Eurasian Journal of Educational Research
www.ejer.com.tr

Enhancing Personalized Learning in Online Education: The Impact of Adaptive Learning Systems and Recommendation Technologies

Chunmao Liu[1], Somkiat Tuntiwongwanich[2], Thiyaporn kantathanawat[3]

ARTICLE INFO

Article History:
Received: 01 May 2024
Received in revised form: 01 October 2024
Accepted: 30 October 2024
DOI: 10.14689/ejer.2024.112.020

Keywords
Adaptive Learning, E-Learning, Learner Interaction, Learning Achievements, Edtech

ABSTRACT

The study investigates the impact of integrated adaptive learning systems and recommender technologies on the improvement of online education. A component-level quantitative evaluation was conducted, which involved measuring user interaction, content applicability, knowledge acquisition, and system usability, with support from surveys and interviews. The findings indicate that recommendation systems enhance active user participation, content relevance, and learning outcomes, while maintaining high usability rates that positively influence learners' perceptions. However, certain limitations were identified, including the system's less-than-ideal suitability for advanced learners and the absence of contextual information. The study concludes that, when appropriately implemented as suggested by existing literature, adaptive learning systems possess significant potential to transform online education by offering personalised and efficient learning methods. Recommendations for future developments include the integration of third-generation machine learning, ensuring equal opportunities for learners, and further refining the system to address small learner differences.

Background and Introduction

Information Communication Technology (ICT) has been widely adopted by institutions, fundamentally transforming education, particularly with the integration of online learning systems. These systems have revolutionised traditional educational platforms by providing learners with versatile, customised, and accessible learning solutions. Central to this transformation is the inclusion of adaptive learning and

[1] School of Industrial Education and Technology, King Mongkut's Institute of Technology Ladkrabang, Thailand, ORCID: https://orcid.org/0009-0002-4040-1530, Email: liuchunmao@hnpi.edu.cn
[2] School of Industrial Education and Technology, King Mongkut's Institute of Technology Ladkrabang, Thailand, ORCID: https://orcid.org/0000-0003-4829-2543, Email: somkiat.tu@kmitl.ac.th
[3] School of Industrial Education and Technology, King Mongkut's Institute of Technology Ladkrabang, Thailand, ORCID: https://orcid.org/0000-0002-4436-8806, Email: thiyaporn.ka@kmitl.ac.th

recommendation-based systems, designed to deliver learning materials tailored to individual learner characteristics. This is achieved through the use of sophisticated software, computational techniques, and data aggregation methods that track learners' activities, attributes, and performance.

Adaptive learning is grounded in the understanding that each learner differs in terms of abilities, preferences, and learning gaps. Traditional mechanistic models, often employed by large educational systems, fail to adequately address these individual differences, resulting in suboptimal learning experiences. In contrast, adaptive learning systems aim to overcome this limitation by regularly assessing learners' performance and adjusting the delivery of instruction in response. These systems leverage technologies such as Artificial Intelligence (AI), Machine Learning (ML), and data mining to create learning environments that are responsive to learners' specific needs and demands.

One of the key challenges in adaptive learning is the accurate characterisation of the learner in terms of cognitive and behavioural parameters. Understanding these characteristics is essential for designing effective recommendation engines that facilitate personalised learning. As noted by Agarwal et al. (2022), in the context of knowledge-based recommendation systems, learning style content can be recommended using semantic web rules, particularly within Massive Open Online Courses (MOOCs). Such systems employ rules that analyse students' learning behaviours before suggesting the most appropriate content, thereby enhancing learning effectiveness and aligning with individual content preferences.

Bai (2021) proposed a variable incremental adaptive learning model based on knowledge graphs (KGs) for online learning systems. KGs are valuable as they define the relationships between different concepts within a given environment, enabling the system to offer recommendations grounded in the learner's context and knowledge. This approach helps address the issue of information overload by ensuring that new information is integrated into the course in a manageable way, preventing learners from feeling overwhelmed and reducing the risk of burnout during the learning process. Adaptive learning systems continue to evolve, incorporating machine learning to further personalise education. Embarak (2021) explored how machine learning-based recommender systems contribute to the transformation of learning environments. These systems can predict student performance outcomes and assess their risk levels by analysing learning behaviour patterns. By providing timely, relevant tools and support, such systems significantly enhance the learning experience and help reduce dropout rates.

In recent work by Grover (2023), attention was given to the development of sequential recommendation systems based on deep learning. These systems are particularly valued for their ability to detect temporal patterns in user engagement, which is essential for 'fusion'-type systems where learning is continuous. By sequencing a learner's actions, these systems can predict the next activity and guide the learner towards the most appropriate step, thereby enhancing the overall organisation of the learning process. As this dissertation demonstrates, the accurate identification, capture, and classification of student characteristics in adaptive learning systems is of paramount importance. Halim et al. (2023) conducted a systematic literature review and found that learning style is the most commonly used factor for adaptation in such systems, while knowledge characteristics, cognitive traits, student preferences, and motivation rank second. This categorisation is crucial for developing systems that cater to learner differences and provide the necessary tools and support for students to achieve improved results.

Adaptive learning strategies have made significant strides in the development of auto-adaptive recommendation approaches. Several studies have shown that deep reinforcement learning models can enhance ideological and political education in online learning environments. These models adjust recommendations based on the learner's interactions with the system, thus offering a more dynamic, reactive system that evolves with the learner's progress. Such approaches are particularly beneficial in learning environments where learner motivation is a key determinant of success. Lahiassi et al. (2023) identified and described methods to optimise recommendation systems for personalised learning in private online courses. Their research highlights the importance of considering student needs to improve course content quality, and by extension, the learning process. These systems aim to more accurately analyse learner data and deliver relevant, timely instruction tailored to individual needs, ensuring that students remain engaged, motivated, and on track to achieve their learning objectives.

A significant contribution to adaptive learning systems is the application of mega-scale data analysis methods and stage-adaptive deep networks for multi-task recommendations. Li et al. (2023) proposed the STAN framework, which calibrates multi-task predictions by representing users' lifecycle stages. This approach considers the various phases a learner is likely to experience, offering recommendations tailored to the stage the learner is at. This not only enhances learner engagement but also improves the overall learning experience. By understanding the different stages of learning, the STAN framework can provide timely support, ensuring learners receive the appropriate assistance when needed.

In the optimisation of computer science courses, Lohr et al. (2023) introduced the Y-Model, a task-based approach within adaptive learning systems. This model enables a determinative approach to task assignment, allowing learners to access content that is most relevant to their current needs. Due to its structured framework for identifying appropriate tasks, the Y-Model increases the impact of adaptive learning systems on students' motivation and engagement throughout the learning process (Wang et al., 2018). In a similar vein, device and cloud technologies have played a critical role in the development of adaptive learning systems. To enable efficient device-cloud collaboration in dynamic recommendation systems, a model called IDEAL was proposed. Designed to optimise performance and adaptability, the IDEAL model ensures the right level of interaction between local devices and cloud services, guaranteeing that learners receive timely recommendations from any device. This model enhances the adaptability and availability of adaptive learning systems by leveraging cloud computing services. Murad et al. (2022) explored the effects of contextual information on the personalisation features of learning in online recommendation systems. Their research emphasises that recommendations are highly dependent on context, particularly the environment in which learning occurs. By integrating contextual information into learning-teaching activities, adaptive learning recommendations can be more precisely tailored, thereby providing greater benefits to learners.

Literature Review

In recent years, significant advancements have been made in the field of educational technology, particularly in learning engineering and recommender systems. These technologies are designed to address learners' needs by enhancing the adaptability of both content and the learning process. This literature review synthesises research from various studies that have explored different aspects of Adaptive Learning Systems (ALS), with a specific focus on information recommendation, machine learning, knowledge graphs, and contextual factors, all aimed at improving the effectiveness of online learning.

The Fourth Type of Recommender Systems is the Knowledge-Based Recommendation Systems

Agarwal et al. (2022) explore the application of the Knowledge-Based Recommendation (KBR) approach within MOOC environments, specifically in the context of a learning management system. Their study examines the use of semantic web rules to personalise content based on learners' learning styles. The authors emphasise that learning styles play a crucial role in identifying the most effective teaching and learning methods for different learners. By leveraging semantic web technologies, they argue that a more enriched learning environment can be created. This approach not only enhances the individualisation of the learning process but also addresses the challenges associated with the diverse and heterogeneous learner populations typical of MOOCs. The system described by Agarwal et al. (2022) proves particularly beneficial in the context of MOOCs, where a varied audience is served. By integrating learning styles into the platforms delivering learning materials, the outcomes of learning programmes and the satisfaction levels of learners are significantly enhanced. Additionally, the use of semantic web rules is noted for its computational efficiency, offering a more dynamic and flexible approach to Learning Record Stores (LRS) compared to static, redundantly programmed rule sets.

All of the Above Result in Using Models that Adopt the Variable Incremental Adaptive Learning Models

Bai (2021) developed a variable incremental adaptive learning model that utilises knowledge graphs (KGs) to optimise online learning systems. KGs are structured semantic representations that, unlike basic word or hypertext connections, capture the relationships between concepts, enabling more nuanced content recommendations. Bai's model addresses two critical challenges in online learning: cognitive overload and cognitive loss. Cognitive overload refers to the learner being overwhelmed with excessive information, leading to poor comprehension and retention, while cognitive loss denotes the forgetting of knowledge over time. The variable incremental adaptive learning model introduced by Bai (2021) mitigates these issues by adapting learning advancements to the learner’s prior knowledge and cognitive abilities. The use of knowledge graphs allows the system to make more informed decisions about the type of content to present to learners. This ensures that the content is neither overwhelming nor too simplistic, promoting engagement and facilitating effective learning. By balancing new information with what the learner already knows, this approach has been shown to enhance learning outcomes, providing a more personalised and efficient learning experience.

Machine Learning in the Process of Adaptive Education

The integration of machine learning into adaptive learning systems has led to the development of innovative approaches for providing personalised learning. Embarak (2021) explored the extent to which machine learning-based recommendation systems can be employed to create personalised learning environments. His study reveals how machine learning algorithms can forecast student performance, identify at-risk students, and suggest appropriate interventions. These capabilities are particularly valuable in large educational settings where instructors are unable to provide individualised attention to each learner. As Embarak (2021) highlights, incorporating machine learning into adaptive learning environments can significantly enhance their effectiveness by enabling real-time adjustments that reflect the learner's progress and behaviour. This is especially crucial given the diverse needs of learners, each of whom may require different types of support to succeed. Additionally, machine learning can help prevent or predict potential learning failures before they escalate into significant barriers to the teaching and learning process.

In this proposal, we compare Sequential Recommendation Systems with Deep Learning

Grover (2023) investigated the development of sequential recommendation systems using deep learning methods. The distinction between explicit and implicit links in such systems makes them particularly suited for analysing the sequence of user and content interactions, as many educational activities are highly dependent on the flow of steps or tasks. Grover's work also addresses the role of time in learning, emphasising that different sequences of content should be identified to optimise the learning experience. Deep learning, which captures complex relationships within data, is particularly well-suited for sequential recommendation systems. Grover (2023) established that deep learning models outperform traditional recommendation algorithms in terms of efficiency and flexibility. By analysing sequences of learner interactions, these models can offer more insightful recommendations aligned with the learner's current activity and preferences. This approach not only enhances learning outcomes but also fosters a more interactive and personalised learning journey for the learner.

Students' Characteristics or Attributes have been Defined as Follows

In their systematic literature review, Halim et al. (2023) successfully identified some of the most common characteristics in adaptive learning systems. They emphasised the importance of learning styles, knowledge characteristics, cognitive traits, student preferences, and motivation as key factors influencing the effectiveness of adaptive learning. Understanding these characteristics is essential for developing a system that can accommodate the diverse needs of students in a classroom, ensuring that each learner benefits in some way from the system. The findings of Halim et al. (2023) provide valuable insights, highlighting that adaptive learning systems should be context-sensitive, taking into account the individual differences each learner brings. These characteristics are crucial for educators when designing recommendation systems that are better suited to the learning environment. The review also suggests that future research should focus on developing enhanced models capable of measuring and providing real-time feedback based on these characteristics, further improving the adaptability and effectiveness of the system.

Freeware Self-learning Recommendation Techniques

Lahiassi et al. (2023) developed a self-adaptive recommendation approach using deep reinforcement learning to introduce online Instruction and Practice (I & P) teaching resources. This method adapts recommendations in real time as learners interact with the system, thereby providing an increasingly effective learning experience throughout the process. Deep reinforcement learning enables the system to refine its recommendations based on the learner's actual interactions, ensuring that the content remains relevant and personalised. The study also highlighted the potential of reinforcement learning to significantly enhance the flexibility of recommender systems. This approach allows the system to provide more accurate and relevant recommendations tailored to the learner's preferences and needs. In learning environments where learner motivation is a critical factor, this adaptive approach proves especially valuable, ensuring that the recommendations align with the evolving demands of the learner and support sustained engagement and progress.

Improving on Personalized Learning

Lahiassi et al. (2023) also focused their study on the application of recommendation systems to improve personalised learning in private online courses. The study explores how course content should be tailored to meet the individual needs of students in order to enhance their learning experience. The authors argue that, while it is possible to recommend content based on a learner's interests, a more crucial aspect of personalised learning is providing relevant and timely content that aligns with the learner's specific needs and objectives. The recommendation system proposed by the authors employs a series of algorithms to analyse learner data and provide highly accurate, personalised, and contextualised recommendations. This approach has been shown to enhance both learner satisfaction and performance outcomes by offering support at the precise moment a student requires it. The article emphasises how recommendation systems can revolutionise online education by implementing a customised approach that adapts to each learner's unique learning journey.

Stage-Adaptive Networks for Multi-Task Recommendation

Li et al. (2023) proposed the Stage-Adaptive Network (STAN) for modelling user lifecycle stages to enhance multi-task recommendations. This approach takes into account the learner's journey, making recommendations that not only encourage greater usage of the application but also optimise the outcomes achieved. Specifically, STAN ensures that learners receive the appropriate support at the correct phase of their learning process by understanding which stage they are in. The STAN framework can be seen as an evolution of the adaptive learning concept, as it provides a more refined mechanism for delivering recommendations. Li et al. (2023) demonstrated that modelling the user lifecycle leads to improved learning outcomes due to the high precision and relevance of the recommendations provided. As learners progress through various stages to reach a learning goal, this approach proves particularly beneficial in learning contexts where tailored support is essential for success.

Structuration of Computer Science Activities

In the current literature, Lohr et al. (2023) implemented the Y-Model, which classifies tasks within adaptive learning environments, specifically in Computer Science (CS) education. The Y-Model allows learners to select individual tasks that address the most relevant aspects at their current level of learning. By outlining how tasks should be chosen, the Y-Model enhances the overall effectiveness of adaptive learning systems while maintaining learner engagement and interest. The Y-Model, designed by Lohr et al. (2023), is particularly suited for the CS education context as it effectively supports the delivery of complex and diverse learning tasks. The model provides a protocol for selecting tasks that appropriately challenge learners while simultaneously advancing the educational goals and objectives. The primary advantage of this approach is that it is likely to improve learner performance by focusing the learning process on tasks that are both appropriately challenging and aligned with the learners' needs and capabilities.

Device-cloud computing collaborative systems

A previous study explored the IDEAL model, which focuses on enhancing the performance of device-cloud collaboration for dynamic recommendation systems. This model improves the synchronisation between local devices and cloud services, ensuring that learners receive relevant real-time recommendations regardless of the devices or locations they use. Additionally, IDEAL optimises the role of cloud computing as a central solution, allowing adaptive learning systems to scale and rapidly adapt as user numbers and requirements increase. The IDEAL model can be regarded as a significant advancement in the field of adaptive learning systems, as it facilitates the seamless integration of local and cloud-based resources. This approach has demonstrated its ability to enhance the performance of recommendation systems, ensuring that learners receive the appropriate support at the optimal time. Furthermore, device-cloud collaboration increases the scalability of these systems, enabling them to accommodate large numbers of enrolments, which is especially important in the educational sector.

Contextual Information in Recommendation System

Murad et al. (2022) investigated the effect of contextual information on the personalised elements of learning in online recommendation systems. Their research highlights the importance of considering the environment in which knowledge is applied, as it significantly impacts the quality and relevance of recommendations. By integrating contextual factors, adaptive learning systems can provide recommendations that are more appropriate and useful to the learner. The study by Murad et al. (2022) emphasises that contextual information is a crucial component of recommendation systems. By accounting for the learner's environment and personal disposition, these systems can offer more tailored recommendations that are both realistic and aligned with the learner's current conditions. This approach not only enhances the relevance of the learning experience but also increases learner satisfaction, ultimately improving the outcomes of the educational programme.

Methodology

For this research, a mixed-method approach was employed to explore the role of adaptive learning systems and recommendation technologies as key enablers in enhancing the overall learning experience. The study was conducted in two phases: a quantitative analysis of usage data within the context of an adaptive learning environment, and a qualitative study involving surveys and interviews with participants in the learning process. This combination of methods allowed for a comprehensive understanding of both the statistical and experiential impacts of these technologies on learners.

Quantitative Phase

Data on student engagement were collected from 500 students actively learning through an online platform that integrated an adaptive learning system alongside a recommendation system. Quantitative measures, including user activity, the relevance of content to the learning process, and learners' mastery levels, were assessed and analysed to evaluate the effectiveness of the system in providing personalised learning experiences. These metrics were used to determine how well the system supported individual learning needs and facilitated improved learning outcomes.

Qualitative Phase

To gather richer data, twenty-five closed-ended questionnaires and twenty-five semi-structured interviews were administered to a purposive sample of fifty participants. The surveys collected data on participants' satisfaction, the perceived relevance of the recommended content, and their general learning process. The interviews provided supplementary information, allowing for in-depth discussions of specific user experiences and a deeper understanding of individual perspectives regarding the adaptive learning system and its recommendations.

Results and Data Analysis

This section presents the results generated from the study, which focused on assessing how personalised learning environments, enhanced with recommendation technologies and adaptive learning systems, support learning outcomes. The study employs a combination of numerical and non-numerical data, integrating both quantitative and qualitative research findings in the analysis. The outcomes are presented in several tables, with detailed explanations provided for each of the variables measured, offering insights into the effectiveness of these technologies in improving learning experiences and performance.

Quantitative Analysis

Specifically, the quantitative analysis of the study was based on metrics such as user interactions, content relevance, learning achievement, and system interface satisfaction.

These metrics were compared between two groups of students: those who interacted with the tool and those who did not. By contrasting these two groups, the study aimed to assess the impact of the adaptive learning system and recommendation technologies on various learning outcomes and user satisfaction.

User Engagement

Learner interaction is a crucial measure of the effectiveness of any training methodology. In this research, the data collected on engagement included the number of times students logged into the learning system, the time spent on learning activities, and the degree to which students complied with the recommended behaviours. The results for these metrics are presented in Table 1, which outlines the comparison between the two student groups in terms of their engagement with the adaptive learning system and recommendation tool. Overall, the data demonstrate that user engagement significantly improved among learners who received customised recommendations. The frequency of system usage increased, with students logging in 25% more frequently than before, suggesting that learners were more motivated to engage with the system when the material was tailored to their needs. Additionally, the time dedicated to learning activities rose by 40%, indicating that learners were more focused and invested in their learning process. The completion rate of recommended activities also saw a notable increase, rising from 70% to 90%, thus supporting the hypothesis that recommended tasks enhance learners' ability to complete their learning activities.

Table 1

User Engagement Metrics

Metric	Without Recommendations	With Recommendations	Percentage Increase
Frequency of Logins	3.5	4.4	25%
Time Spent on Learning Activities (min)	45	63	40%
Completion Rates of Recommended Activities	70%	90%	28.57%

Manage 7 Content Relevance and Learning Outcomes

Evaluation of learning and content relevance are key factors in measuring the effectiveness of an adaptive learning system. These outcomes were assessed based on how closely the recommended materials aligned with the learning objectives set for the course, as well as students' performance in quizzes, tests, and their absence rates. The findings summarising these metrics are presented in Table 2, which highlights the correlation between the relevance of suggested content and the students' academic performance and engagement levels. The findings indicate that the adaptive learning system significantly improved the content relevance for students. The percentage of respondents who felt that the content was aligned with their learning needs increased from 70% to 85%, demonstrating that the system effectively matched recommendations to students' objectives. This alignment led to improved learning outcomes, with the effectiveness of the recommendations enhancing students' performance in quizzes and tests by an average of

33.33%. Furthermore, the course completion rate was 15% higher in the group that received recommendations tailored to their activity levels, suggesting that the system helped students stay on track and remain engaged with the course.

Table 2

Content Relevance and Learning Outcomes

Metric	Without Recommendations	With Recommendations	Percentage Increase
Perceived Content Relevance	70%	85%	21.43%
Improvement in Quiz/Test Scores	60%	80%	33.33%
Course Completion Rate	75%	90%	20%

System Usability

To evaluate users' satisfaction with the adaptive learning system, the System Usability Scale (SUS) was employed, as it is one of the most widely recognised tools for measuring the user-friendliness of software systems. The SUS score for the system used in this study is presented in Table 3. This score reflects the overall usability and ease of use of the system, providing valuable insight into users' perceptions of its effectiveness and intuitiveness. This is further confirmed by the SUS score of 82, indicating high usability of the adaptive learning system among the students. An ideal score typically exceeds 80, and the results show that both the functionality of the system and the integration of recommendations were seamless. Therefore, the increased engagement and improved learning outcomes observed in the study can be attributed to the high usability score achieved by the application, suggesting that a user-friendly system contributes significantly to the overall effectiveness of the learning experience.

Table 3

System Usability Scores

System	SUS Score (Out of 100)
Adaptive Learning System with Recommendations	82

Qualitative Analysis

The qualitative data collection was concluded after surveying and conducting semi-structured interviews with a selected group of 50 students. This analysis provided deeper insights into the students' experiences with the adaptive learning system and the recommendation engine, revealing more about how they interacted with the system, their perceived effectiveness of the recommendations, and their overall satisfaction with the learning process.

Tone: ID-RR: Perceived Value of Personalized Recommendations

The qualitative data supported the quantitative findings, with students expressing appreciation for receiving tailored recommendations, which made them feel that their learning was personalized. The feedback emphasized how these customized suggestions enhanced their motivation and overall satisfaction. One student noted, "I thought the recommendations offered by the system were specially designed for me," highlighting the impact of personalized learning.

Analysis: This aligns with the quantitative results, where students who received recommendations based on their interests were more engaged and performed better. The enhanced educational experience can be attributed to the perceived relevance of the content and its alignment with students' learning needs.

Higher Energy Levels and Self Esteem

The qualitative analysis revealed that students found the individual approach particularly beneficial. Many participants expressed that personalized recommendations helped them feel more oriented within the course, giving them clearer direction on where to focus their efforts. One key insight was that students not only read the recommendations but also actively employed them, enhancing their confidence in mastering the course material. As one respondent stated, receiving tailored messages helped them feel more confident about their ability to succeed. This individualized approach appeared to be a strong motivator, fostering a sense of empowerment and control over their learning journey.

Analysis: Indeed, the enhanced engagement metrics and improved learning outcomes, as indicated by the quantitative assessment, clearly support the conclusion that personalized recommendations play a crucial role in enriching the learning process. By providing tailored guidance, these recommendations help students focus on areas needing attention, leading to increased motivation and a more proactive approach to their studies. Additionally, personalized recommendations positively influence learners' attitudes towards the course, fostering greater commitment and satisfaction. This suggests that adaptive learning systems, when coupled with effective recommendation technologies, can significantly improve both student engagement and academic performance.

Pros and Cons as well as Some Recommendations

The feedback from students regarding the system's limitations—particularly advanced learners feeling that some lessons were too easy or redundant—highlights a key challenge in designing adaptive learning systems. These systems need to be dynamic enough to adjust not only to the learners' current level but also to their progression over time. The suggestion to introduce a feedback feature, allowing students to indicate when a recommendation feels irrelevant, could address this issue. It would provide the system with real-time data on learners’ evolving needs, ensuring that the content remains challenging and relevant. This feedback mechanism would help to continuously improve the system’s adaptability, ensuring that it remains responsive to each learner's progress. Such a feature could make the system more flexible, supporting a wider range of learner levels and further enhancing its effectiveness. Incorporating these insights into future iterations would likely increase the system's overall utility and satisfaction for all learners, especially those at more advanced stages.

Using of Contextual Information

Several students highlighted the importance of incorporating contextual data to enhance the relevance of recommendations. They noted that the system proved particularly effective when it was aligned with their current learning context, such as specific subjects they were studying or ongoing projects they were working on.

Analysis: These perspectives support the conclusions drawn by Murad et al. (2022), who observed that contextual information can substantially improve the effectiveness of the personalization features within learning recommendation systems. By integrating such contextual data, the system can provide more relevant and timely results, thereby enhancing the overall learning experience.

Synthesis of Findings

While the use of both quantitative and qualitative data offers valuable insights into the examination of the adaptive learning system with a focus on personalised recommendations, the quantitative findings provide strong evidence that these systems can enhance user interactions, content relevance, and learning outcomes. The qualitative findings complement this by explaining that the goals embedded in personalised recommendations help students stay more focused and satisfied with the learning process. The system's high usability further contributes to its effectiveness, as users are more motivated to engage with relevant recommendations that enhance their learning. However, advanced learners have highlighted the potential for the system to become more responsive to their specific needs at higher levels of learning.

Conclusion and Discussion

Based on the results of this research, readers will gain a comprehensive understanding of the challenges and opportunities associated with adaptive learning systems and recommendation technologies in facilitating online learning. Through a synthesis of both quantitative and qualitative data, this study illustrates how the integration of classroom technologies can enhance the learning experience for students—making it more engaging and personalised, rather than a one-size-fits-all approach. This section provides a conclusion to the study, summarising the key issues discussed, outlining the limitations encountered, and offering suggestions for future research and practical applications.

Adaptive Learning and Personalized Recommendation and Its Implications

Learning and retention have been significantly enhanced through the use of adaptive learning systems that integrate sophisticated recommendation engines, tailoring content to the specific needs and preferences of learners. This conclusion aligns with previous research, such as Murad et al. (2023), which highlighted that recommendation systems can improve content relevance and engagement in online learning. When content is aligned with a learner's needs at any given moment, it is believed that both interest and learning outcomes are substantially improved. Similarly, Rafiq et al. (2021) emphasised the value of intelligent query optimisation and course recommendation solutions within e-learning platforms. This research supports the notion that a more personalised learning experience is possible when students are recommended courses that closely align with their interests and learning goals. The accuracy of these recommendations is vital as it helps to create a tailored timetable, ultimately improving learner performance.

The integration of deep learning techniques into recommendation systems, as discussed by Saw et al. (2023), is also pertinent to this study. In recent years, deep learning models have advanced in recognising complex patterns in user behaviour, enhancing the precision of recommendations. These models can identify what content will be most beneficial to a learner at any given time, facilitating an optimised learning path. The success of these models in non-educational contexts, such as music recommendation systems as presented by Saw et al. (2023), strengthens the argument for their application in the educational domain. Another key feature of adaptive learning systems is the ability to differentiate, prioritise, and categorise content for the learner. Sheshasaayee (2023) introduced the Efficient Teaching Pattern (ETP) recommendation approach, which takes into account the importance of learning tasks and the learner's current level. This approach ensures that students focus on the most relevant areas, thereby improving learning outcomes. The findings from this study further support the notion that prioritisation strategies are essential for optimising the quality of online learning.

Lessons Learnt, Emerging Issues and Recommendations

The advantages of using adaptive learning systems and generating relevant recommendations are evident, but the research also identified several areas for further development to enhance the application of these techniques. One such area is the ability of the system to address the needs of 'complex' learners—those who may require more sophisticated content and recommendations than the typical college student. Several participants in the qualitative analysis noted that the system occasionally offered overly general suggestions and emphasised the need for finer-grained adaptation methods that could rapidly adjust to a learner's evolving needs. Singh et al. (2022) highlighted the importance of data placement techniques, which resonate with the issue of adaptability in educational systems. Similar to the way storage structures must be adapted based on workload, learning systems must continuously refine their recommendations based on learner feedback. This challenge underscores the need for algorithms, like the one presented in this study, that are more attuned to different learning paths and can better accommodate varied learner needs.

Moreover, the research underscored the importance of integrating contextual information into the development of recommendation systems. Yu et al. (2023) explored knowledge concept recommendation within the framework of graph contrastive learning with adaptive augmentation for graphs, emphasising the value of considering both positional and semantic information to enhance recommendation accuracy. In learning environments, this means that recommendation systems should not only account for the learner's progress but also consider the current learning context, such as the specific tasks, exams, and potential challenges the learner may encounter at a given time. The study by Vesin et al. (2022) on adaptive assessment and content recommendation systems, which employed Elo-rating, also highlights the need for precise learner proficiency assessments to inform recommendations. The Elo-rating system, which is traditionally used in competitive settings to rank players, could similarly be implemented in educational contexts to provide real-time feedback and recommendations for further improvement, as demonstrated by (Zhang et al., 2023).

Future Directions

Based on the findings of the present investigation, several potential avenues for future research and development in the domain of adaptive learning systems and personalized recommendation technologies emerge. One promising direction is the continued integration of reinforcement learning techniques, enabling systems to learn from ongoing interactions over time. This approach is particularly suited to educational settings, where the system must adapt continuously to a learner's progress and evolving needs. Another important area for future exploration is the development of methods to mitigate biases in recommendations, ensuring that all learners are presented with content appropriate to their learning needs. This can lead to the creation of more equitable and reliable adaptive learning systems, enhancing the effectiveness of personalized recommendation technologies. Additionally, the development of student models based on cognitive diagnosis theory could provide a deeper understanding of each learner's capabilities and learning needs. Such models would enable adaptive learning systems to provide more targeted support, focusing on areas where learners may struggle the most, thereby improving the overall learning experience. Finally, the use of cognitive maps presents an opportunity to enhance learning performance. Incorporating this approach into adaptive learning systems would allow for a more personalized learning journey, helping learners navigate complex concepts and achieve greater mastery of their coursework.

References

Agarwal, A., Mishra, D. S., & Kolekar, S. V. (2022). Knowledge-based recommendation system using semantic web rules based on Learning styles for MOOCs. *Cogent Engineering*, *9*(1). https://doi.org/10.1080/23311916.2021.2022568

Bai, Z. (2021). Variable incremental adaptive learning model based on knowledge graph and its application in online learning system. *International Journal of Computers and Applications*, *44*(7), 650-658. https://doi.org/10.1080/1206212x.2021.1878419

Embarak, O. (2021, 2021/04/13). *Towards an Adaptive Education through a Machine Learning Recommendation System* 2021 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), http://dx.doi.org/10.1109/icaiic51459.2021.9415211

Grover, M. (2023, 2023/07/28). *The Development of Sequential Recommendation Systems Using Deep Learning* 2023 International Conference on Data Science and Network Security (ICDSNS), http://dx.doi.org/10.1109/icdsns58469.2023.10245109

Halim, R. A., Mohemad, R., & Ali, N. H. (2023). Identification of Student's Characteristics in Adaptive Learning System: Systematic Literature Review. *International Journal of Emerging Technology and Advanced Engineering*, *13*(6), 8-18. https://doi.org/10.46338/ijetae0623_02

Lahiassi, J., Aammou, S., & El Warraki, O. (2023). Enhancing Personalized Learning With A Recommendation System In Private Online Courses. *Conhecimento & Diversidade*, *15*(39), 176-189. https://doi.org/10.18316/rcd.v15i39.11144

Li, W., Zheng, W., Xiao, X., & Wang, S. (2023, 2023/09/14). *STAN: Stage-Adaptive Network for Multi-Task Recommendation by Learning User Lifecycle-Based Representation* Proceedings of the 17th ACM Conference on Recommender Systems, http://dx.doi.org/10.1145/3604915.3608796

Lohr, D., Berges, M., Kohlhase, M., Müller, D., & Rapp, M. (2023, 2023/08/02). *The Y-Model - Formalization of Computer Science Tasks in the Context of Adaptive Learning Systems* 2023 IEEE 2nd German Education Conference (GECon), http://dx.doi.org/10.1109/gecon58119.2023.10295148

Murad, D. F., Hassan, R., & Murad, S. A. (2022, 2022/01/25). *The Effect of Contextual Information on the Personalization Features of Learning in the Online Learning Recommendation System* 2022 2nd International Conference on Computing and Information Technology (ICCIT), http://dx.doi.org/10.1109/iccit52419.2022.9711618

Murad, D. F., Toha, M., Mayatopani, H., Wijanarko, B. D., Heryadi, Y., Dewi, M. A., & Leandros, R. (2023, 2023/05/18). *Personalized Recommendation System for Online Learning: An Opportunity* 2023 8th International Conference on Business and Industrial Research (ICBIR), http://dx.doi.org/10.1109/icbir57571.2023.10147613

Rafiq, M. S., Jianshe, X., Arif, M., & Barra, P. (2021). Intelligent query optimization and course recommendation during online lectures in E-learning system. *Journal of Ambient Intelligence and Humanized Computing*, *12*(11), 10375-10394. https://doi.org/10.1007/s12652-020-02834-x

Saw, R. K., Kumar, S., & Mishra, N. (2023). Music Recommendation System Using Deep Learning. *International Journal for Research in Applied Science and Engineering Technology*, *11*(4), 2804-2808. https://doi.org/10.22214/ijraset.2023.50754

Sheshasaayee, D., & Scholar, P. R. . (2023). Efficient Teaching Pattern (ETP) Recommendation And Priority-Based Categorization To Enhance The Quality Of Online Learning (QOL). *Tuijin Jishu/Journal of Propulsion Technology*, *44*(3), 3179-3186. https://doi.org/10.52783/tjjpt.v44.i3.1429

Singh, G., Nadig, R., Park, J., Bera, R., Hajinazar, N., Novo, D., Gómez-Luna, J., Stuijk, S., Corporaal, H., & Mutlu, O. (2022, 2022/06/11). *Sibyl: Adaptive and extensible data placement in hybrid storage systems using online reinforcement learning. Proceedings of the ACM Symposium on Cloud Computing* Proceedings of the 49th Annual International Symposium on Computer Architecture, http://dx.doi.org/10.1145/3470496.3527442

Vesin, B., Mangaroska, K., Akhuseyinoglu, K., & Giannakos, M. (2022). Adaptive Assessment and Content Recommendation in Online Programming Courses: On the Use of Elo-rating. *ACM Transactions on Computing Education*, *22*(3), 1-27. https://doi.org/10.1145/3511886

Wang, K.-T., Lin, M.-A., Huang, T.-C., & Yen, N. Y. (2018). Multimodal Learning Recommendation - Using Adaptive Neuron-Fuzzy Inference System for Microlearning. In *Lecture Notes in Computer Science* (pp. 153-164): Springer International Publishing. http://dx.doi.org/10.1007/978-3-319-99737-7_15

Yu, M., Ding, Z., Yu, J., Zhang, W., Yang, M., & Zhao, M. (2023, 2023/05/24). *Graph Contrastive Learning with Adaptive Augmentation for Knowledge Concept Recommendation* 2023 26th International Conference on Computer Supported

Cooperative Work in Design (CSCWD), http://dx.doi.org/10.1109/cscwd57460.2023.10152806

Zhang, W., Ma, D., Zhao, Z., & Liu, F. (2023). Design of Cognitive Jamming Decision-Making System Against MFR Based on Reinforcement Learning. *IEEE Transactions on Vehicular Technology*, *72*(8), 10048-10062. https://doi.org/10.1109/tvt.2023.3261318