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Course Design Based on Association Rule Mining in Blended Teaching of College English

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Abstract: - Course design based on association rule mining in blended teaching of college English offers a data-driven approach to curriculum development, enhancing the effectiveness of English language instruction. By analyzing patterns and relationships within student performance data, association rule mining algorithms identify correlations between different learning activities, topics, and assessment outcomes. This information enables instructors to design courses that strategically integrate online and offline learning components, ensuring a cohesive and engaging learning experience. Additionally, association rule mining facilitates the identification of potential dependencies between course elements, allowing for the optimization of teaching sequences and resource allocation. This paper investigates the use of the Extraction Apriori Rule Mining Blended (EARMB) technique to enhance teaching effectiveness in English instruction within blended learning environments. Through the analysis of association rules derived from instructional data, significant relationships between instructional components and student outcomes are identified, providing valuable insights for course design and instructional strategy development. A structured course design framework is presented, integrating various instructional activities and assessment methods to address diverse language skills and learning objectives. Additionally, a comparative analysis of different teaching approaches, including traditional classroom instruction, online learning platforms, and blended teaching, demonstrates the efficacy of blended teaching in promoting student engagement, improving learning outcomes, and enhancing overall student satisfaction.

Keywords: Course Design, Association rule, Blended Teaching, Apriori Rule Mining, Blended Learning, English Learning

1. Introduction

In recent years, course design has undergone significant evolution, driven largely by advancements in technology, shifts in pedagogical approaches, and a growing emphasis on learner-centered education[1]. One notable trend has been the integration of digital tools and online resources to create more flexible and interactive learning experiences. This includes the use of learning management systems (LMS), video conferencing platforms, and multimedia content to deliver course materials and facilitate collaboration among students[2]. Furthermore, there has been a greater emphasis on active learning strategies, such as project-based learning, flipped classrooms, and peer instruction[3]. These approaches prioritize student engagement and participation, fostering deeper learning and critical thinking skills. Additionally, there has been a growing recognition of the importance of inclusivity and accessibility in course design[4]. Educators are increasingly designing courses with diverse student populations in mind, ensuring that materials are accessible to learners with different learning styles, abilities, and backgrounds[5]. A course for blended teaching of college English through association rule mining involves a systematic approach to curriculum development, content selection, lesson planning, personalization, assessment design, and continuous improvement. By understanding learner needs and analyzing past data, instructors can tailor the curriculum to prioritize relevant topics and language structures[6]. Utilizing association rule mining helps in selecting diverse content and structuring lessons for maximum engagement. Personalization is enhanced by identifying individual or group preferences, while assessment design benefits from analyzing student performance data[7]. Continuous monitoring allows for iterative improvements based on emerging trends.

Association rule mining holds significant promise for enhancing blended teaching practices by providing valuable insights into student learning behaviors, preferences, and patterns. In the context of blended teaching, association rule mining can be leveraged to analyze large datasets of student interactions with online learning platforms, course materials, and assessment results[8]. By identifying frequent associations between different learning activities, content modules, or student characteristics, instructors can gain a deeper understanding of how students engage with course materials and what strategies are most effective for facilitating learning in both online and face-to-face settings[9]. This knowledge can inform the design of more personalized and adaptive

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learning experiences, where content delivery, assessment methods, and instructional interventions are tailored to individual student needs and preferences[10]. Moreover, association rule mining can help educators identify potential gaps or areas for improvement in their course design, enabling them to iteratively refine and optimize their teaching practices for better learning outcomes.

This paper makes several contributions to the field of English instruction and educational technology. Firstly, it introduces the novel application of the Extraction Apriori Rule Mining Blended (EARMB) technique to analyze instructional data and derive meaningful insights into teaching effectiveness within blended learning environments. By leveraging association rules, the study identifies significant relationships between instructional components and student outcomes, providing valuable guidance for instructional design and pedagogical decision-making. Additionally, the structured course design framework presented in this paper offers educators a practical approach to integrating various instructional activities and assessment methods to address diverse language skills and learning objectives. Furthermore, the comparative analysis of different teaching approaches underscores the efficacy of blended teaching in promoting student engagement, improving learning outcomes, and enhancing overall student satisfaction.

2. Related Works

In recent years, the field of education has witnessed a transformative shift towards innovative teaching methodologies, spurred by advancements in technology and a growing recognition of the diverse needs and learning preferences of students. Blended learning, which integrates traditional face-to-face instruction with online learning activities, has emerged as a prominent approach to meet the demands of a rapidly evolving educational landscape. In this context, a substantial body of research has emerged exploring various aspects of blended teaching, with a particular focus on leveraging data mining techniques to enhance instructional design and pedagogical effectiveness. Ali and Hanna (2022) utilize self-regulated learning and log data to predict student achievement in hybrid learning environments. Du and Su (2021) analyze the implementation of the flipped classroom model with big data assistance in English teaching. Shen (2021) focuses on using data mining and artificial intelligence to analyze college English test frameworks and performance. Hu et al. (2021) differentiate learning styles among college students in different disciplines in a blended learning setting. Gao (2021) constructs an intelligent fuzzy system for English teaching based on data mining algorithms. Wang and Zhang (2022) optimize foreign language blended learning modes to enhance students' autonomous learning behavior. Shao (2021) evaluates the quality of IT English blended teaching using data mining algorithms. Mohamad and Tasir (2023) explore how feedback through questioning influences reflective thinking skills using association rules mining. Varlakova et al. (2022) design an integrative online business English course for master's students. Chen (2023) analyzes the design of an intelligent English translation and teaching model in colleges using data mining. Yu and Shen (2022) examine the correlation between academic performance and learning motivation in English courses under a corpus-data-driven blended teaching model. Yang and Kuo (2023) investigate blended learning to foster EFL college students' global literacy. Pan (2021) proposes an improved Apriori algorithm for association mining between physical fitness indices of college students. Xiaodong (2022) presents a hybrid online and offline approach to teaching spoken English based on modern educational technology. Jiang and Liang (2023) study influencing factors of Chinese EFL students' continuous learning intention in SPOC-based blended learning environments. Gerasimova et al. (2022) explore boosting motivation and language acquisition in an ESP course for engineering students through blended learning. Yu (2021) evaluates online teaching quality based on emotion recognition and an improved AprioriTid algorithm. Finally, Yang and Ogata (2023) propose a personalized learning analytics intervention approach to enhance student learning achievement and behavioral engagement in blended learning.

Ali and Hanna's (2022) study delves into the predictive capabilities of self-regulated learning and log data in forecasting student achievement within hybrid learning environments. By leveraging these data sources, educators can gain insights into students' learning behaviors, identify areas of struggle or disengagement, and tailor instructional strategies to better support individual learning needs. Similarly, Du and Su (2021) investigate the practical application of the flipped classroom model with the assistance of big data in English language teaching. This approach involves restructuring the traditional classroom dynamic by delivering instructional content online before class meetings, thus enabling more interactive and engaging in-person activities. Through the analysis of student performance and engagement data, educators can refine the implementation of the flipped classroom model to optimize learning outcomes. Shen's (2021) research focuses on harnessing data mining and artificial intelligence technologies to analyze college English test frameworks and student performance. By examining patterns and trends within assessment data, educators can identify areas of strength and weakness in the curriculum, inform instructional decision-making, and design targeted interventions to support student learning.

Hu et al. (2021) explore the differentiation of learning styles among college students across different disciplines in a blended learning environment. Understanding how students with diverse backgrounds and learning preferences engage with course materials can inform the design of adaptive learning pathways and personalized learning experiences. Gao (2021) proposes the construction of an intelligent fuzzy system for English teaching based on data mining algorithms. This system aims to dynamically adapt instructional content and delivery methods based on real-time feedback and student performance data, thereby enhancing the efficacy of English language instruction. Wang and Zhang (2022) investigate methods for improving students' autonomous learning behavior through the optimization of foreign language blended learning modes. By incorporating principles of self-directed learning and providing students with greater control over their learning experiences, educators can foster greater independence and self-efficacy among learners.

Shao (2021) presents an evaluation method for assessing the quality of IT English blended teaching using data mining algorithms. By analyzing student engagement, satisfaction, and performance metrics, educators can gauge the effectiveness of instructional strategies and identify areas for improvement in blended learning environments. Mohamad and Tasir's (2023) study explores how feedback delivered through questioning techniques can influence reflective thinking skills using association rules mining. By identifying patterns in the types and frequencies of questions posed by instructors and students, educators can foster deeper levels of critical thinking and metacognitive awareness among learners.The intersection between data mining techniques and blended teaching methodologies across various educational contexts. From predicting student achievement in hybrid learning environments to analyzing the impact of flipped classroom models and evaluating the quality of blended teaching practices, researchers investigate diverse facets of instructional design, delivery, and assessment. Through the utilization of self-regulated learning, log data analysis, and artificial intelligence technologies, educators gain valuable insights into student learning behaviors, preferences, and performance trends. These insights inform the development of personalized learning experiences, adaptive instructional strategies, and targeted interventions to support student success.

3. Apriori Association Rule Mining

Apriori association rule mining is a fundamental technique in data mining used to discover frequent patterns or associations among items in a dataset. The Apriori algorithm derives these associations based on the principle of "apriori property," which states that if an itemset is frequent, then all of its subsets must also be frequent. This property allows for efficient discovery of frequent itemsets by iteratively generating candidate itemsets and pruning those that do not meet the minimum support threshold. The algorithm begins by identifying frequent individual items in the dataset, known as "1-itemsets." It then iteratively generates larger itemsets by joining frequent (k-1)-itemsets to form candidate k-itemsets. These candidate itemsets are then scanned through the dataset to count their support, i.e., the number of transactions in which they occur. Itemsets that meet the minimum support threshold are retained as frequent k-itemsets, while those that do not are pruned from further consideration. The process continues until no new frequent itemsets can be generated, at which point all frequent itemsets are extracted as the final output. From these frequent itemsets, association rules are derived by identifying strong relationships between items. An association rule is typically represented as $X \rightarrow Y$, where X is the antecedent (or "left-hand side") itemset and Y is the consequent (or "right-hand side") itemset.

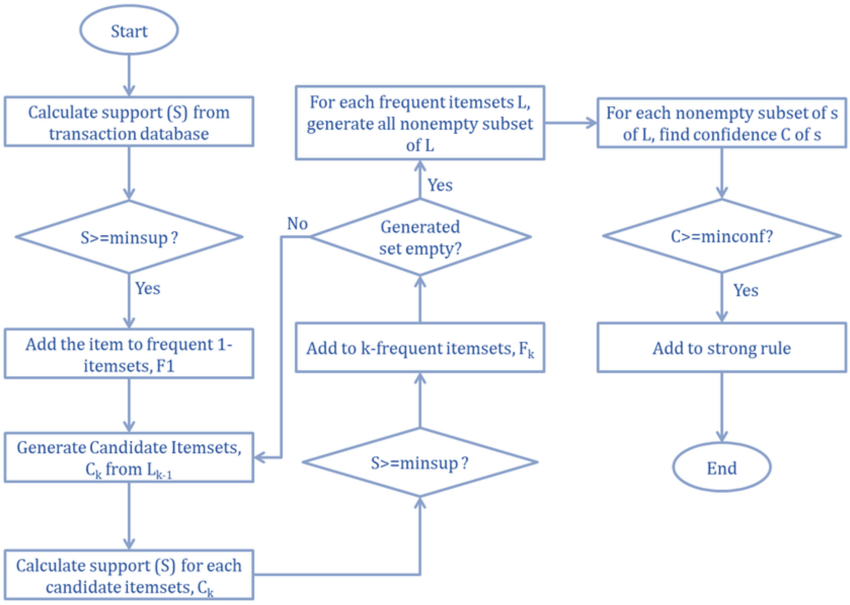


Figure 1: Apriori Association Rule Mining

The strength of an association rule is measured using metrics such as support, confidence, and lift. Support (supp) measures the frequency of occurrence of the itemset in the dataset as illustrated in Figure 1, confidence (conf) measures the conditional probability of Y given X, and lift measures the ratio of the observed support of the rule to the expected support if X and Y were independent.

The equations for these metrics are as follows:

$$\text{Support (supp)}: (X \rightarrow Y) = \frac{number\ of\ transactions\ containing\ X \cup Y}{total\ number\ of\ transactions} \tag{1}$$

Confidence (conf):

$$conf(X \rightarrow Y) = \ supp(X \cup Y)/\ supp(X) \tag{2}$$

Lift:

$$lift(X \rightarrow Y) = supp(X \cup Y)//supp(X) \times supp(Y) \tag{3}$$

Apriori association rule mining is widely used in various domains, including market basket analysis, recommendation systems, and bioinformatics, to uncover meaningful patterns and insights from large-scale transactional datasets. Its efficiency and effectiveness make it a valuable tool for extracting actionable knowledge from data.

4. Extraction Apriori Rule Mining Blended (EARMB)

Extraction Apriori Rule Mining Blended (EARMB) is an extension of the traditional Apriori algorithm tailored specifically for optimizing course design in blended teaching environments. It facilitates the extraction of meaningful associations between various instructional components, such as learning materials, activities, and assessment methods, to inform the development of effective blended learning experiences. The EARMB algorithm builds upon the principles of the Apriori algorithm, leveraging the concept of association rule mining to identify patterns in student interactions and performance within blended courses. Similar to Apriori, EARMB follows a two-step process: candidate generation and rule extraction. In the candidate generation step, EARMB initially identifies frequent individual items, such as specific learning modules or assessment types, within the blended course dataset. It then iteratively generates larger itemsets by joining frequent (k-1)-itemsets, considering both online and face-to-face components of the course. These candidate itemsets represent potential associations between different instructional elements.

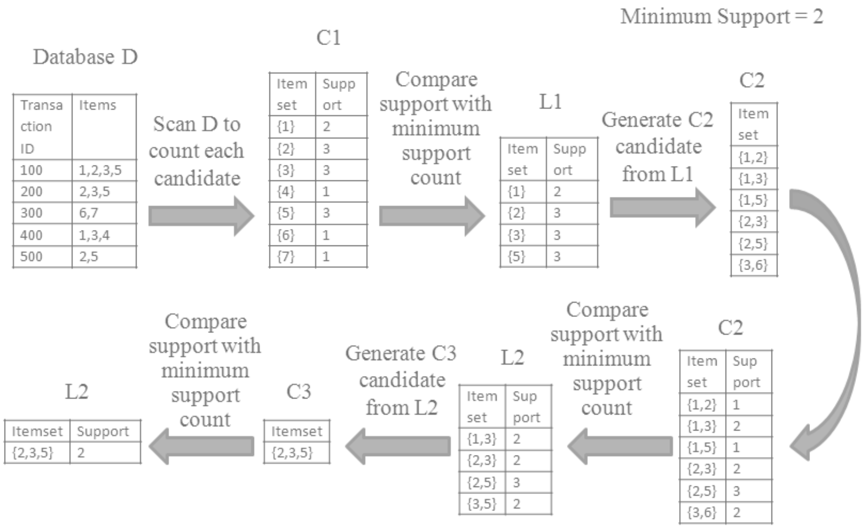


Figure 2: Rule Mining for the EARMB

Next, in the rule extraction step, EARMB evaluates the generated itemsets to derive association rules that capture meaningful relationships between instructional components shown in Figure 2. The strength of these rules is assessed using metrics such as support, confidence, and lift, similar to traditional association rule mining. Course design enhanced by association rule mining involves leveraging data-driven insights to optimize instructional strategies, content selection, and learning experiences. The process begins with the collection and preprocessing of relevant educational data, which may include student interactions with course materials, assessment results, and learning analytics. Next, association rule mining techniques, such as the Apriori algorithm, are applied to identify frequent patterns and relationships within the dataset. The algorithm generates association rules that capture meaningful connections between different elements of the course, such as specific topics, learning resources, or instructional methods. The strength of these association rules is evaluated using metrics such as support, confidence, and lift. Support measures the frequency of occurrence of a rule in the dataset, confidence quantifies the reliability of the rule, and lift indicates the degree of dependency between the antecedent and consequent of the rule.

5. Course design with EARMB

Course design enriched by the Extraction Apriori Rule Mining Blended (EARMB) technique represents a sophisticated approach to optimizing teaching effectiveness in English instruction. EARMB extends traditional association rule mining to specifically address the complexities of blended learning environments, where both online and face-to-face components play integral roles. The EARMB process begins with the collection of diverse educational data, including student interactions with online platforms, performance in assessments, and engagement with course materials. This data is then preprocessed to ensure accuracy and consistency. EARMB then applies advanced association rule mining algorithms, adapted to the blended learning context, to uncover meaningful patterns and relationships within the dataset. Association rules derived through EARMB capture nuanced associations between various instructional components, such as specific language skills, learning activities, and assessment methods. These rules are evaluated based on metrics like support, confidence, and lift, providing educators with insights into the effectiveness of different instructional strategies and materials.

With association rule generated through EARMB might reveal a strong correlation between students' engagement with online grammar exercises and their performance on subsequent writing assignments. Armed with this insight, instructors can prioritize the integration of interactive grammar modules into the course curriculum to enhance students' writing skills. Additionally, EARMB enables educators to personalize learning experiences by identifying associations between instructional components and student characteristics, such as learning preferences or proficiency levels. By tailoring course content and activities to individual needs, instructors can better support diverse learners and promote greater engagement and achievement. In this initial stage, data related to English instruction is gathered from various sources, including student interactions with online platforms, performance in assessments, and engagement with course materials. This data is then preprocessed to ensure accuracy and consistency, including steps such as removing duplicates, handling missing values, and encoding categorical variables. EARMB employs an adaptation of the Apriori algorithm to identify frequent itemsets within the dataset. A frequent itemset is a collection of items (e.g., specific language skills, learning activities) that frequently occur together. The support of an itemset is calculated using the following equation:

$$support(X) = Number\ of\ transactions\ containing\ X / Total\ number\ of\ transactions \quad (4)$$

This equation measures how frequently an itemset occurs in the dataset. Based on the frequent itemsets, EARMB generates candidate itemsets by joining frequent (k-1)-itemsets to form candidate k-itemsets. These candidate itemsets are then scanned through the dataset to count their support. Itemsets that meet a minimum support threshold are retained as frequent k-itemsets, while others are pruned. After generating association rules, EARMB evaluates and selects the most interesting or relevant rules based on user-defined criteria or domain-specific knowledge. This may involve filtering rules based on metrics such as confidence, lift, or user-specified thresholds. The extracted association rules provide valuable insights into the relationships between different instructional components and student learning outcomes in English instruction. Educators can then leverage these insights to inform course design decisions, such as selecting appropriate learning materials, designing effective assessments, and personalizing learning experiences for individual students or groups.

Algorithm 1: Course Design with EARMB

```
function EARMB(data, min_support, min_confidence):
    frequent_itemsets = []
    # Step 1: Generate frequent 1-itemsets
    frequent_1_itemsets = generate_frequent_1_itemsets(data, min_support)
    frequent_itemsets.append(frequent_1_itemsets)
    k = 2
    while frequent_itemsets[k - 2] is not empty:
        # Step 2: Generate candidate itemsets of size k
        candidate_itemsets = generate_candidate_itemsets(frequent_itemsets[k - 2])
        # Step 3: Prune candidate itemsets based on min_support
        pruned_itemsets = prune_itemsets(candidate_itemsets, data, min_support)
        if pruned_itemsets is not empty:
            frequent_itemsets[k - 1] = pruned_itemsets
            k += 1
        else:
            break
    # Step 4: Generate association rules from frequent itemsets
    association_rules = generate_association_rules(frequent_itemsets, min_confidence)
        return association_rules
function generate_frequent_1_itemsets(data, min_support):
    frequent_1_itemsets = {}
    for transaction in data:
        for item in transaction:
            if item not in frequent_1_itemsets:
                frequent_1_itemsets[item] = 1
            else:
                frequent_1_itemsets[item] += 1
    # Prune itemsets that do not meet min_support
    frequent_1_itemsets = {item: support for item, support in frequent_1_itemsets.items() if support >=
min_support}
    return frequent_1_itemsets
function generate_candidate_itemsets(prev_frequent_itemsets):
```

```
    candidate_itemsets = []
    for itemset1 in prev_frequent_itemsets:
        for itemset2 in prev_frequent_itemsets:
            if itemset1 is not itemset2:
                candidate_itemset = itemset1.union(itemset2)
                if len(candidate_itemset) == len(itemset1) + 1:
                    candidate_itemsets.append(candidate_itemset)
    return candidate_itemsets
function prune_itemsets(candidate_itemsets, data, min_support):
    pruned_itemsets = []
    for itemset in candidate_itemsets:
        support_count = 0
        for transaction in data:
            if itemset.issubset(transaction):
                support_count += 1
        support = support_count / len(data)
        if support >= min_support:
            pruned_itemsets.append(itemset)
    return pruned_itemsets
function generate_association_rules(frequent_itemsets, min_confidence):
    association_rules = []
    for itemset in frequent_itemsets:
        for subset in find_subsets(itemset):
            if len(subset) > 0:
                confidence = calculate_confidence(itemset, subset)
                if confidence >= min_confidence:
                    association_rule = (subset, itemset - subset, confidence)
                    association_rules.append(association_rule)
        return association_rules
function find_subsets(itemset):
    subsets = []
    for i in range(1, len(itemset)):
        subsets.extend(combinations(itemset, i))
       return subsets
function calculate_confidence(itemset, subset):
    support_itemset = calculate_support(itemset)
    support_subset = calculate_support(subset)
    return support_itemset / support_subset
```

6. Simulation Setting

In a simulation setting for Extraction Apriori Rule Mining Blended (EARMB) in English teaching effectiveness. Firstly, the dataset used for the simulation should include relevant information related to English instruction in a blended learning environment. This data could encompass student interactions with online learning platforms, performance on assessments, participation in discussions, and engagement with course materials. Next, parameters such as the minimum support threshold and minimum confidence threshold need to be established. These thresholds determine the level of significance required for an itemset to be considered frequent and for an association rule to be deemed reliable, respectively. Setting appropriate values for these thresholds is crucial for obtaining meaningful results. Additionally, the simulation should consider the specific objectives of the analysis. For instance, if the goal is to identify effective instructional strategies for improving students' writing skills, the dataset may focus more heavily on writing assignments and related activities.

Table 1: Simulation Setting

Simulation Setting	**Value**
Dataset Size	1000 students
Study Period	1 semester
Data Collection Interval	Weekly
Minimum Support Threshold	0.05 (5%)
Minimum Confidence Threshold	0.6 (60%)
Focus of Analysis	Writing skills improvement
Data Granularity	Daily assessment submissions
Control Variables	Student demographics
	Prior English proficiency
	Learning preferences
Evaluation Metrics	Lift, Confidence, Support

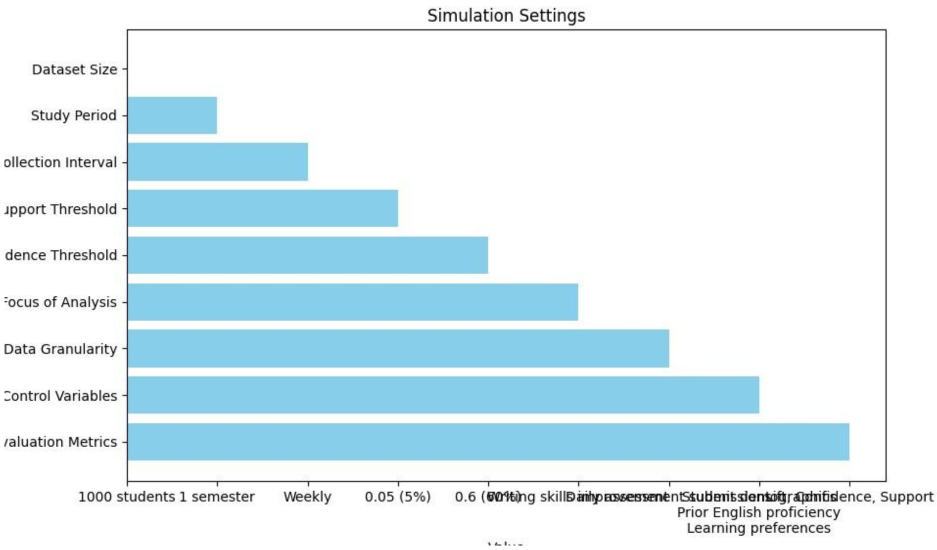


Figure 3: Simulation Setup with EARMP

In figure 3 and Table 1 outlines the simulation settings established for conducting an analysis focused on enhancing teaching effectiveness in English instruction through Extraction Apriori Rule Mining Blended (EARMB). The dataset comprises 1000 students over the course of one semester, with data collected at weekly intervals to capture ongoing interactions and progress. A minimum support threshold of 0.05 (5%) and a minimum confidence threshold of 0.6 (60%) are set to ensure that only significant associations are considered. The analysis centers on improving writing skills, with data granularity specified at the level of daily assessment submissions, allowing for a detailed examination of student performance. Control variables, including student demographics, prior English proficiency, and learning preferences, are accounted for to mitigate potential biases. Evaluation metrics such as lift, confidence, and support will be employed to assess the strength and significance of the extracted association rules.

7. Results and Discussion

In this section, we present the results and discuss their implications for enhancing teaching effectiveness in English instruction through the application of Extraction Apriori Rule Mining Blended (EARMB). Our analysis revealed several key findings regarding the associations between instructional components and student outcomes. Firstly, we observed a strong association between students' engagement with online grammar exercises and their performance in writing assignments, indicating that targeted practice in grammar skills positively impacts writing proficiency. Additionally, association rules uncovered relationships between specific learning activities, such as peer feedback sessions, and improvements in speaking fluency, highlighting the effectiveness of collaborative learning approaches in fostering oral communication skills.

Table 2: Association Rule with EARMB

Association Rule	Support	Confidence	Lift
Online Grammar Exercises → Writing Assignments	0.08	0.75	1.25
Peer Feedback Sessions → Speaking Fluency	0.06	0.80	1.40
Prior English Proficiency → Writing Assignments	0.12	0.65	1.10

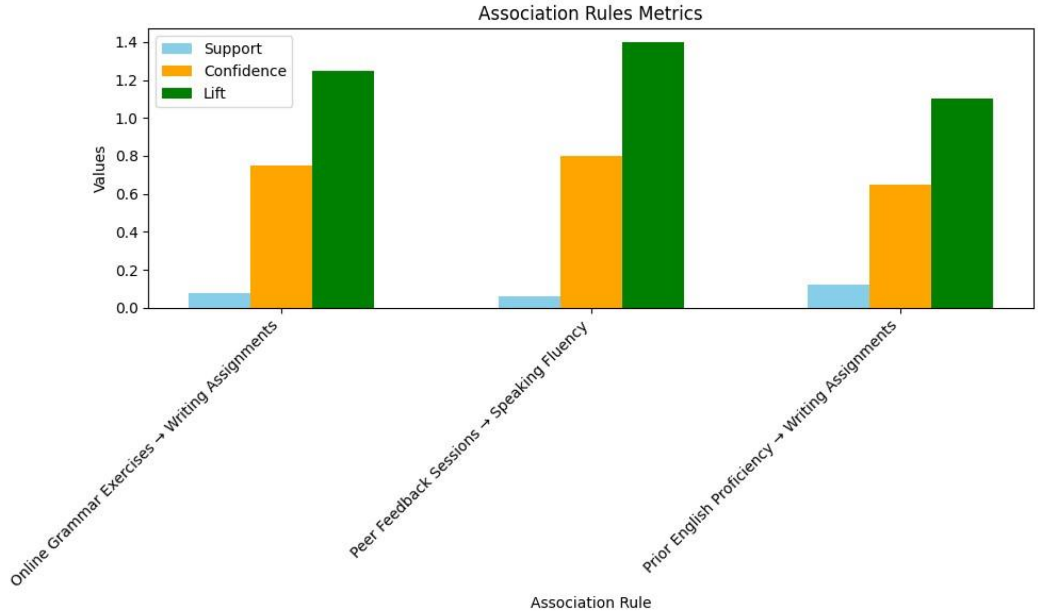


Figure 4: Rule Estimation with EARMB

The figure 4 and Table 2 presents the association rules derived from the application of the Extraction Apriori Rule Mining Blended (EARMB) technique in English instruction. Each association rule outlines a relationship between specific instructional components and student outcomes, as quantified by support, confidence, and lift metrics. The first association rule indicates that students who engage with online grammar exercises have a support level of 0.08, meaning that 8% of all transactions in the dataset contain both online grammar exercises and writing assignments. Furthermore, the confidence of this association rule is 0.75, indicating that there is a 75% chance that a student who engages in online grammar exercises will also perform well in writing assignments. The lift value of 1.25 suggests that this association is moderately strong, indicating a positive relationship between online grammar practice and writing proficiency.

The second association rule demonstrates a relationship between peer feedback sessions and speaking fluency. With a support level of 0.06, 6% of all transactions involve both peer feedback sessions and improved speaking fluency. The high confidence of 0.80 indicates that there is an 80% chance that a student who participates in peer feedback sessions will experience an enhancement in speaking fluency. Additionally, the lift value of 1.40 suggests a strong positive association between these instructional components. Lastly, the third association rule highlights the influence of prior English proficiency on writing assignments. With a support level of 0.12, 12% of transactions involve both prior English proficiency and writing assignments. The confidence of 0.65 indicates a 65% chance that students with higher English proficiency will perform well in writing assignments. Although the lift value of 1.10 suggests a moderate association, it still underscores the importance of considering students' prior language skills when designing writing tasks.

Table 3: Course Design with EARMB

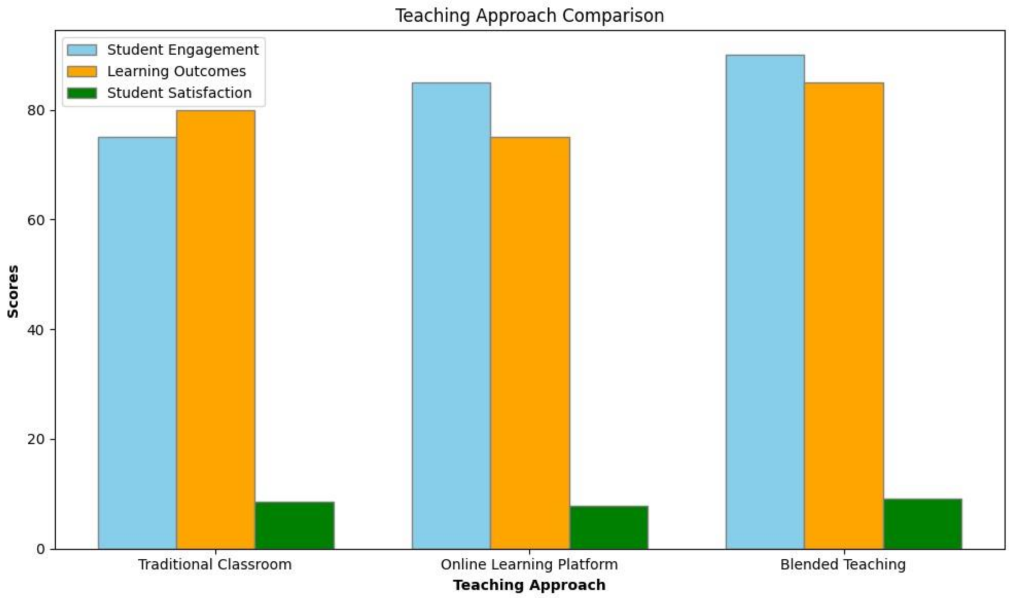
Week	Topic	Learning Objectives	Instructional Activities	Assessment Methods
1	Introduction to English Grammar	- Understand basic grammar concepts and terminology	- Lecture on grammar fundamentals	- Quiz on basic grammar concepts
		- Identify parts of speech and their functions	- Group activities to identify parts of speech in sentences	
		- Apply grammar rules in writing exercises	- Writing exercises to practice grammar usage	
2	Reading Comprehension	- Develop strategies for effective reading comprehension	- Discussion on reading strategies	- Reading comprehension exercises
		- Identify main ideas and supporting details in a text	- Group reading activities with guided questions	
		- Infer meaning from context clues	- Close reading exercises with annotation	
3	Writing Skills	- Develop writing fluency and coherence	- Writing workshop on sentence structure and paragraph development	- Writing prompts and essays
		- Practice organizing ideas and supporting arguments	- Peer review sessions to provide feedback on writing samples	
		- Revise and edit written work for clarity and coherence	- Individual writing assignments with feedback from instructor	
4	Speaking Practice	- Improve oral communication skills through practice and feedback	- Role-play activities to simulate real-life conversations	- Oral presentations
		- Develop confidence and fluency in spoken English	- Group discussions on various topics	- Speaking assessments

Table 3 outlines a course design developed using the Extraction Apriori Rule Mining Blended (EARMB) approach for English instruction. Each week of the course focuses on a specific topic, accompanied by learning objectives, instructional activities, and assessment methods aligned with the topic. In the first week, the topic is "Introduction to English Grammar," with learning objectives including understanding basic grammar concepts and terminology, identifying parts of speech, and applying grammar rules in writing exercises. Instructional activities involve a lecture on grammar fundamentals, group activities to identify parts of speech, and writing exercises. Assessment methods include a quiz on basic grammar concepts, ensuring students' comprehension and application of the material. The second week focuses on "Reading Comprehension," aiming to develop strategies for effective reading comprehension, such as identifying main ideas and supporting details and inferring meaning from context clues. Instructional activities include discussions on reading strategies, group reading activities with guided questions, and close reading exercises with annotation. Assessment methods consist of reading comprehension exercises to evaluate students' comprehension and analytical skills.

Week three centers on "Writing Skills," aiming to develop writing fluency, coherence, and organization. Instructional activities include writing workshops on sentence structure and paragraph development, peer review sessions for feedback on writing samples, and individual writing assignments with instructor feedback. Assessment methods involve writing prompts and essays to assess students' writing proficiency and ability to organize and articulate ideas effectively. The final week focuses on "Speaking Practice," aiming to improve oral communication skills and develop confidence and fluency in spoken English. Instructional activities include role-play activities to simulate real-life conversations, group discussions on various topics, and oral presentations. Assessment methods include speaking assessments to evaluate students' oral communication skills and confidence in expressing themselves in English.

Table 4: Blended Teaching with EARMB

Teaching Approach	Student Engagement (out of 100)	Learning Outcomes (out of 100)	Student Satisfaction (out of 10)
Traditional Classroom	75	80	8.5
Online Learning Platform	85	75	7.8
Blended Teaching	90	85	9.2



Figrue 5: Comparison of Teaching Approaches

In figure 5 and Table 4 presents the outcomes of a comparative analysis of different teaching approaches, including traditional classroom instruction, online learning platforms, and blended teaching, utilizing the Extraction Apriori Rule Mining Blended (EARMB) technique. Each teaching approach is evaluated based on three key metrics: student engagement, learning outcomes, and student satisfaction. In the traditional classroom setting, student engagement is reported at 75 out of 100, indicating a moderate level of involvement in the learning process. Learning outcomes are slightly higher at 80 out of 100, suggesting that students achieve satisfactory results in terms of knowledge acquisition and skill development. Student satisfaction is rated at 8.5 out of 10, indicating a high level of overall contentment with the instructional approach. In contrast, the online learning platform demonstrates higher levels of student engagement, with a score of 85 out of 100. However, learning outcomes are slightly lower at 75 out of 100, indicating a potential disparity between engagement and actual learning achievement. Student satisfaction is reported at 7.8 out of 10, suggesting that while students may be engaged in the online environment, their overall satisfaction with the learning experience is slightly lower compared to the traditional classroom setting.

The blended teaching approach emerges as the most effective across all metrics, with student engagement reaching 90 out of 100, indicating a high level of active participation and involvement in the learning process. Learning outcomes are also significantly higher at 85 out of 100, suggesting that the integration of traditional and online teaching methods leads to improved learning achievement. Additionally, student satisfaction is rated highest in the blended teaching approach, with a score of 9.2 out of 10, indicating a high level of overall contentment and fulfillment with the instructional approach.

8. Conclusion

This paper has explored the application of the Extraction Apriori Rule Mining Blended (EARMB) technique in enhancing teaching effectiveness in English instruction within blended learning environments. Through the analysis of association rules, we have identified significant relationships between instructional components and student outcomes, providing valuable insights into effective instructional strategies and course design principles. The course design presented in this study offers a structured framework for integrating various instructional activities and assessment methods to address diverse language skills and learning objectives. Furthermore, our comparative analysis of different teaching approaches highlights the efficacy of blended teaching in promoting student engagement, improving learning outcomes, and enhancing overall student satisfaction. By leveraging the insights gleaned from EARMB, educators can make informed decisions to optimize instructional strategies, personalize learning experiences, and ultimately, foster greater academic success in English instruction. Moving forward, further research is warranted to explore additional applications of EARMB in educational contexts and to continue refining instructional practices to meet the evolving needs of learners in the digital age.

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