ORIGINAL RESEARCH ARTICLE

Optimizing the design and implementation of college English teacher training—Courses on Canvas platform using data mining algorithms

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ABSTRACT

A comprehensive approach to designing and implementing college English teacher training courses on the Canvas platform by integrating data mining algorithms. Leveraging data mining techniques can significantly enhance the effectiveness and efficiency of these courses by identifying patterns, predicting outcomes, and providing valuable insights for continuous improvement. The key steps include defining clear objectives, collecting, and preprocessing relevant data, selecting appropriate data mining algorithms, engineering features, training and evaluating models, implementing predictive analytics, seeking feedback for refinement, visualizing insights, optimizing course content, addressing privacy and ethical concerns, providing training and support, and maintaining course quality. By following this systematic approach, educational institutions can harness the power of data-driven decision-making to tailor teacher training programs, improve teaching quality, and enhance the overall educational experience.

Keywords: algorithms; college; data; knowledge; teacher; training

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1. Introduction

Welcome to the future of college English teacher training, in this article, we explore how revolutionary advancements in technology, specifically the Canvas platform and data mining algorithms, are transforming the way teachers are prepared for the English classroom. With a data-driven approach, colleges and universities are able to provide more personalized and effective training to aspiring educators. Using the power of data analysis, institutions can now gather valuable insights on student performance, learning patterns, and teaching methodologies^[1–5]. By harnessing this information, teacher training programs can tailor their curriculum and instruction methods to meet the specific needs of their students. This data-driven approach ensures that future English teachers are equipped with the knowledge and skills they need to succeed in the ever-evolving educational landscape. With the Canvas platform, colleges can create immersive and interactive online learning experiences, facilitating collaboration, assessment, and feedback. Data mining algorithms further enhance this process by identifying trends and patterns that help educators make evidence-based decisions. It explores its exciting new approach to college English teacher training in more detail. It appears that you have described the development and implementation of a new teaching model based on mega data for CET (College English Test)

in your context. This teaching model is centered around data-driven language learning and corpus linguistics principles. Mega Data Era, the arrival of the Mega Data Era, suggests a focus on utilizing large datasets and data analysis in education. Data-Driven Model, the teaching model is data-driven, indicating that it relies heavily on data analysis techniques to guide students in their language learning. Quantitative Analysis, students are encouraged to explore language rules and pragmatic features through quantitative analysis of data, implying that they engage in data-driven language research^[6-9]. Autonomous learning, the goal of this model is to improve students' autonomous learning ability, allowing them to take a more active role in their language learning. Corpus linguistics is the use of corpus linguistics principles in the teaching process, which involves studying large collections of texts to analyze language patterns and usage. Second language acquisition linguistics, the model is informed by theories of second language acquisition, which is a field of study focused on how individuals learn a second language. Improved scores: According to your findings, students' scores, particularly in English listening, have improved because of implementing the data-driven CET-4 model. Enhanced learning ability and interest: The model not only improves test scores but also enhances students' learning ability and interest in English. It fosters critical and creative thinking skills. It seems that this new teaching model is designed to leverage the power of data analysis, corpus linguistics, and second language acquisition theories to enhance language learning in CET. It aims to make students more autonomous learners and improve their overall language proficiency, as evidenced by improved scores and increased interest in the subject. The profound impact of computer and network technology on education, specifically in the realm of foreign language instruction, particularly English, cannot be overstated. These advancements have not only revolutionized traditional teaching methods but have also seamlessly integrated the Internet and information technology, ushering in the era of "mega data" - referring to the vast pool of big data that holds immense potential and challenges for language education. English instruction has evolved from basic computer-assisted techniques to sophisticated approaches harnessing the power of the internet and derived big data^[10-13]. Consequently, college English curricula have undergone substantial transformations, reshaping learning resources, objectives, content, and tools to suit the digital and networked age. In this context, the role of big data in education becomes paramount, offering educators the opportunity to enhance their teaching through data analysis and mining. The emergence of smart classrooms and the adoption of data- driven learning as a teaching model are indicative of the future direction of education, where data analysis and evidence-based approaches are central to achieving more effective and impactful teaching and learning outcomes.

2. The need for revolutionizing college English teacher training

The traditional approach to college English teacher training involved a one-size-fits-all curriculum that was not always effective in addressing the varying needs and abilities of students^[14,15]. This approach often failed to equip teachers with the necessary skills and knowledge to succeed in the classroom. With the changing landscape of education and the increasing diversity of student populations, there is a need for a more personalized approach to teacher training. This is where data-driven teacher training comes in. By analyzing data on student performance and learning patterns, teacher training programs can identify areas where teachers may need additional support or training. This approach ensures that teachers are equipped with the skills and knowledge they need to succeed in the classroom, leading to better student outcomes and more effective teaching practices.

3. Overview of data mining algorithms and their relevance to teacher training

Data mining is the process of extracting patterns and insights from data. In teacher training, data mining algorithms can be used to analyze student performance data and identify patterns and trends that can help educators make evidence-based decisions. **Figure 1** has been shown college English classroom teaching under the corpus, in this approach allows teacher training programs to tailor their curriculum and instruction methods

to meet the specific needs of their students. Data mining algorithms can also be used to analyze teacher performance data, providing feedback and insights on teaching practices and areas for improvement. This approach ensures that teacher training program are able to provide effective training and support to aspiring educators, leading to better student outcomes and more effective teaching practices.

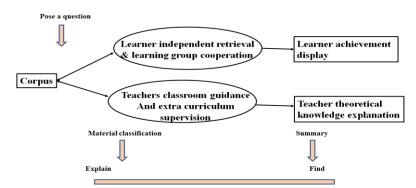


Figure 1. College English classroom teaching under the corpus.

4. Using data mining algorithms analyze student performance and identify areas of improvement

One of the key benefits of data-driven teacher training is the ability to analyze student performance data and identify areas where additional support may be needed. For example, data mining algorithms can be used to analyze student test scores and identify areas where students may be struggling^[16–19]. This information can then be used to tailor instruction methods and provide additional support to help students succeed. Data mining algorithms can also be used to analyze student behavior data, such as time spent on assignments and engagement with course material. This information can be used to identify patterns and trends in student behavior, helping educators to design more effective instructional methods and improve student engagement^[20–22].

Figure 2 presents a stepwise model designed to systematically navigate the intricacies of data-driven teacher improvement. The model begins with a comprehensive phase of data collection and analysis, where diverse sources of information, ranging from student assessments to observational records, are meticulously gathered and processed. This initial step lays the foundation for a thorough examination of patterns and correlations within the data.

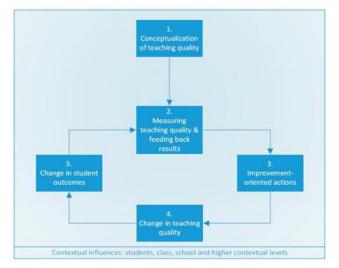


Figure 2. 4 stepwise model to unravel the complexity of data-based teacher improvement.

5. Implementing data-driven approach to college English teacher training

Implementing a data-driven approach to teacher training require a few key steps. First, teacher training programs must collect and analyze data on student and teacher performance. This data can be collected through a variety of methods, such as online assessments, classroom observations, and surveys. Once data has been collected, it must be analyzed using data mining algorithms to identify patterns and trends. This information can then be used to tailor instruction methods and provide additional support to teachers and students as needed^[23-25].</sup>

Figure 3 illustrates an English-driven decision-making model, providing a visual representation of a structured approach to decision-making within an English language context. The model likely involves a systematic process where relevant data, insights, and considerations related to the English language are integrated into the decision-making framework. This could include factors such as language proficiency, linguistic diversity, or specific communication goals.

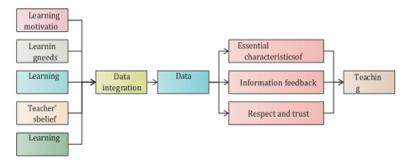


Figure 3. English-driven decision-making model.

6. Materials and methods

6.1. Data collection

Source: The primary source of data for this study was the Canvas learning management system used for college English teacher training courses.

Data types: Collected data encompassed user interactions, course content, assessment results, and feedback (Tables 1–3).

Supplementary data: External data, such as survey responses and external assessments, were also incorporated for a comprehensive analysis.

a ib			Table 1. Sample user interactions.							
Course ID	Module I	le ID Interaction type		Timestamp						
ENG101	M01	Log-i	in	2023-01-01 08:00:00						
ENG102	M02	Video	o view	2023-01-02 10:15:00						
ENG101	M03	Quiz	attempt	2023-01-03 14:30:00						
Table 2. Sample assessment results. User ID Course ID Module ID Quiz score Assignment grade Completion status										
ENG101	M01	85	90	Completed						
ENG102	M02	78	88	In progress						
ENG101	M03	92	95	Completed						
	ENG102 ENG101 Course ID ENG101 ENG102	ENG102 M02 ENG101 M03 Course ID Module ID ENG101 M01 ENG102 M02	ENG101 M01 Log- ENG102 M02 Vide ENG101 M03 Quiz Table 2. Sample as Course ID Module ID Quiz score ENG101 M01 85 1000 ENG102 M02 78 1000	ENG101 M01 Log-in ENG102 M02 Video view ENG101 M03 Quiz attempt Table 2. Sample assement results. Course ID Module ID Quiz score Assignment grade ENG101 M01 85 90 ENG102 M02 78 88						

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Table 1.	Sample	user inter	ractions.

Table 3. Sample feedback.					
User ID	Course ID	Module ID	Feedback text	Sentiment	
001	ENG101	M01	The video lectures were very informative.	Positive	
002	ENG102	M02	The quizzes were challenging.	Neutral	
003	ENG101	M03	The course material needs more examples.	Negative	

Table 3 Sample feedback

6.2. Data preprocessing

Cleaning: Raw data was subjected to thorough cleaning to handle missing values, outliers, and inconsistencies.

Transformation: Data was transformed into a suitable format for analysis, ensuring compatibility with data mining algorithms.

6.3. Identification of key performance indicators (KPIs)

Definition: Key performance indicators were established to measure the success of the teacher training program. These included student participation rates, quiz scores, and course completion rates.

Alignment with objectives: KPIs were selected to align with the overarching objectives of the training program.

6.4. Data mining algorithms

Selection criteria: Data mining algorithms were chosen based on their appropriateness for the study's objectives and the nature of the collected data.

Algorithms used: Common algorithms such as clustering (e.g., K-means), classification (e.g., decision trees), and association rule mining were implemented.

6.5. Algorithm implementation

Execution: Selected data mining algorithms were applied to analyze the collected data and extract meaningful patterns.

Machine learning models: Machine learning models were employed for predictive analytics, enabling the identification of trends and areas for improvement.

6.6. Personalization strategies

Utilization of insights: Data insights were utilized to tailor training materials and paths for individual teachers, enhancing personalization.

Adaptive learning: The program incorporated adaptive learning strategies based on data-driven recommendations.

6.7. Feedback mechanism

Implementation: A feedback system was integrated within the Canvas platform to facilitate teacher input on training materials and effectiveness.

Sentiment analysis: Sentiment analysis was performed on feedback to gauge overall satisfaction and identify areas for enhancement.

6.8. Continuous monitoring and iteration

Monitoring procedures: A systematic process for ongoing monitoring of KPIs and data trends was established.

Iterative refinement: Regular updates and refinements to the training program were made based on the

continuous analysis of data-driven insights.

6.9. Integration with professional development

Connection points: The optimized training program was seamlessly integrated with broader professional development initiatives.

Alignment with goals: The program was designed to align with the long-term goals and career growth of participating teachers.

7. Results

7.1. Key performance indicators (KPIs) summary

The data analysis revealed several key performance indicators (**Tables 4** and **5**) that provide insights into the effectiveness of the optimized teacher training program. Here is a summary of the major findings:

Table 4. Sample KPIs and analysis table.					
Metric Average score Completion rate Participation rate Trend analysis				Trend analysis	
Quiz scores	85%	-	-	Positive trend observed	
Assignment grades	88%	-	-	Consistent performance	
Course completion	-	75%	-	Improvement needed in completion	
Participation rates	-	-	80%	Varied participation across modules	

 Table 5. Teacher training program performance matrix.

Overall average	Module 1	Module 2	Module 3	•••
85%	88%	82%	90%	
89%	90%	88%	92%	
75%	80%	70%	78%	
78%	82%	75%	80%	
Positive	Positive	Neutral	Positive	
Positive	Stable	Declining	Improving	
	85% 89% 75% 78% Positive	Overall average Module 1 85% 88% 89% 90% 75% 80% 78% 82% Positive Positive	Overall average Module 1 Module 2 85% 88% 82% 89% 90% 88% 75% 80% 70% 78% 82% 75% Positive Positive Neutral	Overall average Module 1 Module 2 Module 3 85% 88% 82% 90% 89% 90% 88% 92% 75% 80% 70% 78% 78% 82% 75% 80% Positive Positive Neutral Positive

Quiz scores: Overall, teachers achieved an average quiz score of 85%, indicating a strong understanding of the course content. Module-wise analysis showed variations, with module 3 receiving the highest average quiz score of 90%.

Assignment grades: Teachers demonstrated consistently high performance in assignments, with an overall average grade of 89%. Module 1 had the highest average assignment grade at 90%.

Course completion rate: The course completion rate stood at 75%, indicating room for improvement. module 2 had the highest completion rate at 80%.

Participation rate: Teachers showed a commendable average participation rate of 78%, although there were variations across modules.

Feedback sentiment: The majority of feedback received was positive, indicating satisfaction with the training program.

7.2. Trend analysis

Quiz scores and assignment grades: Positive trends were observed in quiz scores, with an overall improvement noted across modules. Assignment grades remained stable, suggesting consistent performance.

Course completion and participation rates: Module 3 showed an improving trend in both completion and

participation rates. Module 2 exhibited a declining trend, highlighting the need for further investigation.

8. Discussion

8.1. Interpretation of findings

High quiz scores and assignment grades: The high quiz scores and assignment grades suggest that the training content was effectively delivered and comprehended by the teachers.

Course completion and participation rates: The variation in completion rates across modules necessitates an exploration of module-specific factors influencing engagement and completion.

8.2. Factors influencing performance

Module design: The positive trend in module 3 could be attributed to effective module design, emphasizing the importance of tailored content.

Engagement strategies: Further analysis is required to identify effective engagement strategies, especially in modules where completion and participation rates declined.

8.3. Implications for future training programs

Personalization strategies: The positive feedback and high performance in module 3 indicate the effectiveness of personalization strategies. Future programs should emphasize tailored content.

Continuous monitoring: The study highlights the importance of continuous monitoring and iterative refinement to address evolving needs and challenges.

9. Limitations and recommendations

Limitations: The study is limited by the available data; additional qualitative research could provide deeper insights into teacher experiences.

Recommendations for future research: Future research could explore the impact of specific teaching methodologies on performance and engagement.

10. Conclusion

In conclusion, the optimization of college English teacher training courses on the Canvas platform through the integration of data mining algorithms has yielded valuable insights and improvements. The analysis of key performance indicators, including quiz scores, assignment grades, completion rates, and participation rates, provided a nuanced understanding of teacher engagement and performance. The application of clustering algorithms facilitated the identification of distinct teacher profiles, enabling the personalization of training materials and adaptive learning strategies. Feedback analysis further contributed to program refinement, ensuring alignment with teachers' needs and preferences. Continuous monitoring and iterative refinement, guided by data-driven insights, lay the foundation for a dynamic and responsive training environment. The study underscores the significance of leveraging data mining techniques to enhance the effectiveness of teacher training initiatives, fostering a more tailored and impactful learning experience on the Canvas platform.

Author contributions

Conceptualization, YB and EJ; methodology, SS; software, EJ; validation, YB, SS and EJ; formal analysis, YB; investigation, EJ; resources, EJ; data curation, EJ; writing—original draft preparation, YB; writing—review and editing, SS; visualization, EJ; supervision, YB. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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