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RECOMMENDATION SYSTEM FOR PERSONALIZED LESSON LEARNING

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Abstract
This research presented the development of recommendation system for a personalized lesson recommendation system in online learning environments. The system combined ontology techniques to represent learner knowledge and lesson content with machine learning techniques to predict suitable lessons based on individual behaviors and characteristics. The developed system used information from students in the information technology course through an e-Learning platform and evaluated performance by comparing it with traditional Content-Based Filtering and Collaborative Filtering techniques. The results showed that the system could increase the average F1-score to 0.80 and reduce Mean Absolute Error (MAE) by an average of 18 percent compared to traditional methods. Additionally, students showed significantly improvement in academic achievement ($p < 0.05$) and reported high satisfaction with the system. This research demonstrated that combining ontology with machine learning algorithms enhanced the accuracy of lesson recommendation and helped promote effectively personalized learning.

Keywords: Recommendation System, Personalized Lesson Learning, Personalized Learning, Ontology, Machine Learning,

INTRODUCTION

In the digital age, e-learning systems have become the primary platform for promoting learning and education. However, many students face difficulties in selecting suitable content. Recommendation systems help solve this problem, especially when ontology technology is combined with machine learning to gain a deeper understanding of lesson structure and student profiles. As digital learning rapidly expands, e-learning systems have become one of the essential mechanisms that allow students to access knowledge content anytime, anywhere. However, a significant challenge for these systems is adapting content to suit the characteristics of individuals (personalised learning) to maximise learning effectiveness (Johnson et al., 2010).

Recommendation systems have been developed to solve this problem by selecting or ranking learning resources that match students' needs, background knowledge, or interests (Adomavicius & Tuzhilin, 2005). However, traditional recommendation systems, such as Collaborative Filtering (CF) and Content-Based Filtering (CBF), often have limitations in understanding the relationships between the meaning of content and student profiles (Su & Khoshgoftaar, 2009). To improve accuracy and contextual adaptation, many researchers have proposed using Ontology technology, which is a knowledge representation model that can systematically define relationships between different concepts. Ontology can be used to create more deeply understood student profiles and match them meaningfully with learning content (Henze et al., 2005; Tarus et al., 2018).

For example, Tarus et al. (2017) developed a hybrid recommendation system that combines ontology with Collaborative Filtering for lesson recommendations, finding it could improve accuracy better than traditional methods. Meanwhile, Al-Shamri Al-Shamri (2021) proposed a recommendation system that utilises knowledge from ontology, combined with Machine Learning, to analyse student behaviour, enabling more accurate content recommendations in e-learning systems. From this context, this research aimed to develop a personalised lesson recommendation system by combining ontology techniques and machine learning to improve recommendation accuracy that matches each student's characteristics and behaviour. It is expected to enhance user learning experiences in e-learning systems significantly.

Research Objectives

1. To design and develop a recommendation system for a personalised learning lesson using ontology and machine learning to recommend learning content for each individual student effectively
2. To create an ontology model for students and lessons that can describe how students' background knowledge, abilities, and learning behaviours relate to the meaningful structure of lesson content

3. To develop a predictive lesson content model by using machine learning techniques (such as XGBoost, Decision Tree, or Neural Networks) that learn from student learning behaviour data in e-learning systems.
4. To compare the effectiveness of the recommendation system and the traditional Content-Based Filtering and Collaborative Filtering techniques, using various indicators including Precision, Recall, F1-score, and Mean Absolute Error (MAE)

Research Hypotheses
H1: The development of a recommendation system using ontology techniques combined with Machine Learning has a significantly higher F1-score than the traditional Collaborative Filtering systems.
H2: The development of the recommendation system will perform better in recommending lessons that match each student's individual needs than the Content-Based Filtering with statistically significant.
Scope of the study
1. Population and Sample
The sample group for this research consisted of undergraduate students studying information technology-related courses through e-Learning systems (Thaimooc), totalling approximately 400 people.
2. Scope of Technology
A Personalised Lesson Recommendation System was developed using:
Protégé for creating ontologies of students and lesson content
Machine Learning algorithms such as XGBoost and Decision Tree for learning students' behaviour
3. Scope of content
Lessons were limited to Information Technology subjects, such as Programming, Databases, or Web Development.
4. Scope of evaluation
The effectiveness of the system was tested using the performance metrics system (Precision, Recall, F1-score), and the user satisfaction was evaluated through a questionnaire (a 5-point Likert scale).

LITERATURE REVIEWS

1. Recommender Systems
Recommender Systems are systems that help filter large amounts of data to present what is suitable for individual users, based on their behaviour, preferences, or profiles. The systems play an important role in digital learning environments, especially in e-learning systems where students face overwhelming amounts of content that are difficult to choose from. Recommendation systems can help filter and suggest content that matches each student's interests, background knowledge, or learning behaviour.
Recommendation systems are divided into three main types, including (1) Collaborative Filtering (CF), which recommends based on preferences of similar users, (2) Content-Based Filtering (CBF), which recommends based on characteristics of items the user has been interest, and (3) Hybrid Approach, which combines the advantages of both CF and CBF to improve accuracy (Bobadilla, 2013; Manouselis, 2011). Designing recommendation systems in e-Learning also incorporates Data Mining techniques and machine learning to analyse student data deeply, such as using association rules with Collaborative Filtering (Khan et al., 2025; Garcia et al., 2009) or incorporating learning analytics to help track student behaviour in MOOCs (Drachsler & Kalz, 2016).

2. Ontology
Ontology is a form of Knowledge Representation that uses concepts, relations, and facts to create meaningful structures that machines can understand. In learning recommendation systems, ontology can be used to create lesson content structure, semantic student profiles, and match rules between students and content (Gruber, 1993; Liu & Huang, 2018)
Related researches such as Tarus et al. 2017) and Al-Shamri (2021) have demonstrated that recommendation systems utilising ontology combined with CF or ML have significantly improved accuracy in recommendations. Meanwhile, Henze et al. (2005) and Santos & Boticario (2015) demonstrated that using Ontology in context-aware recommendation can adapt recommendations to a student's context, such as learning progress or skill level.

3. Machine Learning
Machine Learning is a technique for developing algorithms that can learn from data and apply learning to predict or classify new data. In recommendation systems, techniques such as Decision Trees, Support Vector Machines (SVMs), Random Forests, and XGBoost are commonly used, which help improve recommendation accuracy and can handle large amounts of data (Channuwong et al., 2022; Jordan & Mitchell, 2015; Nilashi et al., 2016).
XGBoost, in particular, offers advantages in speed and high accuracy, and can effectively handle overfitting problems, making it suitable for complex and diverse learning datasets. Additionally, Deep Learning applications, such as neural networks and LSTM, are being used to enhance performance in learning from user behaviour (Mustafa et al., 2020; Zhang et al., 2019).

4. Personalised Learning
The concept of Personalised Learning emphasises providing students with content that matches their individual needs, knowledge level, and interests to increase motivation and learning effectiveness (Walkington, 2013). Brusilovsky & Millán (2007) proposed that creating structured Learner modelling helped systems automatically assess knowledge levels and suggest appropriate content, especially when combined with Ontology and Machine Learning. Similarly,

Papanikolaou et al. (2009) proposed designing multilayered activities to accommodate students with different backgrounds. Additionally, research has found that applying Learning Analytics and Adaptive Systems technologies helps systems adjust learning in real-time according to student characteristics, creating flexible learning experiences (Zorrilla & García-Saiz, 2013; Romero & Ventura, 2013).

5. Combining Ontology Techniques with Deep Learning

Over the past few years, a growing trend has emerged in merging ontology technology with deep learning techniques to enhance the performance of recommendation systems, particularly in e-learning environments where behavioural data and content structures can be highly complex. While deep learning approaches, such as CNN, LSTM, or BERT, excel at learning intricate patterns, they often fall short when it comes to truly understanding the semantic meaning behind the data. Current research addresses this gap by proposing ontologies as a semantic knowledge layer that feeds into deep learning models, enabling systems to better grasp the conceptual relationships between learners, lessons, and content in a more structured manner (Channuwong et al., 2025; Al-Shamri, 2021).

Xie and colleagues (2022) developed a hybrid model that utilises ontological structures to create semantic vectors, which are then fed into deep neural networks, thereby improving the accuracy of lesson recommendations. Meanwhile, Chakraborty and Gupta (2023) combined BERT models with ontological frameworks to generate recommendations that could understand learner contexts more deeply. Building on this work, Mishra and Shukla (2024) explored the use of Graph Neural Networks (GNN) alongside ontologies to create graph-based representations capable of analysing complex knowledge structures with greater precision. These research efforts highlight how combining ontologies with deep learning enhances not only accuracy but also contextual adaptability and the ability to explain recommendations, crucial features for learner-centred recommendation systems.

6. Related researches

Proposed a hybrid recommendation system using Ontology and Machine Learning for personalised lesson recommendations

Authors	Details	Strengths
Tarus et al. (2017)	Developed a recommendation system for e-Learning using ontology combined with Collaborative Filtering	Improve recommendation accuracy compared to traditional CF
Al-Shamri (2021)	Proposed a hybrid recommendation system using Ontology and Machine Learning for personalized lesson recommendations	Effectively uses semantic knowledge in student profiles
Santos & Boticario (2015)	Used Ontology and Context-Aware Recommendation to suggest activities in Moodle	The system can adapt to student context, such as progress in lessons
Mustafa et al. (2020)	Analysed the recommendation systems using Deep Learning and Ontology to understand students' knowledge structure	Enhance deep learning capabilities from user data

Designing concept for Ontology

Basic Ontology structure

Classes

Class	Description
Learner	Representative of each student (user)
Lesson	Recommended lessons or contents
Topic	Sub-topic of lessons such as Programming, Database
Skill Level	Skill levels such as Beginner, Intermediate, Advanced
Learning Style	Visual, Auditory, Kinesthetic
Assessment	Tests or evaluations related to the content
Recommendation	Recommendation of lesson for students

Object Properties

Property	Domain → Rang	Interpret
Skill Level	Learner → Skill Level	What is skill level of student?
Interested in	Learner → Topic	What topic that students is interested?
Learning Style	Learner → Learning Style	Learning style of student
covers Topic	Lesson → Topic	What topics does this lesson cover?

Recommended For	Lesson → Learner	Which student is this lesson suitable for?
Assessed By	Lesson → Assessment	What assessments are included with this lesson?
Suggests Lesson	Recommendation → Lesson	Which lesson does this recommendation point to?
Target User	Recommendation → Learner	Which student is this recommendation targeted at?

RESEARCH METHODOLOGY

This study was applied research, aimed at developing a personalised lesson recommendation system for students in digital learning systems. The research employed knowledge processing techniques, combined with ontology and machine learning algorithms, to present lesson content tailored to each student's characteristics.
Population and Sample
The sample consisted of undergraduate students who studied Information Technology courses through e-learning systems at Rajamangala University of Technology Suvarnabhumi, Nonthaburi Centre, with a total of approximately 400 students. Using the Krejcie and Morgan (1970) table, the sample size was 196 students, selected through multistage sampling as follows:
In the first stage, the researcher divided the population by faculties or departments in Information Technology that use e-Learning systems, then randomly selected specific faculties/departments using simple random sampling.
In the second stage, sample students were randomly selected from the enrolment lists of technology-related courses, such as Programming, Database, or Web Development, in each selected faculty, using systematic sampling to obtain a total sample of 196 students.
The personalised lesson recommendation system, completed satisfaction questionnaires, and attended pre- and post-test of learning system achievement assessments were tested among the sample group.
Research instruments
Personalised Lesson Recommendation System developed using the following technologies:
Protégé for creating ontology for student and lesson content
Python using XGBoost technique for machine learning algorithms to train models that predict suitable lessons for new students by considering various characteristics such as skill level, interests, and learning style.
Django for developing the system interface
MySQL database for storing student data and system usage
Satisfaction Questionnaire measuring satisfaction in 3 areas: recommendation accuracy, ease of use, and overall satisfaction
The Achievement Test is used to measure student understanding before and after using the recommendation system
Ontology Development and Machine Learning Application
For ontology development, researchers began by defining the main classes in the system, including Learner, Lesson, Topic, Skill Level, and Learning Style, and establishing relationships (Object Properties) such as interested in and has skill level. Then researchers created individuals from actual student data and lesson content, imported this data into the recommendation system using .owl files created in Protégé, and performed reasoning with a reasoner to group content that matches each student.
For a machine learning application, the researchers collected data on student learning behaviour, including lessons viewed, time spent on learning, and exercise completion success. The XGBoost technique was then used to train models that predict suitable lessons for new students, considering various characteristics such as skill level, interests, and learning style. The machine learning model was integrated with the ontology structure to provide both data-driven and semantic recommendations.
Data Collection
Data were collected from actual students, including student profiles and learning behaviour questionnaires, activity logs in the system, such as login times, lesson selections, and tests taken, followed by learning achievement data before and after using the system.
Data Analysis
Quantitative analysis was conducted using descriptive statistics, including mean and standard deviation, and the pre- and post-test achievement was compared using t-test statistics. System recommendation performance was analysed using precision, recall, and F1-score, while user satisfaction was analysed using SUS scores.
For system evaluation, recommendation performance was measured by comparing with traditional recommendation systems (content-based filtering). The user evaluation was measured based on satisfaction, understanding, and achievement after using the system.
The accuracy of the ML model was verified using K-fold cross-validation.

RESULTS

In this section, it is explained the results of research and at the same time is given the comprehensive discussion.

Table 1: Efficiency of Recommendation System

Indicators	Developed System (Ontology+XGBoost)	Content-Based Filtering	Collaborative Filtering
Precision	0.81	0.69	0.66
Recall	0.79	0.66	0.63
F1-score	0.80	0.67	0.64
Mean Absolute Error (MAE)	18%	-	-

1**. Efficiency of Recommendation System**
After testing the system using ontology techniques combined with Machine Learning (XGBoost), the results showed that this system recommended lessons more accurately than traditional systems such as Collaborative Filtering (CF) and Content-Based Filtering (CBF). The performance metrics presented an average Precision of 0.81, an average Recall of 0.79, a F1-score of 0.80, and a Mean Absolute Error (MAE) reduced by an average of 18% compared to Collaborative Filtering.

Table 2: User Learning Achievement

Test	n	$\bar{x}$	S.D	t	p-value
Pre-test	196	58.4	7.8	7.82*	0.0000
Post-test	196	72.9	6.5		

2. **User Learning Achievement**
Pre-test and post-test scores showed a statistically significant difference ($p<0.05$), with average pre-test scores of 58.4 and average post-test scores of 72.9. The t-test value was 7.82, with $p = 0.000$, demonstrating that the recommendation system would improve learning achievement.
Conduction of Learning achievement assessment of the sample group through pre-test and post-test to measure knowledge, understanding, and learning that resulted from using the developed personalised lesson recommendation system. The sample group consisted of 196 undergraduate students selected through a multistage sampling process from a total of 400 students enrolled in Information Technology courses via e-Learning systems at Rajamangala University of Technology Suvarnabhumi, Nonthaburi Centre.
Both test sets were designed based on content from related course categories such as Programming, Database, and Web Development, which referred to the content areas that the system can recommend. The tests had equal numbers of questions and covered knowledge skills from basic to analytical levels. Three experts verified content validity, and the reliability coefficient showed a Cronbach's Alpha of 0.82, indicating good reliability.
Data collection was conducted, following these steps:
Before the sample group used the recommendation system, they took a pre-test to measure their baseline knowledge level.
After students used the personalised lesson recommendation system according to the content the system suggested, the sample group took the identical post-test
Both pre- and post-learning scores were compared using a Dependent Sample t-test analysis to test for statistically significant score differences at the $\alpha=0.05$ level
Analysis results, as shown in the table, indicate that the average pre-test score was 58.4 points (SD = 7.8), and the average post-test score was 72.9 points (SD = 6.5), with statistically significant differences in scores ($t = 7.82$, $p < 0.0001$). It demonstrated that using the developed lesson recommendation system would significantly improve students' learning achievement.
3. User Satisfaction Assessment Results From the 5-point Likert scale questionnaire, we found that recommendation accuracy had an average score of 4.38, ease of use averaged 4.21, and overall satisfaction averaged 4.35. Satisfaction levels were high in all areas. Most students indicated that the system recommended content that matched their interests and knowledge level, the interface was easy to use, and they could quickly select relevant lessons.
4. Machine Learning Model Performance (XGBoost), using the XGBoost technique on student behaviour data such as study time, lesson clicks, and learning styles, enabled the system to predict appropriate content efficiently. Through K-Fold Cross-Validation testing (k=5), the model showed consistent F1-scores between 0.79 and 0.82 across all testing rounds, demonstrating that it consistently and accurately predicted suitable lessons.
5. Integration of Ontology with Machine Learning, the ontology structure helped the system understand the "meaning" and relationships between students and lessons, such as aptitude, interests, and skill levels. Combining semantic data with data-driven learning resulted in more accurate and in-depth recommendations than considering behaviour alone.

CONCLUSIONS

This research aimed to develop a personalised lesson recommendation system using ontology techniques combined with Machine Learning to improve accuracy in recommending appropriate content for students in e-learning systems. The findings showed that the developed personalised lesson recommendation system, which integrated ontology with Machine Learning, achieved 12.5% higher accuracy compared to traditional methods and could significantly enhance learning achievement and user satisfaction. Additionally, the system effectively addressed personalised learning needs in e-Learning systems based on student behaviour data, learning styles, and skill levels.

4.1 **DISCUSSIONS**

The research findings demonstrated that the developed personalised lesson recommendation system, which integrated ontology technology with Machine Learning techniques (XGBoost), performed significantly well in recommending content that matches each student's characteristics and needs. It was evident in the accuracy of recommendations, learning achievement, and user satisfaction. From our test, the developed system improved the F1-score by up to 12.5% compared to traditional Collaborative Filtering techniques, which aligns with a study by Tarus et al. (2017) that suggested applying ontology structures would improve recommendation quality in e-Learning systems better than traditional methods. It can systematically represent semantic knowledge and relationships between students and lessons. Additionally, using the XGBoost technique, which is one of the highly effective

Students who used the recommendation system had significantly higher average post-learning scores, increasing from 58.4 to 72.9, $p < 0.05$. It suggests that recommendations tailored to students' background knowledge, interests, and learning styles help them better understand lessons. This finding is relevant with the Personalised Learning concept study by Walkington (2013), which stated that adapting content to individual student characteristics can increase motivation and learning effectiveness.

Systematic ontology design, which categorises classes of Learner, Lesson, Skill Level, and Learning Style, enables the system to match students meaningfully with lessons and process information computationally. This result supports the work of Gruber (1993), who stated that ontology would serve as an important tool for structured semantic representation in intelligent systems.

This research builds upon Al-Shamri's (2021) concept, which proposes a personalised learning recommendation system based on ontology combined with machine learning techniques, focusing on using semantic knowledge to analyse student behaviour in e-learning systems. However, this research expands the scope and adds multiple dimensions of application, including systematic ontology structure design that comprehensively covers student profiles (such as skill levels, interests, and learning styles), application of highly effective machine learning techniques like XGBoost that can handle complex learning behavior data well, as well as empirical evaluation using real sample groups in system testing and measuring learning achievement before and after using the system.

The research findings further reveal that integrating ontological approaches with machine learning algorithms, such as XGBoost, yields significant improvements in both recommendation system accuracy and learner achievement. It aligns with contemporary research trends that advocate for combining ontological structures with deep learning techniques to enhance deep learning performance while preserving semantic knowledge comprehension.

For example, Xie et al. (2022) developed a hybrid model that incorporates semantic vectors derived from ontological structures into neural networks, thereby enabling more precise content-learner matching. Similarly, Mishra and Shukla (2024) employed Graph Neural Networks (GNNs) to transform ontological structures into dynamic knowledge graphs, enabling the system to provide real-time, context-adaptive recommendations. This approach bears similarity to the context-aware data processing implemented in our developed system.

Meanwhile, Chakraborty et al. (2023) proposed integrating BERT models with ontological frameworks to generate context-aware embeddings that enable a deeper understanding of learner needs through descriptions or learning histories. While our research does not employ deep learning approaches such as BERT, the system's ability to analyse learner behaviour in conjunction with semantic knowledge structures yields comparable results, particularly in enhancing recommendation accuracy and personalising content for individual learners.

Furthermore, experimental results demonstrate that the model developed using Ontology + XGBoost achieves an F1-score of 0.80, which approximates the accuracy levels reported by Mustafa et al. (2020) in their review of deep learning applications with knowledge-based systems. Their findings indicated that hybrid models distinctly improve recommendation accuracy, especially in contexts where data exhibits diversity and relational structure characteristics, such as e-learning systems.

The research results show that, in addition to achieving higher content recommendation accuracy, the system can significantly enhance users' learning achievements. The strength of this research lies in its seamless integration of semantic knowledge from ontology with data-driven Machine Learning models, which differs from previous work that typically focused on only one aspect. Therefore, this research is not merely an application of existing approaches but significantly extends and adds academic value in the context of personalised learning on e-Learning systems.

4.2 Recommendations for further study

Although the research results demonstrate the effectiveness of the developed recommendation system, there are still some limitations that should be considered in further study, including;

Expanding the sample group to cover diverse academic fields to test the model's generalizability
Using real-time data and feedback loops, so the system can immediately adapt through adaptive learning
Incorporating Deep Learning techniques such as LSTM or BERT for deeper analysis of content and behaviour.

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