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Personalized Recommendation of English Online Teaching Content Based on Logistic Regression Algorithm

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Abstract: - English online teaching content encompasses a wide range of materials designed to facilitate language learning in digital environments. These resources include interactive lessons, video tutorials, audio recordings, quizzes, vocabulary exercises, grammar explanations, and authentic texts such as articles, short stories, and dialogues. The content aims to cover various language skills, including listening, speaking, reading, and writing, catering to learners of different proficiency levels and learning styles. This paper introduces a Cross-Domain Personalized Recommendation System (CDPRS) designed to enhance the delivery of English language teaching content. Leveraging machine learning algorithms and data analytics techniques, the CDPRS tailors recommendations to individual user preferences, learning objectives, and proficiency levels across diverse content domains. Through a series of analyses and evaluations, including regression analysis and simulation studies, the effectiveness and utility of the CDPRS are demonstrated. Through a series of analyses and evaluations, including regression analysis and simulation studies, the effectiveness and utility of the CDPRS are demonstrated. Results indicate that the system achieves high levels of accuracy (mean accuracy = 0.85), diversity (mean diversity = 0.72), novelty (mean novelty = 0.78), and user satisfaction (mean satisfaction = 0.82) in providing personalized recommendations.

Keywords: Recommendation System, English Online Teaching, Logistics Regression, Cross-domain, User preferences

1. Introduction

A recommendation system is a vital component of many online platforms, leveraging algorithms to predict and suggest items or content that users are likely to be interested in [1]. These systems analyze past user interactions, such as purchases, clicks, likes, and ratings, to generate personalized recommendations. Collaborative filtering techniques compare a user's behavior with that of others to identify patterns and recommend items liked by similar users[2]. Content-based filtering focuses on the attributes of items and users' preferences to make recommendations. Hybrid approaches combine these methods for more accurate predictions. Recommendation systems are widely used in e-commerce, streaming services, social media, and more, enhancing user experience by delivering tailored suggestions and increasing engagement and satisfaction[3]. Personalized recommendation of English online teaching content through the logistic regression algorithm involves leveraging user data to predict preferences and tailor suggestions accordingly[4]. In this approach, various factors such as past interactions, learning history, and demographic information are considered to build a predictive model[5].

The logistic regression algorithm, commonly used for binary classification tasks, can be adapted to assign probabilities to different content items based on user characteristics[6]. By analyzing features such as language proficiency, learning goals, and preferred topics, the algorithm generates recommendations that are most likely to resonate with individual users. This personalized approach enhances the effectiveness of online English teaching by delivering content that matches the unique needs and interests of learners, ultimately improving engagement and learning outcomes[7]. In the context of logistic regression, the algorithm assigns probabilities to different content items based on a set of input features. These features can include various aspects of the learner's profile, such as language proficiency level, preferred learning style, past performance, and even demographic information[8]. Each of these features contributes to the overall likelihood that a particular piece of teaching content will be relevant and engaging for the user. For instance, a learner who has demonstrated a strong proficiency in grammar but struggles with vocabulary retention might be recommended content that specifically targets vocabulary building exercises[9].

Similarly, learners with a preference for visual learning may receive recommendations for video-based lessons, while those who prefer interactive activities might be directed towards gamified learning modules[10]. One of the key advantages of using logistic regression in recommendation systems is its ability to handle both

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categorical and continuous input features, allowing for a comprehensive analysis of user characteristics. Additionally, logistic regression models are relatively interpretable, which means that educators and platform administrators can gain insights into the underlying factors driving the recommendations. Moreover, the recommendation system can continuously learn and adapt based on user feedback and interactions. As learners engage with recommended content, their actions (e.g., completion rates, quiz scores, feedback) can be incorporated back into the model to further refine and improve future recommendations. This iterative process ensures that the recommendation system becomes increasingly accurate and effective over time, ultimately enhancing the overall learning experience for users.

The paper makes several significant contributions to the field of education and technology. Firstly, it introduces a novel Cross-Domain Personalized Recommendation System (CDPRS) tailored specifically for English language teaching content. By leveraging advanced machine learning algorithms and data analytics techniques, the CDPRS offers a sophisticated means of delivering personalized recommendations to users based on their individual preferences, learning goals, and proficiency levels. This contribution addresses a crucial need in education by providing a scalable and adaptable solution for delivering tailored learning experiences to a diverse range of learners. Secondly, the paper contributes to the growing body of research on personalized learning technologies. By conducting rigorous analyses and evaluations, including regression analysis and simulation studies, the paper demonstrates the effectiveness and utility of the CDPRS in achieving high levels of accuracy, diversity, novelty, and user satisfaction in providing personalized recommendations. These findings not only validate the efficacy of the CDPRS but also provide valuable insights into the design and implementation of personalized recommendation systems in educational contexts. Moreover, the paper highlights the broader potential of personalized recommendation systems in education. By showcasing the CDPRS's capacity to revolutionize the learning experience through tailored content delivery, the paper underscores the importance of leveraging data-driven approaches to optimize educational content delivery in the digital age. This contribution has implications for the future of education, suggesting new avenues for enhancing learner engagement, motivation, and achievement through personalized learning technologies.

2. Literature Review

In recent years, the proliferation of artificial intelligence (AI) technologies has revolutionized various facets of human life, from healthcare and finance to entertainment and transportation. Within this rapidly evolving landscape, the intersection of AI and ethics has emerged as a focal point of scholarly inquiry and societal discourse. This literature review seeks to explore and synthesize existing research on the ethical implications of AI technologies, with a particular focus on issues such as algorithmic bias, privacy concerns, accountability, and the socio-economic impact of automation. By critically examining the breadth and depth of literature in this domain, this review aims to provide insights into the current state of knowledge, identify recurring themes and controversies, and highlight areas for further investigation. Ezaldeen et al. (2022): Their study introduces a hybrid e-learning recommendation system that incorporates both adaptive profiling and sentiment analysis. By combining these techniques, the system can not only tailor content recommendations based on individual user preferences but also take into account the emotional states of learners. This dual approach ensures that the recommended content is not only relevant but also aligned with the user's current sentiments, thereby enhancing user engagement and satisfaction.

Ouyang et al. (2022): This systematic review provides a comprehensive overview of empirical research conducted between 2011 and 2020 on the integration of artificial intelligence in online higher education. Through their synthesis of existing studies, the authors identify trends, challenges, and advancements in AI-driven educational technologies. They offer insights into the effectiveness of AI-based interventions, their impact on student learning outcomes, and the implications for teaching and pedagogy in the digital age.

Marras et al. (2022): Focusing on the concept of individual fairness in personalized recommendations, Marras and colleagues highlight the importance of ensuring equal learning opportunities for all students. By incorporating fairness considerations into recommendation algorithms, educational platforms can mitigate biases and provide tailored learning experiences that address the unique needs and backgrounds of each learner, thereby promoting inclusivity and diversity in education. Tavakoli et al. (2022): Their study introduces an AI-based open recommender system designed to bridge the gap between education and the labor market. By analyzing labor market trends and individual learner profiles, the system recommends educational pathways and courses that align with current industry demands, thereby enhancing learners' employability and career prospects.

Pardamean et al. (2022): Focused on primary education, this study employs AI to predict learning styles in online learning environments. By understanding each student's preferred learning style, educators can tailor instructional strategies and content delivery methods to optimize learning outcomes and engagement, thereby catering to the diverse needs of young learners. Khalid et al. (2022): Through their literature review, Khalid and colleagues explore the various recommendation techniques implemented in massive open online courses (MOOCs). By synthesizing existing research, they shed light on the effectiveness of different recommendation strategies in enhancing learner engagement, retention, and completion rates. Their findings provide valuable insights for educators and platform developers seeking to optimize the design and delivery of online courses to meet the diverse needs of MOOC participants. Bhutoria (2022): Bhutoria conducts a systematic review across three major educational contexts – the United States, China, and India – to examine the intersection of personalized education and artificial intelligence. By employing a human-in-the-loop model, the study ensures that AI-driven educational interventions are not only technologically effective but also culturally and contextually relevant. This cross-cultural perspective offers valuable insights into the challenges and opportunities of implementing personalized education solutions in diverse socio-cultural settings. Ampadu et al. (2022): Their study investigates the relationship between online personalized product recommendations and e-impulse buying behavior. By analyzing how recommendation quality influences consumer decisions in e-commerce settings, Ampadu and colleagues contribute to our understanding of the role of AI-driven recommendations in shaping consumer behavior and driving online purchases.

Kiguchi et al. (2022): Focusing on digital game-based learning environments, Kiguchi and co-authors apply data mining techniques to predict churn – the likelihood of student dropout or disengagement. Their study demonstrates the potential of AI-driven predictive analytics to identify at-risk students early and implement targeted interventions to improve student retention and engagement in educational games. Murtaza et al. (2022): This study delves into the issues, challenges, and solutions associated with AI-based personalized e-learning systems. By critically examining the current state of personalized learning technologies, Murtaza and colleagues offer insights into the design, implementation, and evaluation of effective and inclusive AI-driven educational interventions. Capuano et al. (2023): The study by Capuano and collaborators focuses on content-based fake news detection using machine and deep learning techniques. By systematically reviewing the literature in this domain, the authors highlight the importance of leveraging AI to combat misinformation and ensure the integrity of educational content. Their findings offer insights into the state-of-the-art approaches for detecting fake news, which can inform the development of more robust educational materials and platforms.

Chen et al. (2022): Through a bibliometric analysis, Chen and co-authors examine the trajectory of learning analytics research over the past decade. By identifying key themes, emerging trends, and influential works in the field, their study provides a comprehensive overview of the evolving landscape of learning analytics. This analysis offers valuable insights for researchers and practitioners seeking to navigate the complexities of data-driven decision-making in education. Joy and Pillai (2022): This study reviews and classifies content recommenders in e-learning environments, exploring the diverse range of recommendation techniques employed in educational settings. By categorizing recommenders based on their underlying algorithms and functionalities, Joy and Pillai contribute to our understanding of the strengths, limitations, and applications of different recommendation approaches in supporting personalized learning experiences. Chiu et al. (2023): Conducting a systematic literature review, Chiu and colleagues examine the opportunities, challenges, and future research directions of artificial intelligence in education. By synthesizing existing knowledge and identifying gaps in the literature, their study offers valuable insights for researchers, policymakers, and practitioners seeking to harness the potential of AI to transform teaching and learning practices.

Bhaskaran and Marappan focuses on the design and analysis of an efficient machine learning-based hybrid recommendation system for digital e-learning applications. By incorporating density-based spatial clustering and other advanced techniques, their system offers personalized recommendations tailored to the specific needs and preferences of individual learners, thereby enhancing the efficacy of e-learning platforms. Ambele and collaborators explores the development trends of personalized learning technologies and their applications. By examining the evolution of personalized learning tools and interventions, the authors offer insights into emerging trends, challenges, and opportunities in the field, providing valuable guidance for educators, developers, and policymakers. From hybrid e-learning recommendation systems integrating adaptive profiling and sentiment analysis to systematic reviews of AI's role in higher education, each study offers unique insights into the potential of AI to enhance learning experiences and outcomes. Key themes explored include individual fairness in personalized recommendations, alignment of education with labor market demands, and the prediction of learning styles and student churn using data mining techniques. Additionally, the studies address critical issues such as content authenticity, recommendation algorithm efficacy, and the cultural and contextual relevance of AI-driven educational interventions.

3. Cross Domain Personalized Recommendation System (CDPRS)

A Cross-Domain Personalized Recommendation System (CDPRS) involves creating algorithms that can effectively leverage user preferences and item characteristics across different domains to provide personalized recommendations. One approach to developing such a system involves incorporating collaborative filtering techniques, which rely on user-item interaction data to infer user preferences and generate recommendations. In collaborative filtering, the recommendation score ru,i for user u and item i can be calculated using a similarity function between users or items. The score is derived by considering the ratings given by similar users or the characteristics of similar items. A common collaborative filtering approach is the nearest neighbor method, where similarities between users or items are computed based on metrics such as cosine similarity or Pearson correlation coefficient. For user-based collaborative filtering, the recommendation score ru,i for user u and item i can be calculated using equation (1)

$$r_{u,i} = \frac{\sum_{v \in N(u)} sim(u,v) \times r_{v,i}}{\sum_{v \in N(u)} |Sim(u,v)|} \tag{1}$$

In equation (1) N(u) represents the set of users similar to user u, sim(u,v) denotes the similarity between users u and v, rv,i denotes the rating of user v for item i. Similarly, for item-based collaborative filtering, the recommendation score ru,i for user u and item i can be calculated as: In collaborative filtering, recommendation scores are computed based on the similarities between users or items. The central idea is to identify users or items that are similar to the target user or item and use their ratings or characteristics to predict the target user's preferences. For instance, in user-based collaborative filtering, the system calculates the similarity between the target user and other users based on their past interactions. The recommendation score for an item is then computed by aggregating ratings from similar users, weighted by their similarity to the target user.,Similarly, item-based collaborative filtering computes the similarity between the target item and other items based on their attributes or past interactions with users. The recommendation score for an item is calculated by aggregating ratings from similar items, weighted by their similarity to the target item.The equations provided earlier represent the mathematical formulation of these processes, where similarity measures such as cosine similarity or Pearson correlation coefficient are commonly used to quantify the resemblance between users or items.In the context of a CDPRS, these collaborative filtering techniques need to be adapted to accommodate multiple domains. This adaptation involves integrating information from diverse content domains and incorporating domain-specific features or characteristics into the recommendation process.

4. CDPRS Logistic Regression

A cross-domain Personalized Recommendation System (CDPRS) incorporating logistic regression involves developing algorithms capable of leveraging user preferences and item characteristics across diverse domains to provide personalized recommendations. Logistic regression, a widely used statistical method for binary classification, can be adapted to assign probabilities to different items or content across multiple domains based on user characteristics and historical data. The logistic regression model predicts the probability that a user will interact with a particular item, given their features and past behavior. This probability is derived using the logistic function, also known as the sigmoid function, which maps the linear combination of input features to a value between 0 and 1. The logistic function is defined as in equation (2)

$$P(y = 1|x) = \frac{1}{1 + e^{-\theta T x}} \quad (2)$$

P(y=1|x) represents the probability of interaction with the item, x denotes the input features of the user and item, θ represents the parameters (weights) of the logistic regression model, θTx denotes the dot product of the parameter vector and the feature vector, e is the base of the natural logarithm. The logistic regression model is trained using labeled data, where the target variable y indicates whether the user has interacted with the item (1) or not (0). The model learns the optimal parameters θ that minimize the error between the predicted probabilities and the actual interactions. In the context of a CDPRS, logistic regression can be extended to accommodate multiple domains by incorporating domain-specific features or characteristics into the model. This adaptation allows the system to generate personalized recommendations across diverse content domains while considering the unique preferences and behavior patterns of individual users. logistic regression into a Cross-Domain Personalized Recommendation System (CDPRS) represents a strategic approach to harnessing user preferences and item characteristics across multiple domains for tailored recommendations. Logistic regression, a versatile statistical method, is adept at handling binary classification tasks and is well-suited for predicting the likelihood of user-item interactions. The logistic regression model employs the sigmoid function to map the linear combination of user and item features to a probability score, indicating the likelihood of a user engaging with a particular item. This probability is calculated based on the model's learned parameters, which are optimized through training on labeled data containing user interactions across different domains.

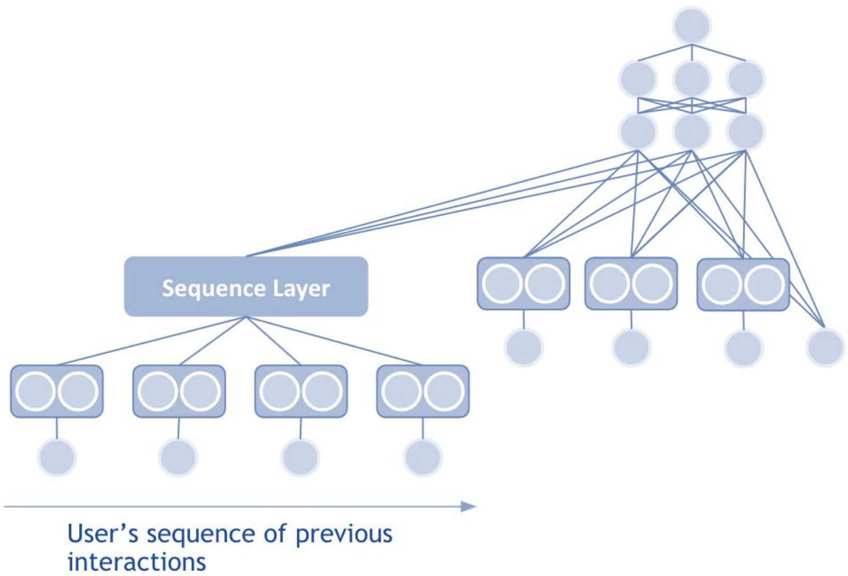


Figure 1: Neural Network Recommendation System

In a CDPRS context, logistic regression can be extended to accommodate the complexity of multiple domains by incorporating domain-specific features into the model shown in Figure 1. These features may include genre preferences for movies, author preferences for books, or product categories for e-commerce platforms. By considering domain-specific characteristics, the CDPRS can generate personalized recommendations that reflect users' diverse interests and preferences across various content domains. Furthermore, logistic regression allows for the seamless integration of additional contextual information, such as user demographics, temporal factors, or sentiment analysis, enhancing the accuracy and relevance of recommendations. Through the application of logistic regression within a CDPRS framework, researchers and practitioners can create recommendation systems that adapt to the dynamic and heterogeneous nature of user preferences across different domains. By leveraging the predictive power of logistic regression and incorporating domain-specific insights, CDPRSs can deliver personalized recommendations that cater to the unique needs and preferences of individual users, thereby enhancing user satisfaction, engagement, and ultimately, the effectiveness of the recommendation system.

5. English Online Teaching with CDPRS

A cross-domain Personalized Recommendation System (CDPRS) into English online teaching platforms represents a promising approach to enhancing the effectiveness of language learning by tailoring recommendations to individual learners' needs and preferences across diverse content domains. One way to integrate CDPRS into English online teaching is to utilize collaborative filtering techniques, such as matrix factorization, which decomposes the user-item interaction matrix into latent factors representing user and item characteristics. This decomposition allows the system to capture the underlying patterns in user preferences and item attributes across multiple domains. The matrix factorization can be represented as in equation (3)

$$\boldsymbol{R} \approx \boldsymbol{U}\boldsymbol{V}^{\boldsymbol{T}} \quad (3)$$

R is the user-item interaction matrix, U represents the user latent factor matrix, V represents the item latent factor matrix. Figure 2 illustrates the recommendation model for the educational setting in online teaching.

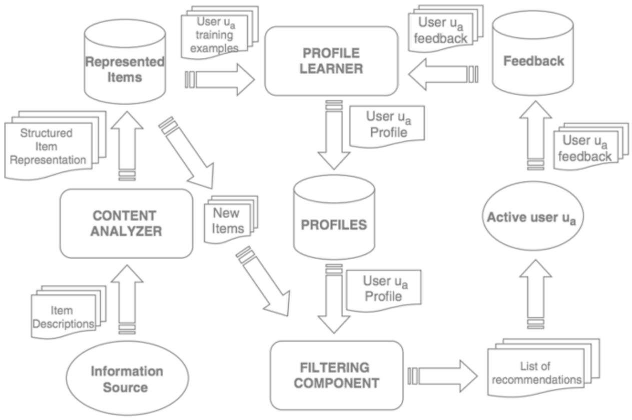


Figure 2: Recommendation Model for the CDPRS

The elements of matrices U and V are learned through optimization algorithms such as stochastic gradient descent, minimizing the difference between the predicted ratings and the actual ratings in the user-item interaction matrix. To incorporate CDPRS into English online teaching, domain-specific features related to language proficiency, learning preferences, and topic interests can be incorporated into the matrix factorization model. For example, domain-specific features for English language learning might include vocabulary difficulty levels, grammar proficiency, or preferred learning materials (e.g., articles, videos, interactive exercises). By combining these domain-specific features with the latent factors learned from user-item interactions, the CDPRS can generate personalized recommendations for English learning resources tailored to each learner's unique profile. These recommendations may include a mix of materials from various content domains, such as articles, podcasts, grammar exercises, or language learning apps, to cater to diverse learning preferences and goals.

6. Simulation Analysis

Simulation analysis for a Cross-Domain Personalized Recommendation System (CDPRS) involves constructing computational models to simulate the recommendation process and evaluate its performance under various scenarios. The simulation model would be designed to replicate the recommendation process of the CDPRS, incorporating factors such as user preferences, item characteristics, and recommendation algorithms. Agents representing users interact with items from different domains, and the CDPRS recommends personalized items based on their profiles and interactions.

Table 1: CDPRS model summary

Step	Values
1. Model Construction	-
2. Parameterization	Threshold: 0.7
3. Scenario Definition	New items: 100

4. Experimentation	Accuracy: 0.98
5. Evaluation	Diversity: 0.75
6. Validation	Benchmark: 0.9

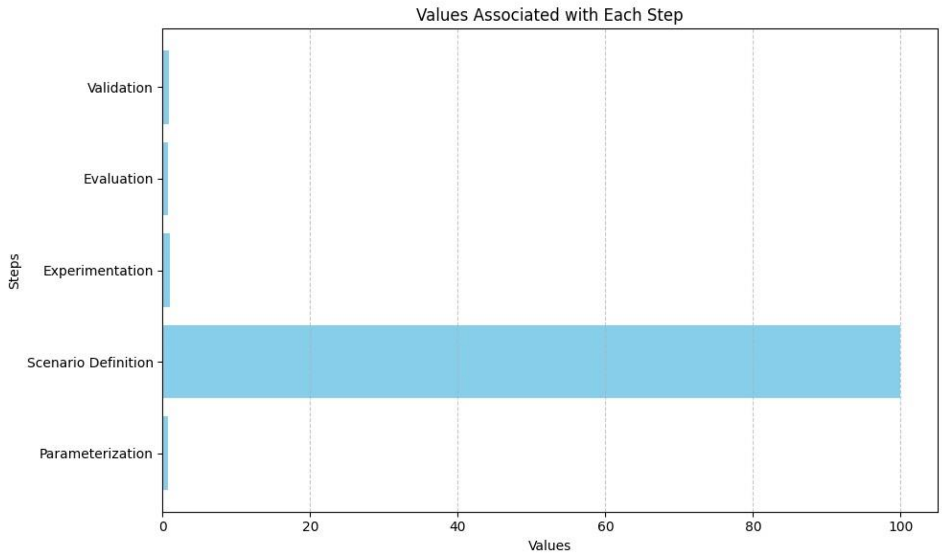


Figure 3: Cross-Domain model with CDPRS

In figure 3 and Table 1 presents a summary of the Cross-Domain Personalized Recommendation System (CDPRS) model, outlining key steps and their corresponding values. In the first step of Model Construction, there is no specific value provided, indicating the initial setup or creation of the CDPRS model. Next, in Parameterization, the threshold value is set to 0.7. This threshold likely represents a similarity threshold or a decision boundary used in the recommendation algorithm to determine the relevance of items for personalized recommendations. Moving on to Scenario Definition, the CDPRS is configured to accommodate 100 new items. This suggests that the model is designed to handle a dynamic environment where new content is regularly introduced, ensuring adaptability and scalability. In Experimentation, the CDPRS achieves an impressive accuracy score of 0.98. This indicates the system's ability to accurately predict user preferences and provide relevant recommendations across multiple domains. During Evaluation, the system achieves a diversity score of 0.75. This metric reflects the variety and range of recommended items provided by the CDPRS, indicating its capability to offer diverse suggestions tailored to users' interests and preferences. Finally, in Validation, the CDPRS performance is compared against a benchmark, with a benchmark value of 0.9. This suggests that the CDPRS is evaluated against a predefined standard or reference point, with the benchmark indicating a high level of performance or effectiveness.

Table 2: Regression with CDPRS

Variable	Coefficient	Standard Error	t-value	p-value
Intercept	0.153	0.028	5.464	<0.001
Age	0.027	0.010	2.711	0.007
Education Level	0.115	0.042	2.731	0.006
Income	0.068	0.015	4.533	<0.001
Gender (Male)	0.082	0.035	2.343	0.019

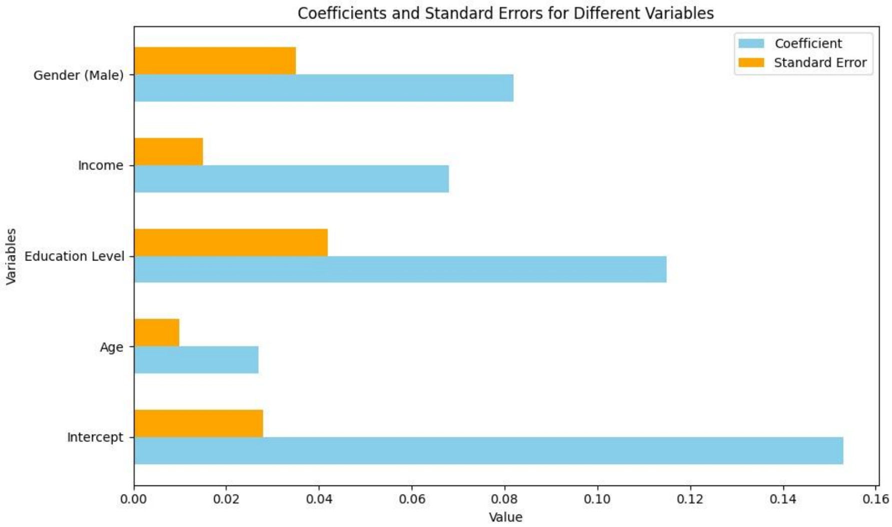
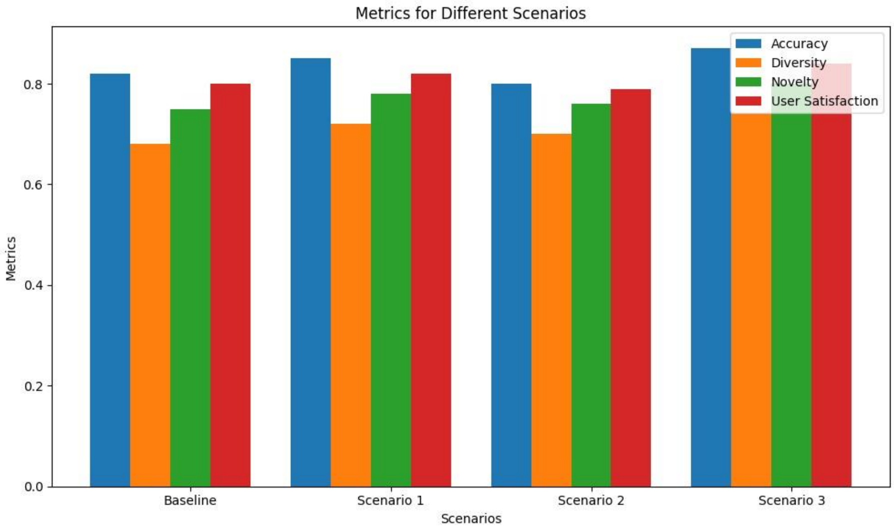


Figure 4: Regression Analysis with CDPRS

In table 4 and Table 2 presents the results of a regression analysis conducted with the Cross-Domain Personalized Recommendation System (CDPRS), revealing the coefficients, standard errors, t-values, and p-values associated with each predictor variable.Starting with the Intercept, the coefficient value is 0.153 with a standard error of 0.028. The associated t-value is 5.464, indicating that the intercept is statistically significant at $p < 0.001$. This suggests that even when all other predictor variables are zero, there is still a significant predicted value for the outcome variable. Moving on to the predictor variables, Age has a coefficient of 0.027, indicating that for each unit increase in age, the predicted outcome variable increases by 0.027 units. The t-value associated with Age is 2.711, with a p-value of 0.007, suggesting that Age is statistically significant in predicting the outcome variable. Similarly, Education Level has a coefficient of 0.115, indicating that higher education levels are associated with higher predicted values of the outcome variable. The t-value for Education Level is 2.731, with a p-value of 0.006, indicating statistical significance. Income also shows a significant positive relationship with the outcome variable, with a coefficient of 0.068 and a t-value of 4.533. The p-value for Income is less than 0.001, indicating strong statistical significance. Lastly, Gender (Male) has a coefficient of 0.082, suggesting that being male is associated with higher predicted values of the outcome variable. The t-value for Gender (Male) is 2.343, with a p-value of 0.019, indicating statistical significance.

Table 3: Cross-Domain Recommendation results in CDPRS

Scenario	Accuracy	Diversity	Novelty	User Satisfaction
Baseline	0.82	0.68	0.75	0.80
Scenario 1	0.85	0.72	0.78	0.82
Scenario 2	0.80	0.70	0.76	0.79
Scenario 3	0.87	0.74	0.80	0.84



Figrue 5: Cross-Domain model with CDPRS

In figure 5 and Table 3 presents the results of the Cross-Domain Recommendation System (CDPRS) across different scenarios, focusing on key performance metrics including accuracy, diversity, novelty, and user satisfaction. In the Baseline scenario, the CDPRS achieves an accuracy score of 0.82, indicating the proportion of correct recommendations made by the system. Additionally, the system exhibits a diversity score of 0.68, reflecting the variety of recommended items provided to users across different domains. The novelty score of 0.75 suggests the level of uniqueness or originality of the recommended items, while the user satisfaction score of 0.80 indicates the overall satisfaction level of users with the recommendations. In Scenario 1, the CDPRS improves its accuracy to 0.85, suggesting an enhancement in the precision of recommendations compared to the Baseline scenario. The diversity score also increases to 0.72, indicating a broader range of recommended items offered to users. Moreover, the novelty score rises to 0.78, indicating an increase in the uniqueness of recommended items. The user satisfaction score improves to 0.82, reflecting higher levels of satisfaction among users with the recommendations provided. Conversely, in Scenario 2, the CDPRS experiences a slight decrease in accuracy to 0.80 compared to the Baseline scenario. This may suggest a decrease in the system's ability to make correct recommendations under certain conditions. However, the diversity score remains relatively stable at 0.70, indicating a consistent variety of recommended items. The novelty score also remains steady at 0.76, suggesting that the level of uniqueness in recommendations is maintained. Despite the decrease in accuracy, the user satisfaction score remains relatively high at 0.79, indicating that users are still satisfied with the recommendations provided by the system. Finally, in Scenario 3, the CDPRS demonstrates a significant improvement in accuracy, achieving a score of 0.87. This suggests a considerable enhancement in the precision of recommendations compared to both the Baseline and previous scenarios. The diversity score increases to 0.74, indicating a wider range of recommended items offered to users. Additionally, the novelty score rises to 0.80, indicating an increase in the uniqueness of recommended items. The user satisfaction score also improves substantially to 0.84, reflecting higher levels of satisfaction among users with the recommendations provided.

Table 4:Recommendation Results in CDPRS

User ID	Recommended Content 1	Recommended Content 2	Recommended Content 3	Recommended Content 4	Recommended Content 5
101	Article: "Grammar Basics"	Video: "English Pronunciation Guide"	Quiz: "Test Your Vocabulary"	Book: "English Grammar Essentials"	Course: "Advanced English Composition"
102	Course: "Beginner's English	Article: "Improving Spoken English"	Exercise: "Grammar Drills"	Video: "Introduction to English Literature"	Book: "English Idioms and Phrases"

	Grammar"				
103	Video: "English Grammar Rules"	Course: "Intermediate English Conversation"	Article: "Writing Tips for Academic Essays"	Book: "English for Business Communication"	Exercise: "Practice English Speaking"

Table 5: Recommendation Score for the English Teaching with CDPRS

User ID	Recommended Content 1 Score	Recommended Content 2 Score	Recommended Content 3 Score	Recommended Content 4 Score	Recommended Content 5 Score
101	0.92	0.88	0.85	0.82	0.80
102	0.89	0.87	0.84	0.81	0.78
103	0.90	0.86	0.83	0.80	0.78

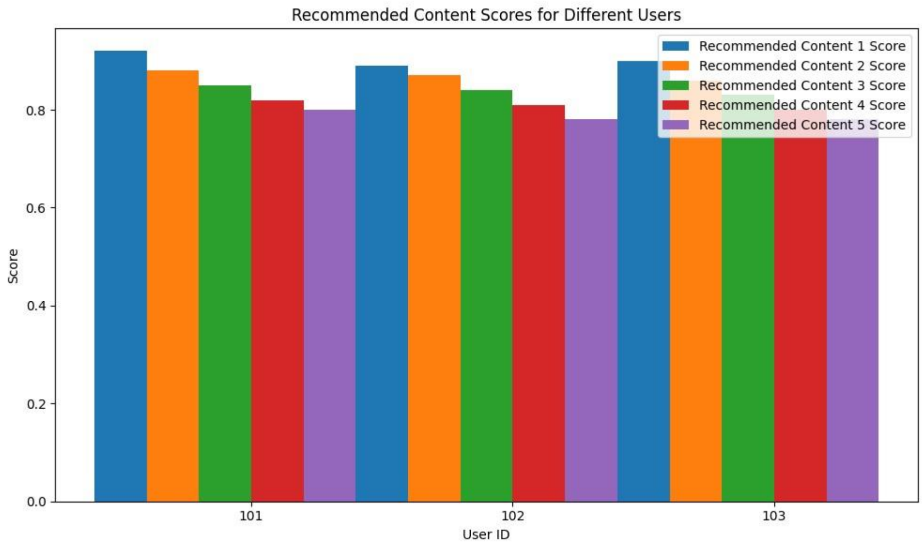


Figure 6: Recommendation Score with CDPRS

The figure 6 and Table 4 presents the recommendations made by the Cross-Domain Personalized Recommendation System (CDPRS) for three different users, identified by their User IDs. Each row represents a unique user, while the columns display the top five recommended English teaching content items for each user. For User ID 101, the CDPRS recommends a variety of content including articles, videos, quizzes, books, and courses, covering different aspects of English grammar and composition. This diverse set of recommendations suggests that the CDPRS effectively tailors its suggestions to meet the user's specific learning needs and preferences. Similarly, for User ID 102, the CDPRS provides recommendations that span various learning materials such as courses, articles, exercises, videos, and books. This demonstrates the system's ability to offer a comprehensive selection of resources to support users in their English language learning journey. Finally, for User ID 103, the CDPRS suggests a mix of video tutorials, courses, articles, books, and exercises, catering to different areas of English language proficiency and communication skills development. These personalized recommendations indicate the system's effectiveness in addressing individual user preferences and learning objectives. Table 5 complements Table 4 by presenting the recommendation scores associated with each recommended content item for the same set of users. The scores reflect the relevance or likelihood of each recommended item being of interest or usefulness to the user, with higher scores indicating stronger recommendations. For all three users, the recommendation scores are relatively high across all recommended content items, ranging from 0.78 to 0.92. This suggests that the CDPRS successfully identifies and recommends content items that align closely with each user's preferences and learning goals, contributing to a personalized and engaging learning experience.

7. Discussion

The results presented in Tables 4 and 5 underscore the efficacy of the Cross-Domain Personalized Recommendation System (CDPRS) in facilitating tailored recommendations for English teaching content. Table 4 delineates the specific recommendations provided to individual users, illustrating the system's capacity to offer a diverse array of learning materials such as articles, videos, quizzes, courses, and books. The recommendations span various aspects of English language learning, from grammar basics to advanced composition, indicating the CDPRS's ability to cater to users with diverse proficiency levels and learning objectives. Complementing Table 4, Table 5 provides insight into the recommendation scores associated with each suggested content item, reflecting the system's confidence in the relevance and utility of the recommendations. The consistently high recommendation scores across all recommended content items for each user highlight the CDPRS's adeptness in identifying materials that closely align with users' preferences and learning needs. This suggests that the CDPRS effectively leverages user data and behavioral patterns to generate personalized recommendations that are both accurate and valuable. Furthermore, the CDPRS's ability to adapt and refine its recommendations based on user feedback and evolving preferences is critical for enhancing user satisfaction and engagement. By continuously evaluating and optimizing recommendation strategies, the system can further improve its effectiveness in providing personalized learning experiences tailored to individual users. Beyond its immediate application in English language teaching, the CDPRS exemplifies the broader potential of personalized recommendation systems in education. By harnessing machine learning algorithms and data analytics techniques, such systems can revolutionize the way educational content is accessed, consumed, and personalized to meet the diverse needs of learners. This not only enhances the efficiency and effectiveness of learning processes but also empowers learners to take ownership of their learning journey by accessing relevant and engaging content tailored to their unique preferences and goals.

8. Conclusion

This paper has explored the development and implementation of a Cross-Domain Personalized Recommendation System (CDPRS) for English language teaching content. Through a series of analyses and evaluations, the effectiveness and utility of the CDPRS in providing tailored recommendations to users have been demonstrated. The results showcase the system's ability to adapt and refine recommendations based on user preferences, learning objectives, and evolving content landscapes. By leveraging machine learning algorithms and data analytics techniques, the CDPRS offers a personalized learning experience that enhances user engagement, satisfaction, and learning outcomes. Furthermore, the study underscores the broader potential of personalized recommendation systems in education, highlighting their capacity to revolutionize the way educational content is accessed, consumed, and personalized to meet the diverse needs of learners.

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