ENHANCING SMART EDUCATION: COMPARATIVE ANALYSIS OF HYBRID RECOMMENDATION ALGORITHMS FOR PERSONALIZED LEARNING

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Abstract. Smart education systems have emerged as pivotal tools in modern education, yet the effectiveness of different recommendation algorithms in personalizing learning experiences remains understudied, particularly in higher education contexts. This study evaluates and compares three recommendation algorithms collaborative filtering, content-based filtering, and a hybrid approach within a web-based smart education system designed for computer science education, focusing on their ability to enhance personalized learning experiences. The author developed a web-based smart education system incorporating these three algorithms and tested it using a dataset of 100 users across 20 courses. The system's performance was evaluated using precision, recall, accuracy, and F1-score metrics. A four-week case study with 20 users was conducted to assess practical implementation outcomes. The hybrid algorithm demonstrated superior performance with 85.96% precision, 98.99% recall, 94.33% accuracy, and a 91.98% F1-score, significantly outperforming both collaborative filtering (precision: 68.09%, recall: 94.12%) and content-based filtering (precision: 72.73%, recall: 90.32%). Case study results showed consistent improvement in user performance, with score improvements ranging from 15% to 23%.The hybrid algorithm proves most effective for personalizing educational content delivery, though with higher computational overhead. These findings suggest that hybrid recommendation approaches can significantly enhance smart education systems' ability to provide personalized learning experiences, despite computational challenges in large-scale deployments.
Keywords: *smart education, recommendation algorithms, hybrid filtering, personalized learning, web-based learning*

Introduction

Education in the digital age has undergone significant transformations, with the integration of information and communication technologies (ICT) offering unprecedented opportunities for innovation in teaching and learning in rapidly evolving educational landscapes and increasing student diversity, the ability to accurately and proactively manage student academic performance has become more critical than ever (Eguavoen and Nwelih, 2024). Traditional educational systems, while effective in their era, often fail to address the diverse needs of modern learners, particularly in adapting to varying learning styles, paces, and preferences (Demir, 2021). Although, Education Institutions have deployed technology accelerated learning systems and innovations for effective learning outcomes (Eguavoen and Nwelih, 2023), the advent of smart education systems presents a paradigm shift, leveraging advanced technologies to create adaptive, personalized, and engaging learning environments. Smart education extends beyond the mere application of technology; it embodies a holistic approach that integrates pedagogy, technology, and learner engagement. Personalized learning,

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adaptive content delivery, and interactive platforms form the core of these systems, enabling learners to take control of their educational journeys. However, the implementation of smart education systems requires robust frameworks and methodologies to ensure effectiveness and scalability.

Traditional education systems predominantly rely on a one-size-fits-all approach, which often disregards individual learning differences. This generalized methodology can lead to disengagement, suboptimal academic outcomes, and limited adaptability to the dynamic needs of learners. Furthermore, the slow adoption of technological advancements in traditional settings exacerbates these limitations, hindering the potential for innovation in education (Ikechukwu and Amos, 2023). Recommendation algorithms have emerged as a transformative tool in various domains, including e-commerce, entertainment, and education. These algorithms analyse user interactions and preferences to provide tailored suggestions, thereby enhancing user engagement and satisfaction. In the context of education, recommendation algorithms can facilitate personalized learning by identifying areas of improvement, suggesting relevant resources, and adapting content delivery to individual needs. Collaborative filtering, content-based filtering, and hybrid approaches are among the most widely used techniques, each offering unique strengths and limitations (Sharma, 2024; Zhou et al., 2018).

This study aims to bridge the gap between traditional and smart education by proposing a web-based smart education system tailored for the Department of Computer Science, University of Benin. The system incorporates three recommendation algorithms-collaborative filtering, content-based filtering, and hybrid-to provide a comparative analysis of their effectiveness in enhancing personalized learning. The objectives include: (1) Simulating a smart education system to evaluate algorithm performance. (2) Analysing precision, recall, and accuracy metrics to determine the most suitable algorithm. (3) Identifying practical challenges and proposing solutions for scalable implementation.

Literature review

Smart education framework

Smart education represents a transformative approach to learning, integrating ICT with modern pedagogical methods to create personalized and adaptive educational experiences. Zhu et al. (2016) proposed a comprehensive framework that emphasizes the synergy between technology, pedagogy, and learner engagement. The framework underscores the importance of personalized learning pathways, adaptive content delivery, and the integration of interactive technologies. Key components of the smart education framework include: Modern Teaching Approaches: Blended learning, flipped classrooms, and adaptive learning are pivotal in addressing diverse learner needs. Educational Technologies: Smart classrooms, learning management systems (LMS), and data-driven analytics enhance the learning experience. Learner-Centric Design: Emphasizes active learner participation and personalized educational trajectories.

Traditional vs education

Traditional education systems are characterized by a teacher-centered approach, relying heavily on rote memorization and uniform content delivery. While effective for standardized curricula, this approach often fails to cater to individual learning

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preferences and paces (Ikechukwu and Amos, 2023). In contrast, smart education leverages technology to offer: Personalization: Tailored content delivery based on learner needs. Interactivity: Enhanced engagement through multimedia and real-time feedback. Flexibility: Learning anytime, anywhere through digital platforms.

Recommendation algorithms

Recommendation algorithms play a crucial role in smart education systems by facilitating personalized learning experiences. They analyse user data to suggest relevant content, fostering engagement and academic improvement. The three primary types of recommendation algorithms are: (1) Collaborative Filtering: Collaborative filtering relies on the collective preferences of users to generate recommendations. It identifies similarities between users or items to predict preferences (Zhou et al., 2018). While effective in providing diverse suggestions, it suffers from challenges like cold-start problems and data sparsity. (2) Content-Based Filtering: This approach focuses on the attributes of items and user preferences. By analysing item features, it recommends content similar to what a user has previously engaged with Sharma (2024). Although precise, it may limit exposure to novel topics. (3) Hybrid Models: Combining collaborative and content-based methods, hybrid algorithms mitigate the limitations of individual approaches. They offer improved accuracy and adaptability, making them ideal for complex systems like education (Gomez-Uribe and Hunt, 2015).

Related works

Several studies have explored the application of recommendation algorithms in education: (Shu et al., 2018): Developed a content-based algorithm for recommending multimedia learning resources. Liu (2019): Proposed a collaborative filtering model leveraging user behaviour patterns to improve recommendation accuracy. Dwivedi et al. (2018): Utilized a genetic algorithm to create optimal learning paths in e-learning systems. Kolekar et al. (2019): Designed an adaptive interface for personalized content delivery in educational platforms. Lin et al. (2018): Developed a course recommendation system for smart education using sparse linear techniques.

While existing studies highlight the potential of recommendation algorithms in education, they often focus on single approaches, neglecting the comparative analysis of multiple methods. Additionally, issues like scalability, computational efficiency, and integration with physical classroom settings remain underexplored. This study addresses these gaps by evaluating collaborative, content-based, and hybrid algorithms in a smart education context.

Materials and Methods

The proposed smart education system is a web-based application designed to provide personalized learning experiences through recommendation algorithms. *Figure 1* illustrates the high-level system architecture which comprises the following components: (1) User Interface: A responsive web interface enabling users to access educational content, quizzes, and recommendations. The interface supports desktop and mobile platforms. (2) Backend Server: Built using Node.js, the server handles client requests, processes user interactions, and manages data flow between the database and recommendation algorithms. (3) Database: A MongoDB database stores user profiles,

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course materials, quiz results, and algorithm-generated recommendations. Its flexibility supports dynamic schema updates and efficient data retrieval. (4) Recommendation Engine: Implements collaborative filtering, content-based filtering, and hybrid algorithms to generate personalized content suggestions. The engine dynamically updates predictions based on user interactions.

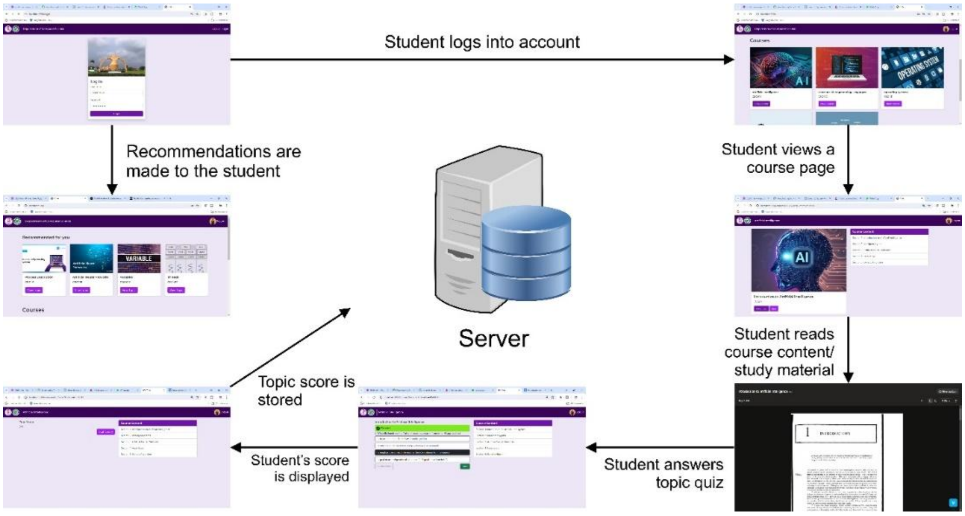

Figure 1. *Web-based smart education system architecture.*

The system operates through the following workflow: (1) User Authentication: Users log in or register to access the platform. New users are guided through a profile setup process to customize their learning preferences. (2) Content Delivery: Users select courses and access structured materials. Each topic includes multimedia resources and interactive quizzes. (3) Performance Tracking: Quiz results are recorded and analysed to identify user strengths and weaknesses. This data serves as input for the recommendation engine. (4) Recommendation Generation: Based on user activity, the engine suggests topics or courses for further study. Recommendations are updated dynamically as users engage with the system. The algorithms implementation are include: (1) Collaborative Filtering: (a) Similarity Calculation: Uses cosine similarity to identify users with similar performance patterns. (b) Prediction: Aggregates ratings from similar users to predict user preferences for unseen topics. (2) Content-Based Filtering: (a) Feature Extraction: Analyses keywords and metadata from course content. (b) Recommendation: Matches user preferences with content features to suggest similar topics. (3) Hybrid Algorithm: (a) Integration: Combines predictions from collaborative and content-based methods. (b) Weight Adjustment: Assigns dynamic weights to each method based on user activity and system performance.

The algorithms were evaluated using the following metrics: Precision: Measures the proportion of relevant recommendations among the total suggestions made. It is mathematically expressed as in Eq. (1) . Recall: Assesses the system's ability to identify all relevant items. It is mathematically expressed as in Eq. (2). Accuracy: Evaluates the overall correctness of the recommendations. It is mathematically expressed as in Eq. (3). F1-Score: Balances precision and recall to provide a comprehensive performance metric. It is mathematically expressed as in Eq. (4).

$$\frac{true\ positives}{true\ positives + false\ positives} \qquad \text{Eq. (1)}$$

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$$\frac{true\ positives}{true\ positives + false\ negatives} \qquad \text{Eq. (2)}$$

$$\frac{true\ positives + true\ negatives}{true\ positives + false\ positives + true\ negatives + false\ negatives} \qquad \text{Eq. (3)}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad \text{Eq. (4)}$$

The system was tested with a dataset comprising: 100 users with diverse learning profiles; 20 courses, each containing 5 topics; and Simulated quiz results to mimic real-world user interactions. The experiments were conducted on a cloud-based platform, ensuring scalability and consistent performance across different environments.

Results and Discussion

The results from the experimental setup provide a comparative analysis of the three recommendation algorithms: collaborative filtering, content-based filtering, and the hybrid approach. Key performance metrics-precision, recall, accuracy, and F1-score-are summarized in *Table 1*. The performance metrics are further visualized in *Figure 2*, providing a clear comparison of the three algorithms. This figure includes a bar chart comparing precision, recall, accuracy, and F1-score across the three algorithms. Insights from algorithm performance are include: (1) Collaborative Filtering: This algorithm performed moderately well, with high recall but lower precision. The results indicate that while it effectively identifies relevant topics, it occasionally suggests irrelevant ones due to user variability. (2) Content-Based Filtering: This method achieved higher precision, making it effective for recommending highly relevant topics. However, its limited exploration of new content resulted in a lower recall score. (3) Hybrid Algorithm: Combining the strengths of the other two methods, the hybrid algorithm outperformed both in all metrics. Its adaptability ensured both precision and recall, making it the most suitable for personalized learning systems.

Table 1*. Performance metrics for recommendation algorithms.*

Algorithm	Precision (%)	Recall (%)	Accuracy (%)	F1-score (%)
Collaborative Filtering	68.09	94.12	71.67	79.01
Content-Based Filtering	72.73	90.32	91.00	80.60
Hybrid Algorithm	85.96	98.99	94.33	91.98

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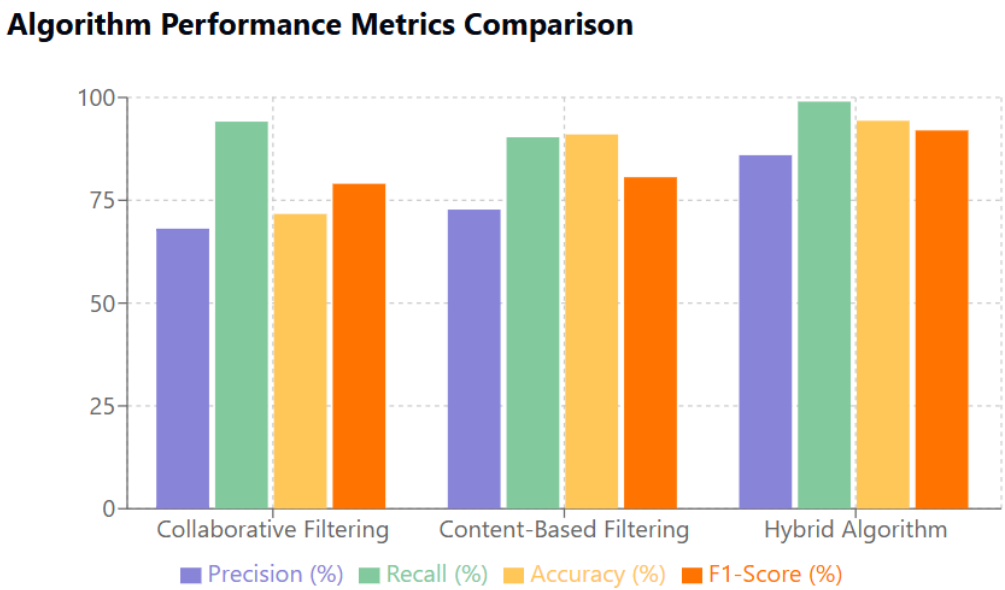

Figure 2. *Performance metrics for recommendation algorithms.*

A case study involving a subset of 20 users demonstrated the hybrid algorithm's practical benefits. Users interacted with the system over four weeks, during which their engagement and quiz scores were tracked. As shown in *Table 2*, the hybrid algorithm consistently recommended topics that improved user performance. The hybrid algorithm's computational demands were evaluated to ensure scalability. *Figure 3* depicts the processing time required for each algorithm under varying user loads. The findings underscore the hybrid algorithm's potential to revolutionize smart education systems by providing tailored, accurate, and efficient recommendations. However, its higher computational cost necessitates optimization strategies, such as precomputed similarity matrices and distributed computing. By integrating these algorithms, educational institutions can enhance engagement, improve academic outcomes, and foster a learner-centric environment.

Table 2*. User performance improvement using hybrid algorithm.*

User ID	Initial score (%)	Final score (%)	Improvement (%)
U001	62	85	23
U002	74	89	15
U003	58	80	22

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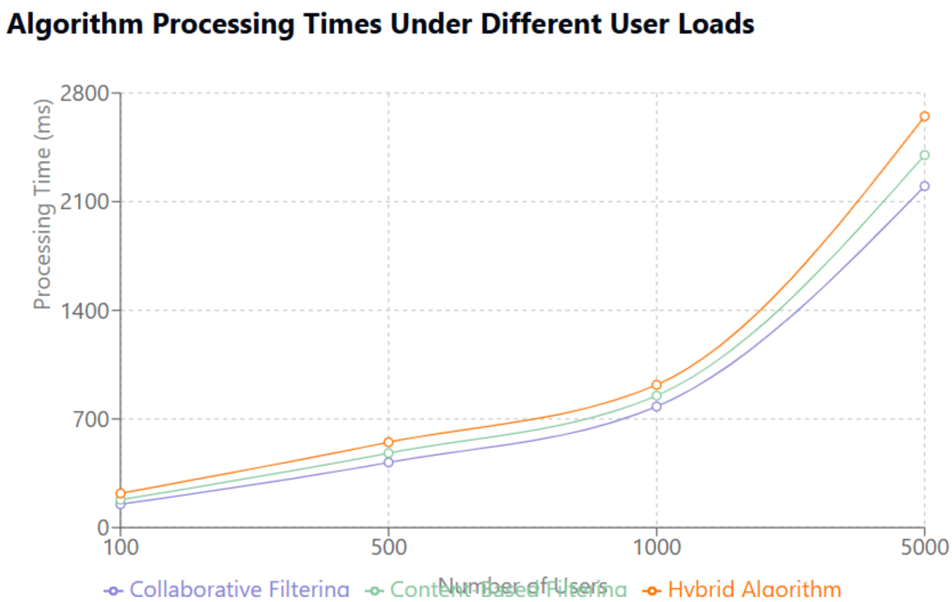

Figure 3. *Computational Efficiency of Algorithms.*

This study evaluated the effectiveness of collaborative filtering, content-based filtering, and hybrid recommendation algorithms within a web-based smart education system designed for personalized learning. The experimental results demonstrated the hybrid algorithm's superiority, achieving the highest precision (85.96%), recall (98.99%), accuracy (94.33%), and F1-score (91.98%). The hybrid approach effectively combined the strengths of collaborative and content-based methods, addressing their individual limitations. The findings underscore the transformative potential of integrating advanced recommendation algorithms into educational systems. By tailoring content to individual learner profiles, smart education systems can enhance engagement, improve learning outcomes, and foster adaptive learning environments. The hybrid algorithm, in particular, offers a scalable and efficient solution for institutions seeking to implement personalized learning frameworks.

Conclusion

While the hybrid algorithm outperformed other approaches, certain limitations warrant consideration: (1) Computational Overhead: The hybrid model requires significant computational resources, which may challenge scalability in large-scale deployments. (2) Cold-Start Problem: Although mitigated by combining collaborative and content-based methods, new user scenarios still present challenges. (3) Dataset Specificity: The study relied on simulated data, which may not fully capture the diversity of real-world educational environments. To address these limitations and further advance the field, the following areas are recommended for future research: (1) Real-World Testing: Deploy the system in diverse educational settings to validate its performance and adaptability. (2) Optimization Techniques: Explore techniques such as matrix factorization, precomputed similarity matrices, and distributed computing to reduce computational overhead. (3) Incorporating Contextual Factors: Integrate contextual data such as time of access, device type, and user mood to enhance recommendation accuracy. (3) Real-Time Adaptation: Develop algorithms capable of real-time learning and adaptation to user behaviour changes. (4) Integration with

Physical Classrooms: Investigate hybrid models that combine digital recommendations with face-to-face classroom interactions. This research highlights the critical role of recommendation algorithms in shaping the future of smart education. By leveraging the hybrid algorithm, institutions can provide personalized and adaptive learning experiences, ultimately fostering a more inclusive and effective educational landscape. Continued exploration and refinement of these systems will be essential in addressing the dynamic needs of learners worldwide.

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Conflict of interest

The authors confirm that there is no conflict of interest involve with any parties in this research study.

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