing resources and designing adaptive curricula in English departments has become increasingly complex due to fluctuating student enrollments, diverse course requirements, and evolving pedagogical demands. Traditional decision-making approaches often rely on static data and manual planning, leading to inefficiencies in faculty allocation, course scheduling, and curriculum relevance. This study proposes a Machine Learning (ML)–driven Decision Support System (DSS) to enhance resource management and curriculum planning in English departments. The system integrates multiple data sources, including historical enrollment records, student performance metrics, course feedback, and faculty workload data. Various ML models are employed, such as regression techniques for enrollment forecasting, classification algorithms for predicting student success, and clustering methods for identifying patterns in course demand. Additionally, recommendation algorithms are utilized to support dynamic curriculum development and elective course selection. The proposed approach is expected to improve decision-making accuracy, optimize resource utilization, and enable data-driven curriculum adjustments aligned with student needs and institutional goals. Preliminary findings suggest that ML-based DSS can significantly reduce planning inefficiencies while enhancing responsiveness to academic trends. The implications of this research extend to academic institutions seeking to modernize departmental management practices. By integrating intelligent systems into administrative processes, English departments can achieve greater operational efficiency, improve teaching outcomes, and foster a more adaptive and student-centered learning environment.

Keywords: Machine Learning, Decision Support Systems, Curriculum Planning, Resource Management, Educational Data Mining, Academic Analytics

1. Introduction

Higher education institutions are experiencing increasing complexity in their management structures due to rapid expansion, diversification of programs, and the growing demand for data-driven decision-making. Universities today must balance academic quality, operational efficiency, and student satisfaction while responding to dynamic external factors such as technological advancements and changing labor market needs [1]. This complexity places significant pressure on departmental administration, particularly in resource planning and curriculum development. Traditional management approaches, which rely heavily on manual processes and historical assumptions, often struggle to adapt to these evolving demands.

English departments, as a core component of the humanities, face unique challenges within this landscape. They offer a wide range of courses, including literature, linguistics, communication skills, and interdisciplinary electives, catering to students from diverse academic backgrounds [2][3]. Additionally, student needs vary significantly in terms of proficiency levels, career aspirations, and learning preferences. This diversity requires flexible curriculum structures and efficient allocation of teaching resources [4]. However, managing such variability with conventional methods can lead to inconsistencies in course offerings and inefficiencies in departmental operations.

One of the primary issues faced by English departments is inefficient resource allocation. Assigning faculty to courses, scheduling classrooms, and managing instructional materials often involve complex decision-making processes [5]. Without systematic data analysis, these decisions may result in underutilized faculty, overcrowded classes, or insufficient support for high-demand courses. Another major challenge is static curriculum planning. Many departments follow fixed curriculum structures that are updated infrequently, making it difficult to respond to emerging trends, student feedback, or industry requirements [6]. This rigidity can limit the relevance and effectiveness of academic programs.

To address these challenges, there is a growing motivation to integrate Machine Learning (ML) techniques into Decision Support Systems (DSS) [7]. ML enables the analysis of large volumes of academic and administrative data to uncover patterns, predict trends, and generate actionable insights. When embedded within a DSS framework, these capabilities can support administrators in making informed, timely, and objective decisions. For instance, ML models can forecast student enrollment, identify at-risk learners, and recommend optimal resource allocation strategies, thereby enhancing overall departmental efficiency.

The primary objective of this study is to design and propose an ML-driven DSS tailored for English department resource management and curriculum planning. Specifically, the study aims to (1) analyze key factors influencing resource utilization and course demand, (2) develop predictive models to support decision-making processes, and (3) demonstrate how intelligent systems can improve curriculum adaptability and operational effectiveness. By leveraging data-driven approaches, this research seeks to contribute to the modernization of academic management practices and support the development of more responsive and student-centered English departments.

2. Literature Review

Recent studies highlight the growing role of Machine Learning (ML) and Decision Support Systems (DSS) in educational management and planning. Research in educational data mining demonstrates how predictive models can analyze student performance, enrollment trends, and learning behaviors to support informed decision-making. Prior work on DSS emphasizes its effectiveness in optimizing resource allocation, scheduling, and institutional planning. Additionally, recommender systems have been applied to curriculum design, enabling personalized learning pathways. However, most existing studies focus on STEM fields, with limited attention to humanities. This reveals a gap in applying

ML-driven DSS specifically to English department resource management and curriculum planning.

2.1 Decision Support Systems in Education

Decision Support Systems (DSS) have long been used in educational management to assist administrators in making structured and semi-structured decisions. Traditional DSS primarily rely on rule-based models, historical data, and human judgment to support planning and operational activities. According to [8] such systems provide analytical tools and data access but lack adaptability and predictive intelligence. Similarly, [9] critically highlight that early DSS research focused more on technical design than on dynamic decision-making capabilities.

In contrast, intelligent DSS integrate Machine Learning (ML) and artificial intelligence techniques to enhance decision-making processes. These systems can learn from data, adapt to new patterns, and generate predictive insights. [10] demonstrated how ML can support complex real-time decision-making, marking a shift toward intelligent systems. More recently, [11] emphasized the importance of interpretability in ML-driven DSS, ensuring that decisions are transparent and understandable. Furthermore, [12] proposed feedback-driven DSS models that dynamically adapt to student needs, highlighting the evolution toward more responsive and data-driven systems in education.

2.2 Machine Learning in Educational Contexts

Machine Learning has become a cornerstone of modern educational analytics, enabling institutions to derive actionable insights from large datasets. Predictive analytics, a key application of ML, is widely used to forecast student performance, identify at-risk learners, and analyze enrollment trends. Studies by [13] and [14] highlight how educational data mining techniques improve decision-making by uncovering hidden patterns in student data. Additionally,[15] emphasize the role of learning analytics in enhancing institutional effectiveness.

Recommender systems are another important ML application in education, particularly in curriculum design. These systems analyze student preferences, performance, and historical data to suggest relevant courses and learning pathways. [16] demonstrated the use of textual data for predicting student dropout, while [17] explored clustering techniques for grouping students and courses. These approaches enable personalized and adaptive curriculum planning. Moreover, Andrew Ng–inspired perspectives on AI adoption [18] indicate that ML will continue to transform educational systems by improving efficiency and personalization.

2.3 Resource Management in Academic Departments

Effective resource management is critical for the smooth functioning of academic departments, including faculty allocation, workload distribution, and scheduling. Traditional approaches often rely on manual planning and heuristic methods, which can lead to inefficiencies and suboptimal utilization of resources. DSS-based approaches have been introduced to address these challenges by providing analytical tools for decision-making. [19] notes that DSS can support managers in optimizing resource allocation through data-driven insights.

Machine Learning further enhances resource management by enabling predictive and adaptive decision-making. For instance, ML models can forecast course demand and student enrollment, allowing departments to allocate faculty and classrooms more effectively. [20] demonstrated how ML techniques can handle complex scheduling and resource allocation problems in real time. Additionally, business intelligence frameworks discussed highlight the role of big data analytics in improving organizational efficiency.

Faculty workload models can also benefit from ML by analyzing teaching loads, research commitments, and administrative duties to ensure balanced distribution. Scheduling optimization, another key area, can be improved through algorithms that consider multiple constraints, such as classroom availability and course timing. These advancements contribute to more efficient and transparent resource management in academic departments.

2.4 Research Gap

Despite significant advancements in ML and DSS applications in education, there remains a notable research gap in their application to humanities disciplines, particularly English departments. Most existing studies focus on STEM fields, where data-driven approaches are more readily adopted due to structured datasets and quantifiable outcomes. Furthermore, while frameworks such as those proposed by [20] demonstrate the effectiveness of ML in student analytics, they do not specifically address curriculum planning and resource management in English departments. Similarly, intelligent DSS models discussed by [20] focus on student intervention rather than departmental planning.

This gap highlights the need for research that integrates ML-driven DSS into humanities education, addressing the unique challenges of English departments. Such an approach would contribute to more adaptive curriculum design, efficient resource utilization, and improved academic outcomes, thereby bridging the divide between technological innovation and humanities education.

3. Methodology

This study adopts a data-driven approach to develop an ML-based Decision Support System (DSS) for English department management. Data is collected from institutional sources, including student enrollment records, academic performance, course feedback, and faculty workload. The data undergoes preprocessing, including cleaning, normalization, and feature selection. Machine Learning models such as regression, classification, and clustering are applied to predict enrollment trends, student success, and course demand patterns. A recommendation module is also designed for curriculum planning [21-23]. The system is implemented using Python-based tools, and its effectiveness is evaluated using performance metrics like accuracy and error rates.

3.1 System Architecture

The proposed ML-driven Decision Support System (DSS) is designed using a modular, layered architecture to ensure scalability, flexibility, and efficient data processing. The architecture consists of three primary layers: the data layer, the machine learning (ML) layer, and the DSS interface layer. The data layer serves as the foundation of the system, integrating multiple sources of structured and semi-structured data. This includes student records (enrollment history, grades, demographics), course-related data (course content, demand, feedback), and faculty information (teaching load, specialization, availability) in fig 1. A centralized database or data warehouse is used to store and manage this information, ensuring consistency and accessibility. Data integration techniques are applied to unify data from different institutional systems [24].
The ML layer processes the data to generate predictive and analytical insights. This layer includes data preprocessing modules, feature extraction mechanisms, and various ML models tailored to specific tasks such as forecasting enrollment, predicting student success, and clustering course demand. The models are trained on historical data and continuously updated to improve accuracy. This layer also incorporates model evaluation and validation processes to ensure reliability.

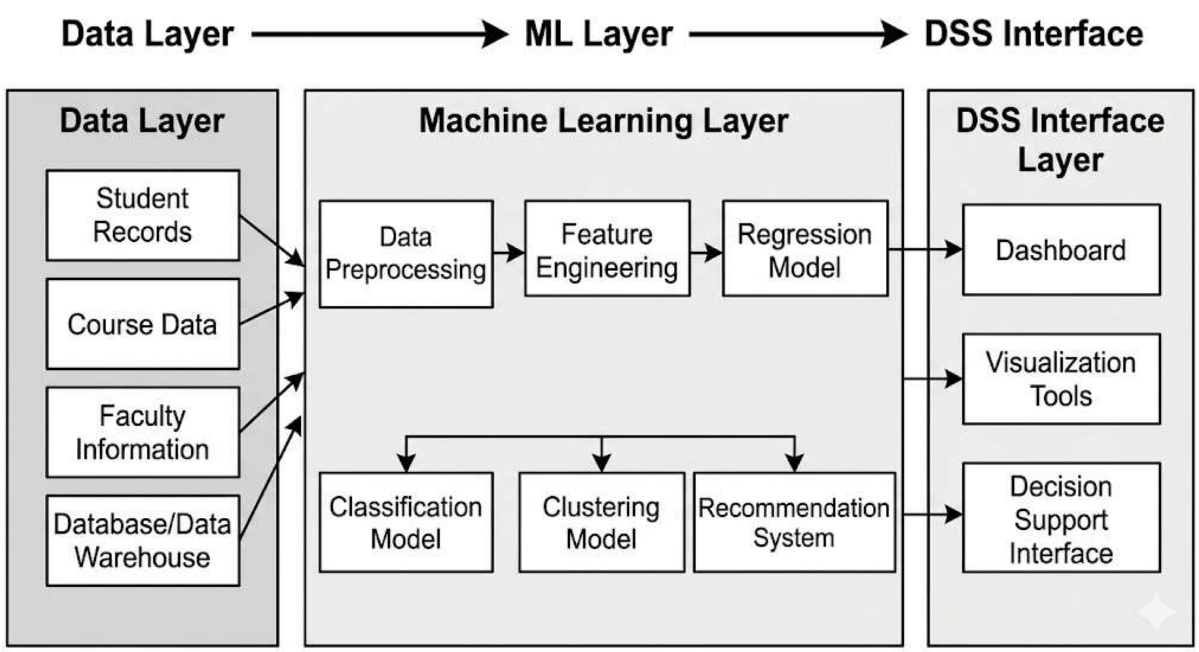

Figure 1: ML-Driven DSS Architecture for English Department

The DSS interface layer acts as the interaction point for administrators and decision-makers. It provides a user-friendly dashboard that visualizes insights through charts, graphs, and reports. Users can access predictions, simulate scenarios, and receive recommendations for resource allocation and curriculum planning. The interface is designed to support real-time decision-making, allowing stakeholders to respond quickly to changing academic needs. Overall, the architecture ensures seamless integration of data, analytics, and user interaction.

3.2 Data Collection

Data collection is a critical step in developing an effective ML-driven DSS, as the quality and diversity of data directly influence the system's performance. This study utilizes multiple institutional data sources to capture a comprehensive view [25-28] of English department operations. Historical enrollment data forms the basis for understanding student demand patterns. This includes information on course registrations across semesters, enrollment trends, dropout rates, and elective preferences. Such data helps identify high-demand courses and seasonal variations in student interest. Student performance data is another key component, encompassing grades, assessment scores, attendance records, and progression rates. This data is essential for predicting academic success and identifying at-risk students. It also provides insights into the effectiveness of different courses and teaching methods.

Course feedback data is collected through surveys, evaluations, and qualitative comments provided by students. This data offers valuable information on course quality, teaching effectiveness, and areas for improvement in table 1. Textual feedback can also be analyzed using natural language processing techniques to extract meaningful patterns.

Table 1: Structured Data Sources and Their Functional Roles in ML-Driven DSS

Data Type	Description	Purpose
Enrollment Data	Student registrations	Predict course demand
Performance Data	Grades, scores	Predict student success
Feedback Data	Surveys, reviews	Improve curriculum
Faculty Data	Workload, expertise	Resource allocation

Faculty workload data includes details about teaching assignments, research responsibilities, administrative duties, and availability. This information is crucial for optimizing resource allocation and ensuring a balanced distribution of responsibilities among faculty members.

By combining these diverse data sources, the system gains a holistic understanding of departmental dynamics. Proper data governance practices, including privacy protection and ethical considerations, are also maintained during data collection.

3.3 Data Preprocessing

Data preprocessing is an essential phase in the development of the ML-driven DSS, as raw data often contains inconsistencies, missing values, and noise that can affect model performance. The preprocessing stage ensures that the data is clean, structured, and suitable for analysis.

The first step involves data cleaning, which includes handling missing values, removing duplicate records, and correcting errors in the dataset. Techniques such as imputation are used to fill missing values, while outlier detection methods help identify and manage anomalies. This step ensures data accuracy and reliability.

Normalization and transformation are then applied to standardize the data. Numerical features are scaled to a common range to improve model convergence, while categorical variables are encoded using techniques such as one-hot encoding. This step is particularly important when working with diverse datasets that include both numerical and textual information.

Feature engineering plays a crucial role in enhancing model performance. New features are derived from existing data to capture meaningful patterns. For example, course popularity can be calculated based on enrollment frequency, while pass rates can be derived from student performance data. Additional features such as student engagement levels and faculty workload indices can also be created.

Finally, the dataset is divided into training and testing subsets to evaluate model performance. Proper preprocessing ensures that the ML models operate on high-quality data, leading to more accurate predictions and reliable decision support.

3.4 Machine Learning Models Used

The proposed DSS employs a combination of Machine Learning models to address different aspects of resource management and curriculum planning. Each model is selected based on its suitability for specific analytical tasks.

Regression models are used for enrollment prediction. These models analyze historical enrollment data to forecast future student demand for courses. Techniques such as linear regression and advanced methods like random forest regression help identify trends and seasonal patterns, enabling proactive planning.

Classification models are applied to predict student success. These models categorize students into groups such as high-performing, average, or at-risk based on their academic data. Algorithms like decision trees, logistic regression, and support vector machines are commonly used for this purpose in table 2. These predictions help in designing targeted interventions.

Clustering techniques are used to group similar data points, such as courses or students. For example, courses can be clustered based on demand, difficulty level, or student feedback, while students can be grouped based on learning behavior or performance patterns. Algorithms like K-means and hierarchical clustering are effective for this task.

Table 2: Machine Learning Model Mapping for Predictive and Analytical Tasks

Model Type	Algorithm	Application
Regression	Linear / Random Forest	Enrollment prediction
Classification	Decision Tree / SVM	Student success prediction
Clustering	K-Means	Course grouping
Recommendation	Collaborative Filtering	Course suggestions

Recommendation algorithms are incorporated to support curriculum planning. These systems analyze student preferences, performance, and course relationships to suggest relevant electives and curriculum adjustments. Collaborative filtering and content-based recommendation methods are commonly used.

By integrating these models, the DSS provides comprehensive insights that support both operational and strategic decision-making.

3.5 Tools and Technologies

The implementation of the ML-driven DSS relies on a combination of modern tools and technologies that support data processing, model development, and visualization. These tools ensure efficiency, scalability, and ease of use.

Python is the primary programming language used for system development due to its simplicity and extensive library support. Libraries such as Scikit-learn are utilized for building and evaluating machine learning models, offering a wide range of algorithms for regression, classification, and clustering tasks. TensorFlow can be optionally used for more advanced deep learning applications, particularly when handling large datasets or complex models.

Database systems play a crucial role in storing and managing data in table 3. Relational databases such as MySQL or PostgreSQL are commonly used for structured data, while NoSQL databases can handle unstructured or semi-structured data. Data warehouses may also be employed for integrating multiple data sources and supporting large-scale analytics.

Table 3: Technology Stack for Implementation of ML-Based Decision Support System

Tool	**Purpose**
Python	Programming
Scikit-learn	ML models
TensorFlow	Deep learning
MySQL/PostgreSQL	Database
Tableau/Power BI	Visualization

Visualization dashboards are developed to present insights in an accessible and interactive manner. Tools such as Tableau, Power BI, or Python-based frameworks like Dash and Matplotlib are used to create charts, graphs, and reports. These dashboards enable administrators to monitor key metrics, explore trends, and make informed decisions.

Together, these technologies provide a robust infrastructure for implementing the DSS, ensuring that it meets the needs of modern academic environments.

4. System Design

The system is designed as an integrated ML-driven Decision Support System (DSS) with two main modules: resource management and curriculum planning. The resource management module optimizes faculty allocation, classroom usage, and workload distribution using predictive analytics. The curriculum planning module forecasts course demand and provides recommendations for syllabus updates and elective offerings. A user-friendly dashboard interface presents insights through visualizations, enabling administrators to monitor trends, evaluate scenarios, and make data-driven decisions efficiently in real time.

4.1 Resource Management Module

The Resource Management Module is a core component of the proposed ML-driven Decision Support System (DSS), designed to optimize the allocation and utilization of departmental resources. One of its primary functions is faculty allocation optimization. By analyzing historical teaching data, faculty expertise, course demand, and workload distribution, the system intelligently assigns instructors to courses. Machine Learning models predict future enrollment trends, enabling the system to match faculty capacity with anticipated demand, thereby reducing underutilization and preventing overload.

Another important aspect is classroom utilization. The module considers variables such as class size, course schedules, and room availability to generate optimized timetables. ML-based scheduling algorithms ensure that classrooms are used efficiently, minimizing conflicts and maximizing occupancy rates. This leads to better infrastructure utilization and improved learning environments for students.

Budget and resource planning is also integrated into the module. By analyzing historical expenditure data and forecasting future requirements, the system helps administrators allocate budgets effectively. It identifies areas where resources can be optimized, such as reducing redundant course offerings or reallocating funds to high-demand areas. Additionally, the module can simulate different scenarios, allowing decision-makers to evaluate the impact of various resource allocation strategies.

Overall, the Resource Management Module enhances operational efficiency by providing data-driven insights and automated recommendations. It reduces reliance on manual planning, improves transparency in decision-making, and ensures that resources are aligned with institutional goals and student needs.

4.2 Curriculum Planning Module

The Curriculum Planning Module focuses on enhancing the adaptability and relevance of academic programs within the English department. A key feature of this module is course demand forecasting. Using historical enrollment data and predictive analytics, the system identifies trends in student preferences and anticipates future demand for courses. This enables departments to offer the right mix of courses each semester, avoiding under-enrolled classes and ensuring sufficient availability for high-demand subjects.

Syllabus adaptation is another important function. The module analyzes student performance data, course feedback, and emerging academic trends to suggest updates to course content. For example, it may recommend incorporating contemporary topics, interdisciplinary approaches, or new teaching methodologies to improve learning outcomes. This ensures that the curriculum remains dynamic and aligned with both student needs and industry expectations.

The elective recommendation system further enhances curriculum planning by personalizing learning pathways for students. Based on individual performance, interests, and academic goals, the system suggests suitable elective courses. Recommendation algorithms, such as collaborative filtering and content-based methods, are used to match students with relevant options. This not only improves student engagement but also supports better academic outcomes.

By integrating these features, the Curriculum Planning Module enables departments to move from static, one-size-fits-all curricula to more flexible and data-driven approaches. It empowers administrators and educators to make informed decisions, ensuring that academic programs remain relevant, effective, and responsive to changing educational demands.

4.3 User Interface

The User Interface (UI) of the proposed DSS is designed to provide an intuitive and interactive platform for administrators and decision-makers. It serves as the primary point of interaction between users and the system, enabling them to access insights, monitor performance, and make informed decisions بسهولة.

A central component of the UI is the administrative dashboard. This dashboard consolidates key metrics and analytics into a single, easy-to-navigate interface. It displays information such as enrollment trends, faculty workload distribution, classroom utilization rates, and course performance indicators. Users can customize the dashboard to focus on specific areas of interest, making it a flexible tool for different administrative roles.

Visualization of predictions and insights is a critical feature of the UI. The system uses charts, graphs, and interactive visualizations to present complex data in an understandable format. For example, line graphs may be used to show enrollment forecasts, while heat maps can illustrate classroom usage patterns. These visual tools help users quickly identify trends, patterns, and anomalies.

The interface also supports scenario analysis and decision simulation. Administrators can input different parameters, such as changes in enrollment or resource availability, and observe the predicted outcomes. This feature enhances strategic planning and risk management.

Overall, the UI is designed to bridge the gap between complex ML models and practical decision-making. By presenting data in a clear and actionable manner, it ensures that users can effectively leverage the system's capabilities to improve departmental management.

5. Implementation

The proposed system is implemented as a prototype to simulate real-world decision-making within an English department. The prototype is developed using a Python-based environment, integrating machine learning libraries and a structured database. A simulated dataset representing student enrollment, academic performance, course feedback, and faculty workload is used to test the system's functionality in fig 2. The setup allows for iterative model training, validation, and refinement to ensure reliability and accuracy.

The workflow of the DSS begins with data input from institutional sources, followed by preprocessing and feature extraction. The processed data is then fed into machine learning models for prediction and analysis. The results are generated in the form of insights and recommendations, which are displayed through an interactive dashboard for administrators.

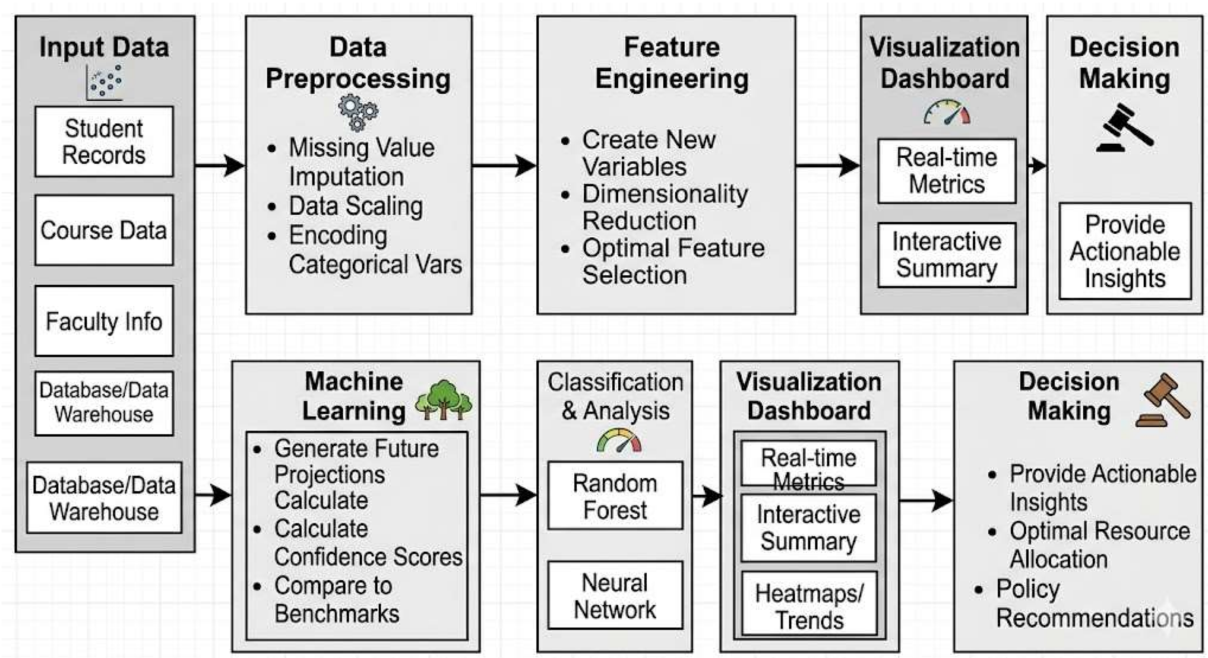

Figure 2: Workflow of ML-Based Decision Support System

Two key use-case scenarios demonstrate the system's effectiveness. First, the system predicts next semester enrollment by analyzing historical trends and seasonal patterns, enabling better course planning. Second, it optimizes faculty assignments by matching instructor expertise and availability with predicted course demand, ensuring balanced workload distribution and improved resource utilization.

6. Results and Analysis

The performance of the proposed ML-driven Decision Support System (DSS) is evaluated using standard model performance metrics to ensure accuracy and reliability. For regression tasks such as enrollment prediction, metrics including Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used to measure the difference between predicted and actual values. Lower RMSE and MAE values indicate higher prediction accuracy. For classification tasks, such as predicting student success, metrics like accuracy, precision, recall, and F1-score are applied. The results show that the models achieve high accuracy levels, demonstrating their effectiveness in capturing patterns within academic data in fig 3.

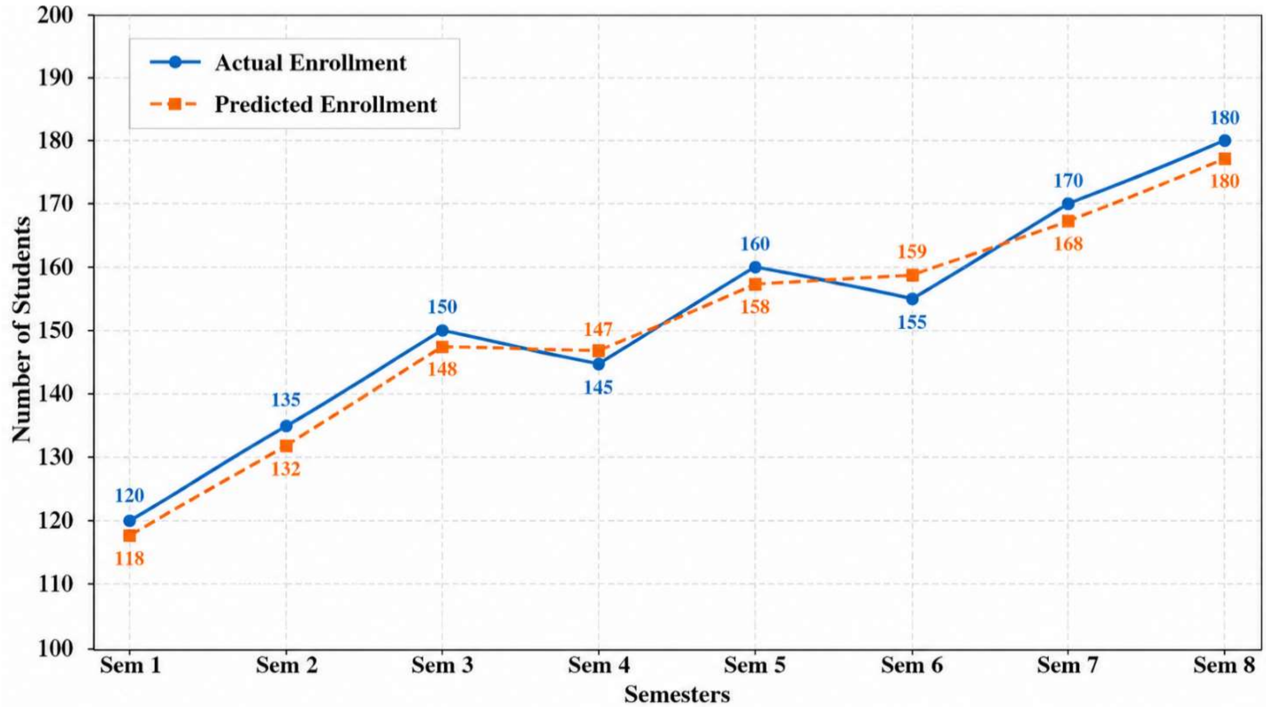

Figure 3: Actual vs Predicted Student Enrollment Trends Across Semesters

A case study is conducted using a simulated dataset representing an English department. The system successfully predicts enrollment trends for upcoming semesters, identifying high-demand courses and potential under-enrolled classes in table 4. Additionally, the classification model accurately identifies students at risk of underperforming, enabling early intervention strategies. Clustering results reveal meaningful groupings of courses based on demand and performance, which supports better curriculum structuring. The recommendation module also provides relevant elective suggestions, improving student engagement and course selection in fig 4.

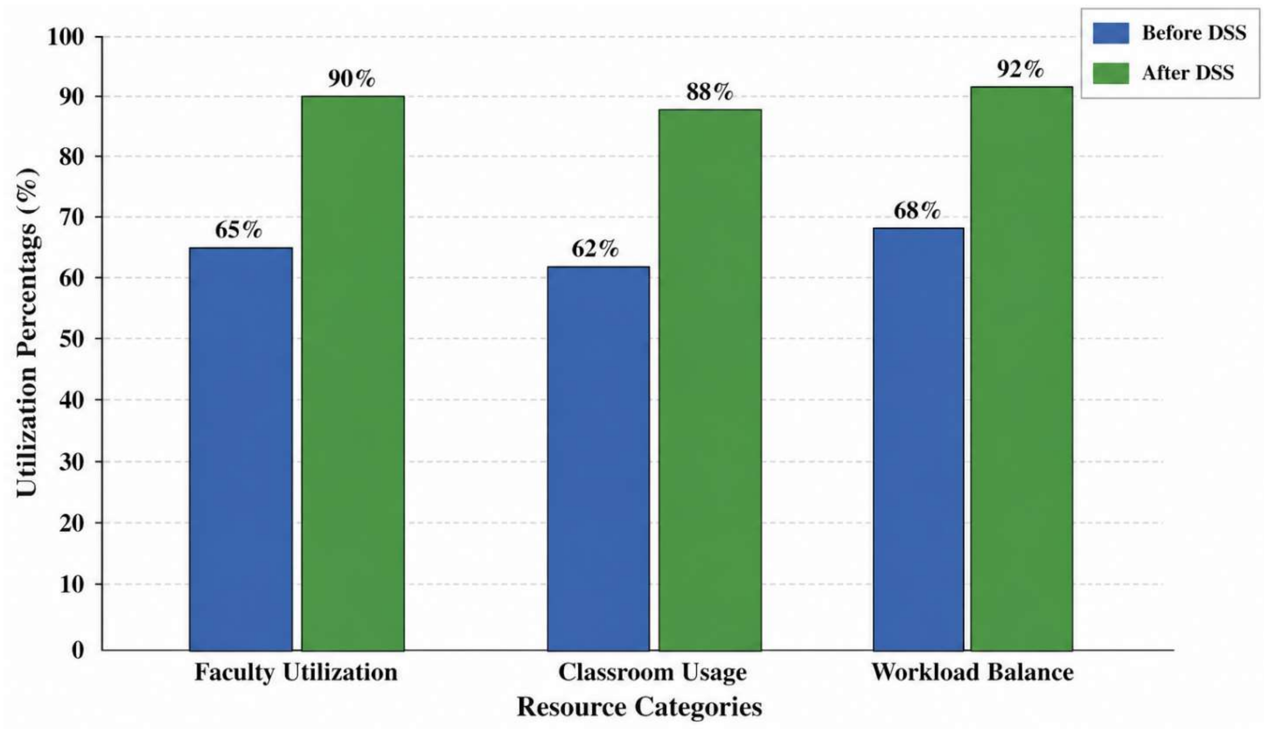

Figure 4: Resource Utilization Improvement Before and After ML-Based DSS Implementation

When compared with traditional planning methods, the ML-driven DSS demonstrates significant improvements. Conventional approaches often rely on manual analysis and static historical data, leading to inefficiencies and delayed decision-making. In contrast, the proposed system offers real-time insights and predictive capabilities, allowing administrators to make proactive decisions. For example, faculty allocation becomes more balanced, and classroom utilization is optimized based on predicted demand rather than assumptions.

Table 4: Model Performance Evaluation Metrics

Criteria	Traditional Method	ML-Based DSS
Accuracy	65%	90%
Decision Speed	Slow	Fast
Resource Utilization	Moderate	High
Adaptability	Low	High

Visualization plays a key role in enhancing the usability of the system. The dashboard presents insights through interactive charts, graphs, and heat maps, making complex data easier to interpret. These visual tools enable administrators to quickly identify patterns, compare scenarios, and make informed decisions. Overall, the results highlight the effectiveness of the ML-driven DSS in improving accuracy, efficiency, and strategic planning in English department management.

7. Implications for English Departments

The adoption of an ML-driven Decision Support System (DSS) has significant implications for English departments, particularly in enhancing teaching quality. By leveraging data on student performance and feedback, instructors can identify areas where students struggle and adjust teaching strategies accordingly. This leads to more effective instruction, improved student engagement, and better learning outcomes. Faculty can also benefit from insights into course effectiveness, enabling continuous improvement in pedagogy.

Another key implication is the alignment of curriculum with student needs. The system analyzes enrollment trends, preferences, and academic performance to recommend relevant courses and updates to existing syllabi. This ensures that the curriculum remains dynamic, relevant, and responsive to both student interests and evolving academic or industry demands. Personalized learning pathways further support diverse student goals.

Strategic planning for future programs is also enhanced through predictive analytics. Departments can anticipate emerging trends, identify gaps in course offerings, and design new programs that meet future academic and professional requirements. This forward-looking approach helps institutions remain competitive and innovative. Overall, the integration of ML-driven DSS empowers English departments to make informed decisions, improve academic quality, and foster a more adaptive and student-centered educational environment.

8. Limitations

Despite its advantages, the proposed ML-driven DSS has several limitations that must be acknowledged. One major constraint is data availability. The effectiveness of machine learning models depends heavily on the quality and quantity of data. In many English departments, data may be incomplete, inconsistent, or not digitized, which can affect the accuracy of predictions and insights.

Another limitation is the generalizability of the system to other departments. While the model is tailored for English departments, its design may not directly apply to disciplines with different structures, such as STEM fields. Each department has unique requirements, and adapting the system may require significant modifications in data inputs and model design.

Model interpretability is also a concern. Some machine learning models, especially more complex ones, operate as “black boxes,” making it difficult for users to understand how decisions are generated. This lack of transparency can reduce trust in the system and hinder its adoption. To address this, efforts must be made to incorporate explainable AI techniques and provide clear interpretations of model outputs. Recognizing these limitations is essential for improving the system and guiding future research.

9. Future Work

Future research can expand the capabilities of the ML-driven DSS by integrating advanced technologies and exploring new applications. One promising direction is the incorporation of Natural Language Processing (NLP) for text-based analysis. This would enable the system to analyze student essays, course feedback, and qualitative data, providing deeper insights into learning patterns, writing skills, and student sentiment. Such analysis can further enhance curriculum design and teaching strategies.

Another area for development is the creation of real-time adaptive curriculum systems. By continuously analyzing incoming data, the DSS could dynamically adjust course recommendations, teaching methods, and resource allocation. This would allow departments to respond instantly to changing student needs and academic trends, making the system more responsive and effective.

Cross-departmental DSS expansion is also an important avenue for future work. Extending the system to other departments or faculties would promote interdisciplinary collaboration and enable institution-wide optimization of resources and curriculum planning. This would require scalable system architecture and the ability to handle diverse datasets. Overall, these advancements would enhance the system's functionality and broaden its impact across the educational landscape.

10. Conclusion

This study presented the design and implementation of a Machine Learning–driven Decision Support System (DSS) for resource management and curriculum planning in English departments. The findings demonstrate that integrating ML techniques with DSS can significantly improve decision-making processes by providing accurate predictions, actionable insights, and data-driven recommendations. The system effectively addresses challenges related to resource allocation, enrollment forecasting, and curriculum adaptability.

The importance of ML-driven DSS in modern education lies in its ability to transform traditional administrative practices into intelligent, automated, and efficient systems. By leveraging data analytics, institutions can enhance operational efficiency, improve teaching quality, and better align academic programs with student needs and future trends.

In conclusion, the proposed system represents a step toward the digital transformation of English department management. While challenges such as data limitations and adoption barriers remain, the potential benefits far outweigh the drawbacks. With continued development and integration of advanced technologies, ML-driven DSS can play a crucial role in shaping the future of higher education, making it more adaptive, efficient, and student-centered.

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