Reducing Learner Disorientation in MOOC Learning Paths: Evidence from a Hybrid Recommender System

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Abstract
Nonlinear learning, which aligns with natural thinking and addresses individual needs, has great potential for e-learning. However, personalized learning paths in MOOCs through in-course recommenders remains limited, with only 18% adoption. Therefore, this research focuses on reducing learners' disorientation by creating personalized adaptive learning paths in MOOCs using a hybrid recommender system, combining ontology and PrefixSpan-based sequential pattern mining. A Moodle-based prototype was tested in a quasi-experimental design with three groups: (1) a comparison group using sequential learning without recommendations, (2) a nonlinear learning group using an ontology-based recommender system, and (3) a nonlinear learning group using a hybrid recommender system. Of 209 registrants, 102 actively participated and consented to data use. The results show that the hybrid recommender group had a higher average efficiency than the ontology recommender group, achieved the highest effectiveness in two of three sub-learning outcomes, and had higher mean scores on 22 of 30 e-learning satisfaction variables. Hypothesis testing with analysis of covariance (ANCOVA) showed no significant differences in efficiency, partial support for effectiveness (significant material access patterns but equivalent assessment scores), and partial support for satisfaction (significant differences in e-learning usability, Moodle preference, and learner behaviour). Visualization using weighted directed graphs of learning paths revealed similar forward-linear learning path patterns across all groups, except for variations in the first three modules of the comparison group. These findings underscore the potential of hybrid recommender systems to reduce learner disorientation, improve learner satisfaction and usability, and optimize learning paths in MOOCs. Future research should consider potential confounding variables such as course duration and sample size, as well as alternative configurations to maximize their benefits across various educational settings.

Keywords: Adaptive learning, hybrid recommender system, learning path, learner disorientation, MOOC, personalized learning

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Nonlinear learning refers to an approach in which learners themselves choose the learning materials, rather than following a sequence pre-defined by instructors (Blaschke & Hase, 2016; Peters, 2002). This approach offers flexibility, enabling learners to explore content aligned with their interests and needs. Although nonlinear learning paths can be beneficial and hold significant potential (Moore, 2020), they also risk causing learning disorientation—a sense of losing direction closely linked to learning outcomes and content structure (Correa, 2017). Therefore, some degree of structure remains necessary since the absence of structure can be equivalent to the absence of learning (Rootzén, 2015).

To minimize learning disorientation, learners (individually or in groups) may receive emotional support or technical competence reinforcement (Kaplan et al., 2021; Mamun et al., 2020; O'Brien & Reale, 2021). However, such support generally targets only a few individuals. This challenge is amplified in large-scale online learning contexts like Massive Open Online Courses (MOOCs). While MOOCs offer broad, inclusive access, their massive scale and diverse learner backgrounds make it harder to provide personalized learning experiences. Consequently, personalization technologies are crucial for improving learners' experiences in MOOCs.

Personalizing e-learning is more complex than in domains such as e-commerce, e-libraries, and e-government (George & Lal, 2019). Two major contributing factors are the dynamic nature of learners' profiles before, during, and after the learning process (Huang et al., 2019) and the limited availability of learner ratings for educational content (Lowenthal et al., 2015). In response, experts have developed various personalization technologies in e-learning—such as Intelligent Tutoring Systems, gamification, and recommender systems. Compared to other approaches, recommender systems can help learners save time by quickly identifying relevant materials from a large content pool (Tondello et al., 2017). Previous studies showed that hybrid recommender systems are becoming more common (George & Lal, 2019; Rahayu et al., 2023). However, studies specifically integrating ontology and sequential pattern mining to adapt to learners' evolving skills and preferences are still limited.

The remaining sections of this paper continue as follows: Section 2 provides a theoretical background and related works. Section 3 describes the research methods, including system architecture, experimentation, and analysis methods. Sections 4 and 5 detail the results that address the research questions and provide a discussion, respectively. Finally, Section 6 concludes the study.

Review of Related Literature

Nonlinear Learning Path

Learning path refers to the sequence of learning materials (Premlatha & Geetha, 2015; Rahayu et al., 2024). There are two types of learning path: linear, where topics are studied in a fixed order, and nonlinear, which allows learners to choose the sequence of topics for a more flexible approach (Robberecht, 2007).

Nonlinear learning utilizes hyperlinks (links) to enable nonsequential access to materials. In online learning environments, these links enhance cognitive processes by creating connections and context among materials, facilitating actions such as navigation, browsing, searching, connecting, collecting, annotating, and editing (Peters, 2002). Nonlinear students may find themselves disoriented by incoherent learning materials. Therefore, personalization is key to prevent such disorientation (Rahayu et al., 2024).

Learning Disorientation

Learning disorientation is the "tendency to lose direction in a nonlinear environment." This phenomenon can arise when learners encounter new uncertainties or perceive a lack of progress in their studies (Leroux et al., 2024). Previous research has identified two primary internal factors contributing to disorientation in nonlinear learning contexts. The first factor is a deficiency in visual-spatial abilities necessary for understanding the structure of information. The second factor involves a lack of metacognitive skills required to assess one's current learning position and determine the subsequent direction for learning (Correa, 2017).

Disorientation disrupts the learning process, causing learners to take longer to complete tasks (Correa, 2017). As a result, disorientation can negatively impact learning outcomes. Furthermore, disorientation is often unstable, irregular, and recurring, and it does not resolve spontaneously, thereby necessitating external support (Leroux et al., 2024).

Recommender Systems

Recommender systems are defined as tools and software techniques that provide suggestions to users based on their preferences and behaviors (Klašnja-Milićević et al., 2015). These systems operate by selecting the most relevant items through user- or item-based dependency principles (Aggarwal, 2016). In the e-learning domain, recommender systems serve as a means of personalization to enhance learner engagement (Huang et al., 2019), optimize academic performance (Harley et al., 2018), and support learners who are facing challenges (Huang et al., 2019).

Recommender systems can be broadly classified into two categories (Aggarwal, 2016): (1) basic recommender systems that utilize interaction data or attributes, and (2) domain-specific recommender systems that incorporate contextual factors. Basic recommender systems include content-based filtering (analyzing item attributes such as learning material topics or difficulty levels), collaborative filtering (using learner interaction patterns and ratings), knowledge-based systems (incorporating explicit learner preferences), and demographic-based approaches (considering learner characteristics). Domain-specific recommender systems extend these foundations by incorporating contextual information such as location, time sensitivity, spatial data, or social network structures.

The application of these recommendation techniques can be categorized into two approaches: standalone and hybrid. Standalone systems rely on a single technique from the basic classification, focusing on one type of data source or recommendation logic. Hybrid systems, in contrast, strategically combine multiple techniques to address two critical needs: (1) utilizing all available knowledge from diverse data sources (such as learner profiles, interaction histories, and contextual information), and (2) compensating for the limitations of individual techniques by leveraging their complementary strengths (Aggarwal, 2016). These hybrid systems can be designed through three structured approaches: ensemble (combining outputs from multiple techniques), monolithic (integrating techniques within a unified algorithm), or mixed designs. Research shows a growing preference for hybrid recommenders, particularly in learning path recommendations (George & Lal, 2019; Rahayu et al., 2023), as they can better address the complexity of personalized learning needs.

Developing effective e-learning recommender systems, however, remains challenging due to the scarcity of learner-provided ratings for educational materials (Salehi et al., 2013). This lack of data complicates material ranking (Aggarwal, 2016) and necessitates advanced methods to address the gap. Knowledge-based artificial intelligence, such as ontology, has proven valuable for overcoming these limitations and supporting personalized recommendations (George & Lal, 2019; Tarus et al., 2018). In the context of learning path recommenders, ontology has been used both as the foundation for standalone systems (Hnida et al., 2014; Romero et al., 2019) and as a key component of hybrid systems (Colace et al., 2020; Vesin et al., 2013).

The performance of recommender systems, evaluated in controlled environments and online experiments, is typically measured across three categories (Erdt et al., 2015): system performance, which includes the accuracy and coverage of the recommendations provided; effects on learning, covering aspects such as efficiency, effectiveness, and learner motivation; and user-centric effects, encompassing learner satisfaction and the perceived usefulness of the recommendations.

Related Work

Based on our systematic literature review of 35 articles retrieved from Google Scholar (search conducted July 19, 2024, using keywords: "recommender" in MOOC), we identified 28 research papers and 7 review papers. Analysis of the research papers revealed that the majority (23 out of 28, or 82%) of recommender systems on MOOC platforms focus on course recommendations, while the remaining systems (5 out of 28, or 18%) target in-course learning components (see Table 1; complete dataset in Appendix A).

Table 1

In-Course Recommender Systems on MOOC Platforms

Recommended Items	Recommender Techniques
Concepts, Meta-concepts	Knowledge graph (Wu et al., 2024), a combination of ontology and deep learning models (Bidirectional Encoder Representations from Transformers or BERT) (Tazi et al., 2023), and a combination of knowledge graphs and deep learning models (Sentence-BERT) (Alatrash et al., 2024)
Learning activities	Markov Decision Process (Amin et al., 2023)
Discussion forums	Knowledge graphs with LightGBM (He et al., 2023)

Several studies, including those related to learning-path recommendations, have noted the increasing use of hybrid recommender systems (George & Lal, 2019; Rahayu et al., 2023; Tarus et al., 2018). Even so, developing recommender systems in the e-learning domain faces an additional challenge, namely that learners seldom provide explicit ratings for learning materials (Salehi et al., 2013). This limited number of ratings complicates ranking-based recommendations (Aggarwal, 2016), suggesting the need for knowledge-based techniques such as ontology (George & Lal, 2019; Tarus et al., 2018). Referring to the proposed recommender-system classification (Aggarwal, 2016), ontology collaborators in hybrid recommender systems can be grouped into model-based collaborative filtering (Colace et al., 2020; Colace & De Santo, 2010; El-Bouhdidi et al., 2013; Vesin et al., 2013), neighborhood-based collaborative filtering (Vesin et al., 2013), content-based recommender (Capuano & Toti, 2019), and others.

Although collaborative filtering has been widely implemented, this study adopts a different perspective by considering findings that learners’ abilities and preferences may change over time (Huang et al., 2019). Accordingly, this hybrid recommender model combines ontology as a knowledge base with sequential pattern mining to incorporate time-based contexts. This combination is expected to produce more adaptive recommendations than a single-technique recommender system.

This study aims to reduce learning disorientation by implementing a hybrid recommender system that integrates ontology (knowledge-based recommender technique) with sequential pattern mining (time-sensitive recommender technique). By combining these approaches, we expect to generate more adaptive recommendations than a single-method recommender system could provide. To evaluate this, we conducted an experiment with three groups: (1) a comparison group following a sequential learning path without a recommender system, (2) a nonlinear learning path group with an ontology-based recommender, and (3) a nonlinear learning path group using a hybrid recommender.

Given that learning disorientation often correlates with low learning outcomes (Shih et al., 2012), we assessed the hybrid system's effects on learning—specifically efficiency and effectiveness—as well as user-centric effects such as satisfaction. In addition, we explored how learners navigated through the materials, particularly whether they tended toward linear or nonlinear paths. Based on these objectives, we address four research questions (RQs):

- **RQ1**: Do learners using the hybrid recommender system achieve higher learning efficiency compared to those using the ontology-based system or no recommender system?
- **RQ2**: Do learners using the hybrid recommender system achieve higher learning effectiveness than those using an ontology-based system or no recommender system?
- **RQ3**: Do learners using the hybrid recommender system report higher satisfaction levels than those using an ontology-based system or no recommender system?
- **RQ4**: How do learners navigate the learning paths when accessing materials and completing assessments?

Methods

System Architecture

This study develops and evaluates an e-learning recommender system that supports nonlinear learning paths, essential for adapting to learners' evolving abilities and preferences over time (Huang et al., 2019). These dynamics are reflected in time-based learning behavior patterns, revealing implicit preferences for specific materials. The system employs ontology to manage the coherence of learning materials (Rahayu et al., 2022) and integrates PrefixSpan, a sequential pattern mining algorithm, to capture and predict individual learning sequences based on temporal behavior (Aggarwal, 2016).

Recommender systems must be customized to the specific platform they are deployed on (Aggarwal, 2016; Oliveira, 2016). In this study, we implement our system within the Moodle LMS environment, chosen for its widespread use in many countries (Fernando, 2020). Moodle's extensive user base also allows our recommender model to be potentially replicated in various learning contexts.

Case Study: Database Course

In this research, the recommender system was adapted and tested to recommend learning paths for Database courses. We selected the Database domain because it is a core subject in various computer science–related programs (Ishaq et al., 2023),and to date, it has not been explored in studies focused on learning paths (Rahayu et al., 2023). Nonetheless, choosing the Database domain does not limit the recommender system’s application, as the system can be implemented in a wide range of learning environments that support nonlinear or nonsequential learning (Hase, 2016).

The Database materials used in this case study refer to the international curriculum document created by ACM/IEEE, namely, the Computing Curricula 2020. The analysis results indicate that the most frequently studied topics among six disciplines are data models, database systems, SQL queries, and SQL data definitions. These four topics form the basis of the course learning outcomes.

In our implementation, we consolidated these four topics into three sub-learning outcomes (Sub-LO) to create a more coherent pedagogical structure, as illustrated in Figure 1. The mapping is as follows:

1. Sub-LO-1: This learning outcome combines the topics of data models and database systems, focusing on students' ability to design relational database models at conceptual, logical, and physical levels. These two topics are integrated because students need to understand database system fundamentals before they can effectively design data models.

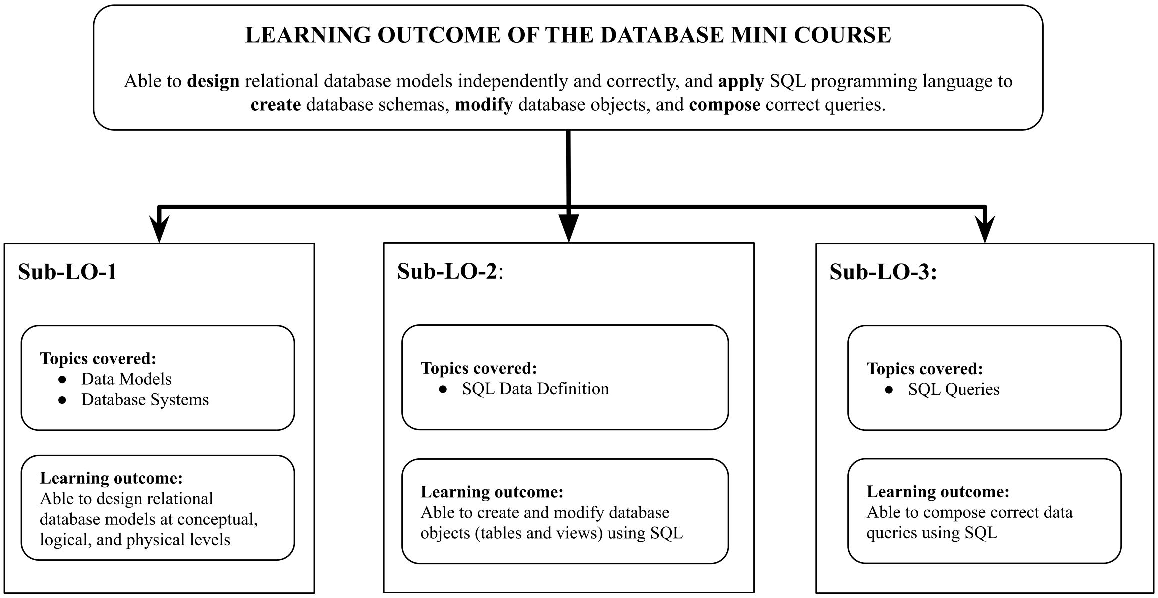
2. Sub-LO-2: This learning outcome addresses the SQL data definition topic, enabling students to create and modify database objects (tables and views) using SQL.

3. Sub-LO-3: This learning outcome covers the SQL queries topic, focusing on students' ability to compose correct data queries using SQL.

These three sub-learning outcomes comprise 11 modules, which include 11 assessments and 97 pages of material.

Figure 1

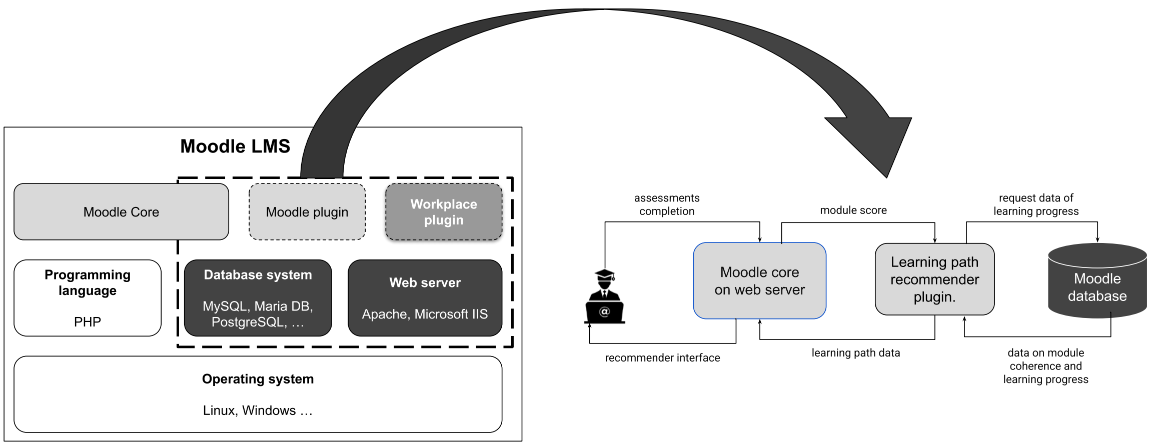
Learning Outcome Structure for Database Mini Course



The recommender system was developed as a Moodle plugin to allow direct integration without modifying Moodle’s core, thus making updates easier and new features more flexible to add (Moodle, 2024). Technically, this recommender plugin runs on the web server; its programming code is stored in the *dirroot* directory, and the plugin-related data is maintained in a database (Buchner, 2022) (see Figure 2).

Figure 2

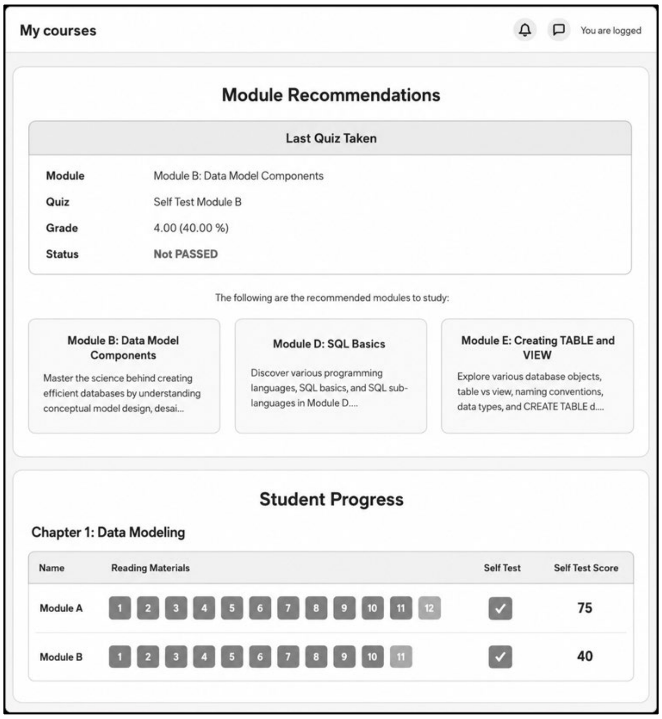
Interaction Between Recommender System and Moodle Components (adapted from Buchner, 2022)



The interfaces of both standalone ontology-based and hybrid recommender systems are similarly designed. Figure 3 shows an example where a learner who has not yet passed Module B receives recommendations to continue their studies by retaking Module B and studying Modules D and E. These recommendations appear as blue-colored text with hyperlinks.

Figure 3

Interface of Recommender Plugin



Participants

A total of 209 learners enrolled and were assigned to three groups: comparison group AC (n = 149), ontology-based recommender group B (n = 28), and hybrid recommender group D (n = 32). Due to the voluntary nature of the MOOC, participation decreased across stages, with 136 learners logging in and 121 providing informed consent for data use. Given learner autonomy in selecting materials and assessments, final sample sizes varied by measurement as shown in Table 2. This variation reflects authentic MOOC engagement patterns where learners independently choose which activities and assessments to complete.

Table 2

Participant Flow and Sample Sizes by Measurement

Stage/Measurement	Group AC	Group B	Group D	Total
Enrolment & Consent				
Enrolled	149	28	32	209
Logged in	97	17	22	136
Consented to data use	87	16	18	121
Efficiency Measures				
accessDuration	74	15	13	102
assessmentDuration	73	14	12	99

Effectiveness Measures				
materialPercentage	74	15	13	102
subLO1Score	75	14	13	102
subLO2Score	54	12	7	73
subLO3Score	51	11	6	68
finalScore	73	14	12	99
Satisfaction				
Survey respondents	35	10	8	53

Note: Sample sizes vary across measurements due to learners' autonomy in completing optional course materials and assessments.

Experimental Design

The prototype of the nonlinear learning path recommender system was evaluated through an online experiment to assess user responses and system effectiveness (Tedre & Moisseinen, 2014). This experiment was important due to the limited availability of relevant e-learning datasets (Tarus et al., 2017).

The experiment involved real learners in a database MOOC. A total of 230 learners across Indonesia registered voluntarily through an online form. The study included participants who were at least 18 years old. The age requirement ensured that learners had developed the self-regulation skills necessary for nonlinear learning (Lowe et al., 2013). After removing duplicates and invalid entries, 209 registrants were accepted. Despite extending the registration period, only 60 learners engaged in nonlinear learning (28 in Period I and 32 in Period II).

Dividing these learners into four groups across the two periods—control and experimental groups for each period—resulted in groups that were too small (Vesin et al., 2013). Therefore, the study utilized one comparison group (Isnawan, 2020) and two nonlinear groups without random assignment, classifying it as a quasi-experiment (Field & Hole, 2002). We implemented a posttest-only nonequivalent group design with covariates (Reichardt, 2019; Rogers & Révész, 2019), where the pretest captured stable traits such as demographics, and the post-test consisted of module assessments.

Demographic and participant characteristic variables were collected to serve as covariates for statistical control (see Section 3.6 for specific variables used in each analysis). Additionally, experimental group participants completed an initial profiling that captured their self-perceived competence and content preferences; this profiling informed the recommender system's personalized module sequencing but did not serve as a baseline outcome measure. The comparison group followed a linear learning path without profiling or system recommendations. Module assessments served as the posttest outcome measure for both groups.

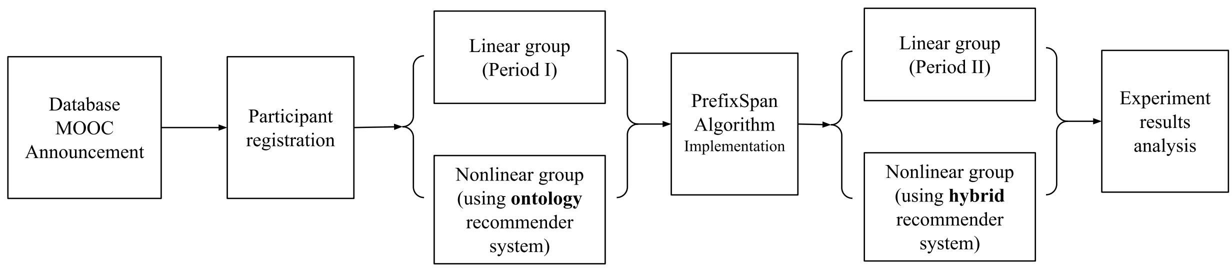
Consent for data use was obtained from all learners, who were informed that their data would be anonymized for scientific evaluation and publication. Those who did not consent were excluded to prevent selection bias.

Experimental Procedure

The experiment was conducted in phases and learners were divided into two periods with different schedules, learning methods, and recommender systems. However, three aspects remained consistent to ensure controlled results: course content, assessments, and instructor interactions. The experiment phases (Jing et al., 2022) are shown in Figure 4.

Figure 4

Summary of Experimental Procedure



Specifically, the experiment aimed to evaluate the impact of the recommender system by comparing three groups:

1. Comparison group: Learners following a linear (sequential) learning path without a recommender system (Period I and II).
2. Ontology-based recommender group: Learners using an ontology-based recommender system (Period I).
3. Hybrid recommender group: Learners using a hybrid recommender system (Period II).

Recommendations in the hybrid system were generated using learners' assessment results and the successful learning paths of their peers during the first period. To enhance learner success, mitigation strategies were implemented that not only adhered to e-learning design recommendations (Cagiltay et al., 2020) but also provided additional incentives upon successful completion, including e-money balances and certificates (Gong et al., 2021). The e-money balance was awarded through a lottery to learners who passed the course, while certificates were provided in two categories:

- Participation certificate (Hasso Plattner Institute, 2023): Given to learners who completed at least 60% of the material and 35% assessments.
- Award certificate (Coursera, 2021): Awarded to learners who completed at least 60% of the material and all assessments with a minimum score of 70 points.

Research variables used in the experiment include independent variables (types of learning path recommender systems) and dependent variables of effects on learning and user-centric effects (Erdt et al., 2015). Effects on learning are evaluated based on learning efficiency and effectiveness, while user-centric effects are assessed through the level of learner satisfaction. The dependent variables for each dimension are detailed as follows:

1. Learning efficiency refers to the time required for students to achieve the course learning outcomes. It was measured by the access time of the first and last materials (accessDuration) (Jerz, 2018) and the duration to complete assessments (assessmentDuration).

2. Learning effectiveness in achieving the learning objectives is measured by the number of materials visited and the assessment scores obtained (Rahayu et al., 2023; Vesin et al., 2013). The assessment scores used include formative scores for each sub-learning outcome as well as the final score (Erdt et al., 2015; Sudijono, 2015). Therefore, effectiveness is measured using five variables: percentage of material accessed, scores of sub-learning outcomes, and final score.

3. Perceived satisfaction: All learners were surveyed on their perceptions of general e-learning, while those in both recommender groups also answered additional questions about the recommender feature. Therefore, measurement is conducted using two types of instruments:

    a. General e-learning satisfaction: Measured using 30 statements in the Evaluating E-learning System Success (EESS) model, which includes six constructs: Technical System Quality (TSQ), Information Quality (INQ), Service Quality (SRQ), Support System Quality (SUP), Learner Quality (LER), and Instructor Quality (INS) (Al-Fraihat et al., 2020).

    b. Satisfaction with the recommender systems: Assessed through Recommender System (REC) construct which includes one essay question on whether the learning experience met learners' expectations (REC2) and three additional questions addressing the frequency of use (REC3), perceived benefits (REC4), and overall satisfaction (REC5).

Analysis Method

The first three research questions were examined through hypothesis testing using inferential statistical methods, while RQ4 was addressed by visualizing the learning paths for each group. The three specific hypotheses are outlined below:

- H1: Learners using the hybrid recommender system achieve better learning efficiency than those using an ontology-based system or no recommender system.

- H2: Learners using the hybrid recommender system achieve better learning effectiveness than those using an ontology-based system or no recommender system.

- H3: Learners using the hybrid recommender system achieve better satisfaction levels than those using an ontology-based system or no recommender system.

For RQ1, RQ2, and RQ3, we conducted Analysis of Covariance (ANCOVA) to assess the differences in learning efficiency, learning effectiveness, and satisfaction levels, respectively, among the three groups. ANCOVA was chosen because it controls for covariate variables that might influence the results, providing a more accurate estimate of the treatment effect. Following ANCOVA, post hoc tests were performed to identify specific group differences where significant effects were detected.

The quasi-experimental approach used in this study has limitations regarding internal validity, although it maintains strong external validity (Reichardt, 2019). One challenge to internal validity is the potential bias arising from natural differences among learners before the treatment (i.e., the use of the recommender system). To address this, we identified factors that might influence the results (referred to as covariates) to minimize potential selection bias.

The covariates for the efficiency and effectiveness dimensions differ from those for the satisfaction dimension to accommodate the distinct constructs being measured and to address variations in data completeness. For efficiency and effectiveness, we used four covariate variables collected during registration: age range, field of study, participation period, and province. In contrast, the satisfaction dimension included six covariates collected through the survey: age range, field of study, participation period, gender, activity or job, and experience using the Moodle platform.

As a supplementary analysis, we examined prior knowledge as an additional covariate for RQ1-RQ2. Prior knowledge was measured through a self-assessment of competency across three course topics (data modeling, data definition language, and SQL queries) using a three-level scale (Beginner = 1, Intermediate = 2, Advanced = 3). A composite prior knowledge score (range 1-3) was calculated as the mean across topics. This analysis was limited to the two recommender groups ($n = 24$) who completed the optional assessment, as the comparison group did not. This supplementary analysis could not be conducted for RQ3 due to anonymous survey administration.

Our analysis began by testing the assumption of data homogeneity. When this assumption was met, we used Analysis of Covariance (ANCOVA). If the homogeneity assumption was not satisfied, we employed the Kruskal-Wallis test to handle data that do not meet parametric assumptions. We also used a significance level (p value) of 0.05 for our statistical analysis. This means that results with a p value less than 0.05 are considered statistically significant, indicating a meaningful difference or relationship unlikely to have occurred by chance. In addition to the p value, we reported effect sizes to show whether the differences were not only significant but also substantial in magnitude.

We addressed RQ4 by applying visualization techniques that employ weighted directed graphs to uncover patterns in learners' behaviors. The learning path graphs were created using navigation log data, which included records of accessed materials and completed assessments. This data was subsequently organized into inter-module matrices. To enhance clarity, matrices were based on the number of modules (11×11) rather than the number of material pages (97×97). Internal module transitions were normalized by dividing the total accesses by the number of materials within the module.

The size of the nodes and the thickness of the edges in the graphs correspond to the matrix values, reflecting the number of accesses to each material or assessment. Additionally, the directionality in the graphs helps reveal whether learners followed linear or nonlinear paths in their learning.

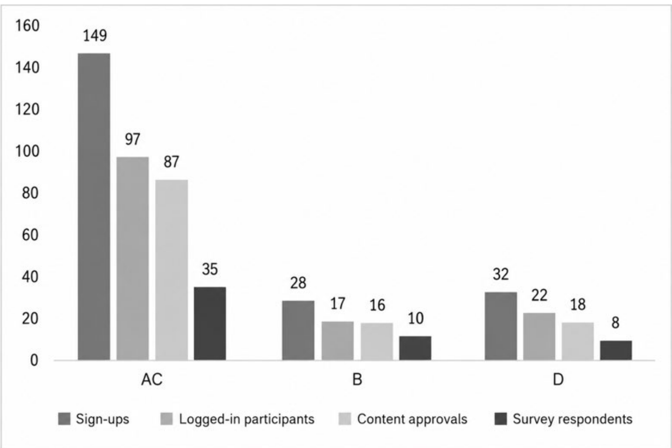
Results

Demography

Figure 5 illustrates the trend of decreasing learner numbers in each group: comparison (Class A Period I, Class C Period II), nonlinear learning path with ontology-based recommender (Class B), and nonlinear learning path with hybrid-based recommender (Class D). Class AC experienced a reduction in login learners by up to 34.9%, with 10 learners withholding data consent. Class B recorded only a 60.7% login rate, while Class D achieved 68.7%. By the end of the experiment, 136 learners had logged in at least once, and 121 of them consented to data.

Figure 5

Participant Flow Showing Declining Enrollment Across Stages for Comparison (AC), Ontology-based (B), and Hybrid (D) groups.

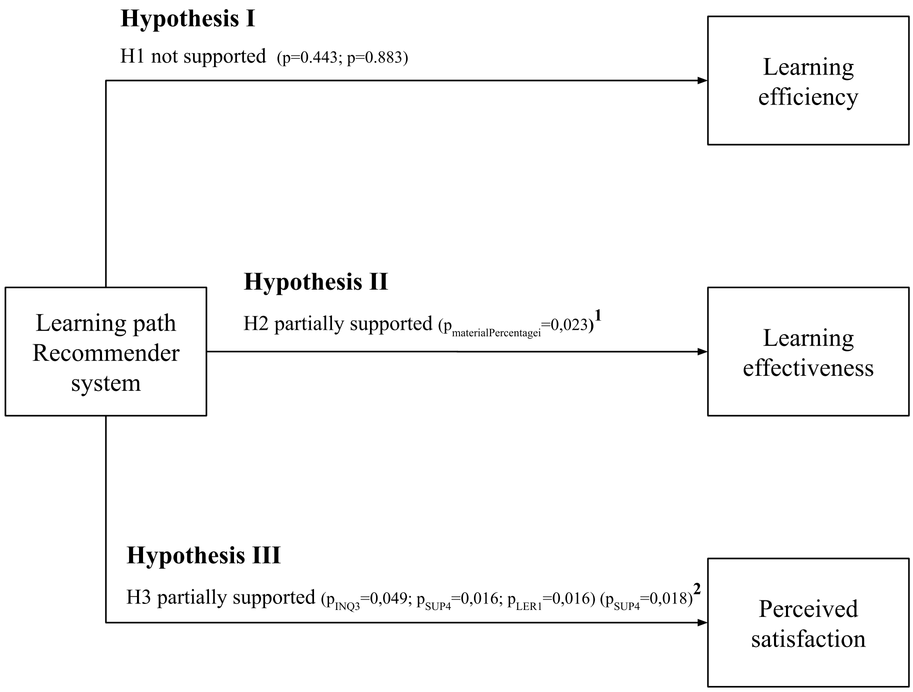


Note: Sample sizes for efficiency and effectiveness measurements are detailed in Table 2.

Of the 121 learners, the majority (77%) were aged 18–24 years, followed by those over 40 years old (11%), then 25–30 years (6%), and 31–40 years (6%). Additionally, 85.1% of learners were from the Design and Engineering disciplines. In the nonlinear groups (Class B and D), 74.3% of learners reported being beginners in Database learning. A total of 102 out of 121 learners were recorded as actively engaging in learning activities. Recapitulation of Moodle log data reveals varied participation, from accessing materials to completing assessments. Of all learners, 53 completed the satisfaction survey, with most being undergraduate students (n = 33).

Figure 6

Research Model with Hypothesis Testing Results



1. Hypothesis 2 was measured by five variables. Results show for `materialPercentage` ($p = 0.023$); the other four variables are not significant.
2. Hypothesis 3: The hybrid recommender group showed significantly higher satisfaction than the ontology-based group in INQ3, SUP4, and LER1 ($p < 0.05$), but not in other satisfaction variables. The ontology-based group showed significantly higher satisfaction than the comparison group only in SUP4 ($p = 0.018$).

Figure 6 presents the overall hypothesis testing results across the three dimensions. H1 (efficiency) was not supported, while H2 (effectiveness) and H3 (satisfaction) received partial support. Detailed analyses for each research question are presented in the following subsections.

> **RQ1:** Do learners using the hybrid recommender system achieve higher learning efficiency compared to those using the ontology-based system or no recommender system?

This study measures efficiency based on study time usage, specifically using the variables accessDuration (n = 102) and assessmentDuration (n = 99), as detailed in Table 2. Class B (*M* = 9953.5; *SE* = 1117.7) accessed materials for the longest duration, whereas Class AC (*M* = 7574.9; *SE* = 459.5) and Class D (*M* = 7591.5; *SE* = 851.7) had nearly identical access durations. Additionally, Class B (*M* = 52.9; *SE* = 9.5) completed assessments in the longest time compared to Class D (*M* = 44.3; *SE* = 10.7) and Class AC (*M* = 42.7; *SE* = 6.5). Since efficiency is inversely related to access duration or assessment duration, the ontology-based recommender group exhibited lower learning efficiency compared to the other two groups.

Table 3

ANCOVA Results for Group Differences in AccessDuration and AssessmentDuration

Dependent variable	F	df	p	ηp^2	Significant covariates
accessDuration	0.822	2, 95	.443	.017	Period (p = .038)
assessmentDuration	0.124	2, 92	.883	.003	none

Note. All group effects tested with df = (2, residual df). Covariates controlled: Age, Field of Study, Period, and Province. Only significant covariates are reported in the table.

Statistical significance tests on learning efficiency using ANCOVA (Table 3) revealed that:

1. The comparison group, ontology-based recommender group, and hybrid-based recommender group did not show significant differences in material reading access duration (p = .443; ηp^2 = .017).

2. The comparison group, ontology-based recommender group, and hybrid-based recommender group also did not exhibit significant differences in assessment completion duration (p = .883; ηp^2 = .003).

3. The participation period in the experiment had a significant effect (p = .038; ηp^2 = .045) on material access duration.

These results indicate that there are no significant differences in material access duration and assessment completion duration among three groups. Therefore, the hypothesis addressing RQ1 ("Do learners using the hybrid recommender system achieve higher learning efficiency compared to those using the ontology-based system or no recommender system?") is not supported.

RQ2: Do learners using the hybrid recommender system achieve higher learning effectiveness than those using an ontology-based system or no recommender system?

Learning effectiveness was measured using five variables: materialPercentage (n = 102), subLO1Score (n = 102), subLO2Score (n = 73), subLO3Score (n = 68), and finalScore (n = 99), as detailed in Table 2. The effectiveness levels across the three groups varied. First, the hybrid recommender group achieved the highest average scores in sub-learning outcomes of subLO2Score (M = 7.786; SE = 0.535) and subLO3Score (M = 7.758; SE = 0.601). Second, the ontology-based recommender group obtained the highest material access percentage (M = 0.786; SE = 0.094), subLO1Score (M = 7.371; SE = 0.552), and finalScore (M = 6.588; SE = 0.734).

To address potential confounding effects of prior knowledge, we conducted supplementary analyses for RQ1 and RQ2 using only the two recommender groups with prior knowledge data (n = 24). Prior knowledge was measured as a composite score (range 1-3) based on self-assessed competency across three course topics. Results showed that prior knowledge was not a significant covariate for any efficiency or effectiveness outcomes (all p > .05). Specifically, for efficiency: accessDuration (p = .648, ηp^2 = .010) and assessmentDuration (p = .873, ηp^2 = .001). For effectiveness: materialPercentage (p = .424, ηp^2 = .031) and other measures similarly showed no significant effect. Group differences between the two recommender systems remained non-significant, consistent with the main three-group analysis. These findings suggest that prior knowledge did not substantially influence the observed treatment effects (see Appendix B).

Table 4

ANCOVA Results for Group Differences in Learning Effectiveness

Dependent variable	F	df	p	ηp^2	Significant covariates
materialPercentage	3.872	2, 95	.024*	.075	Period (p = .009)
subLO1Score	1.836	2, 95	.165	.037	none
subLO2Score	0.170	2, 66	.844	.005	Age (p = *.030)*
subLO3Score	2.061	2, 61	.136	.063	none
finalScore	2.440	2, 95	.093	.049	none

Note. All group effects tested with df = (2, residual df). Covariates controlled: Age, Field of Study, Period, and Province. Only significant covariates are reported in the table.

Table 5

Post Hoc Comparisons - Group

		Mean Difference	SE	t	p_{tukey}
AC	B	-0.151	0.112	-1.350	0.371
	D	0.286	0.117	2.444	0.043*
B	D	0.438	0.163	2.689	0.023*

Analysis of learning effectiveness through statistical significance testing (Table 4 and Table 5) showed that:

1. ANCOVA results revealed a significant group difference in material access percentage (p = .024; ηp^2 = .075), with Period as a significant covariate (p = .009). Post-hoc Tukey tests indicated that the hybrid recommender group (Group D) accessed significantly less learning material compared to both the comparison group (Group AC, p = .043) and the ontology-based recommender group (Group B, p = .023). No significant difference was found between the comparison and ontology-based groups (p = .371).

2. The comparison group, ontology-based recommender group, and hybrid recommender group did not show significant differences in sub-learning objective 1 scores (p = .165; ηp^2 = .037).

3. The three groups also did not exhibit significant differences in sub-learning objective 2 scores (p = .844; ηp^2 = .005), although Age was a significant covariate (p = .030).

4. Similarly, no significant group differences were found for sub-learning objective 3 scores (p = .136; ηp^2 = .063).

5. The comparison group, ontology-based recommender group, and hybrid recommender group did not demonstrate significant differences in final course scores (p = .093; ηp^2 = .049), though the result approached significance.

Based on the above data, the hypothesis addressing RQ2 ("Do learners using the hybrid recommender system achieve higher learning effectiveness compared to those using the ontology-based system or no recommender system?") is partially supported. While the hybrid recommender system significantly influenced material access patterns (1 of 5 effectiveness measures), it did not result in superior learning outcomes as measured by assessment scores. The recommender system appeared to facilitate more efficient material selection without demonstrably improving learning effectiveness.

> **RQ3:** Do learners using the hybrid recommender system report higher satisfaction levels than those using an ontology-based system or no recommender system?

RQ3 examined learner satisfaction through two complementary analyses (see Table 2 for sample sizes). First, general e-learning satisfaction was assessed across all three groups using the EESS model (six constructs: TSQ, INQ, SRQ, SUP, LER, INS) with reliability analysis, radar charts, and ANCOVA (n = 53). Second, recommender-specific satisfaction was evaluated using the REC construct (n = 18), comparing only the hybrid and ontology-based groups through radar charts and qualitative feedback.

Reliability analysis using Cronbach's alpha (N= 53) indicated high internal consistency for four constructs: INQ (Information Quality, $\alpha = .857$), TSQ (Technical System Quality, $\alpha = .846$), SRQ (Service Quality, $\alpha = .845$), and INS (Instructor Quality, $\alpha = .837$). The LER (Learner Quality) construct demonstrated acceptable reliability ($\alpha = .741$), while SUP (Support System Quality) showed questionable reliability ($\alpha = .659$). All constructs except SUP met the acceptable reliability threshold of $\alpha \geq .70$. Detailed item-level statistics are presented in Table 6.

Table 6

Satisfaction Items: Reliability, Descriptive Statistics, and ANCOVA Results Across Three Groups

Construct	**Item**	**Group AC**	**Group B**	**Group D**	**Cronbach alpha**	**F**	***p***	ηp^2	**Sig. Covariates**
TSQ	TSQ1	4.54(0.61)	4.3(0.68)	4.25(0.71)	0.846	.684	.510	.030	Gender (*p* = .038)
	TSQ2	4.29(0.67)	3.9(0.74)	4.25(0.46)		.426	.656	.019	
	TSQ3	4.26(0.74)	4.1(0.88)	4.63(0.52)		.647	.528	.029	
	TSQ4	4.2(0.72)	3.9(0.74)	4.13(0.64)		.657	.523	.029	
	TSQ5	4.17(0.82)	3.8(0.92)	4.38(0.52)		.254	.777	.011	
INQ	INQ1	4.29(0.57)	4.1(0.74)	4.13(0.64)	0.857	.668	.518	.029	
	INQ2	4.14(0.65)	3.6(0.7)	4.13(0.64)		.804	.454	.035	Gender (*p* = .023)
	INQ3	4.23(0.73)	4(0.67)	4.5(0.54)		3.003	.060	.120	Period (*p* = .033)
	INQ4	4.23(0.69)	3.8(0.63)	4.5(0.54)		2.266	.116	.093	
	INQ5	4.23(0.84)	3.9(0.88)	4.13(0.64)		.290	.749	.013	
	INQ6	4.37(0.6)	3.9(0.88)	4.5(0.54)		2.244	.118	.093	
	INQ7	4.03(0.82)	3.8(1.03)	4.38(0.52)		1.168	.320	.050	Field of study (*p* = .035)
SRQ	SRQ1	4.09(0.82)	3.9(0.74)	4.13(0.84)	0.845	.083	.921	.004	

	SRQ2	4.14(0.69)	4.1(0.74)	4.38(0.52)		1.727	.019	.073	
	SRQ3	4.43(0.56)	4.2(0.63)	4.25(0.46)		.670	.517	.030	Employment status ($p < .001$)
	SRQ4	4.31(0.63)	4.1(0.74)	4.25(0.46)		1.102	.341	.048	
	SRQ5	4.23(0.65)	3.9(0.74)	4.25(0.46)		1.155	.325	.050	
SUP	SUP2	4.17(0.71)	3.8(0.63)	4.38(0.52)	0.659	2.218	.121	.092	
	SUP3	4.38(0.7)	4.1(0.57)	4.38(0.52)		1.270	.291	.056	
	SUP4	4.2(0.68)	3.6(0.7)	4.38(0.52)		4.799	.013	.179	
LER	LER1	4.29(0.67)	3.8(0.63)	4.63(0.52)	0.741	4.292	.020	.016	
	LER2	4.34(0.73)	4.1(0.32)	4.5(0.54)		.175	.840	.008	
	LER3	4.43(0.66)	4.1(0.57)	4.63(0.52)		1.072	.351	.046	
	LER4	4.29(0.8)	4.4(0.52)	4.25(0.71)		.137	.873	.006	
	LER5	4.29(0.52)	4.1(0.99)	4.5(0.54)		1.134	.331	.049	
INS	INS1	4.49(0.56)	4.4(0.52)	4.75(0.46)	0.837	.974	.386	.042	
	INS2	4.43(0.61)	4.4(0.52)	4.75(0.46)		.860	.430	.038	
	INS3	4.46(0.66)	4.1(0.74)	4.5(0.76)		.596	.555	.026	
	INS4	4.31(0.72)	4.2(0.63)	4.63(0.52)		1.038	.363	.045	
	INS5	4.46(0.66)	4.5(0.53)	4.75(0.46)		.707	.499	.031	

Average construct scores were plotted in radar charts using Microsoft Excel 16.82, with the following explanations:

1. The hybrid recommender group provided the highest satisfaction perception for TSQ (Figure 7a) in the variables of "Meeting learner needs" ($M = 4.63$) and "System component integration" ($M = 4.38$). The comparison group gave the highest satisfaction score for "Ease of learning" ($M = 4.25$).

2. The hybrid recommender group dominated INQ (Figure 7b) in the variables of usability (M = 4.50), content clarity (M = 4.50), up-to-date content (M = 4.50), and content design quality (M = 4.38).

3. Similar findings were obtained for SRQ (Figure 7c), especially in the variable of online support availability ($M = 4.38$).

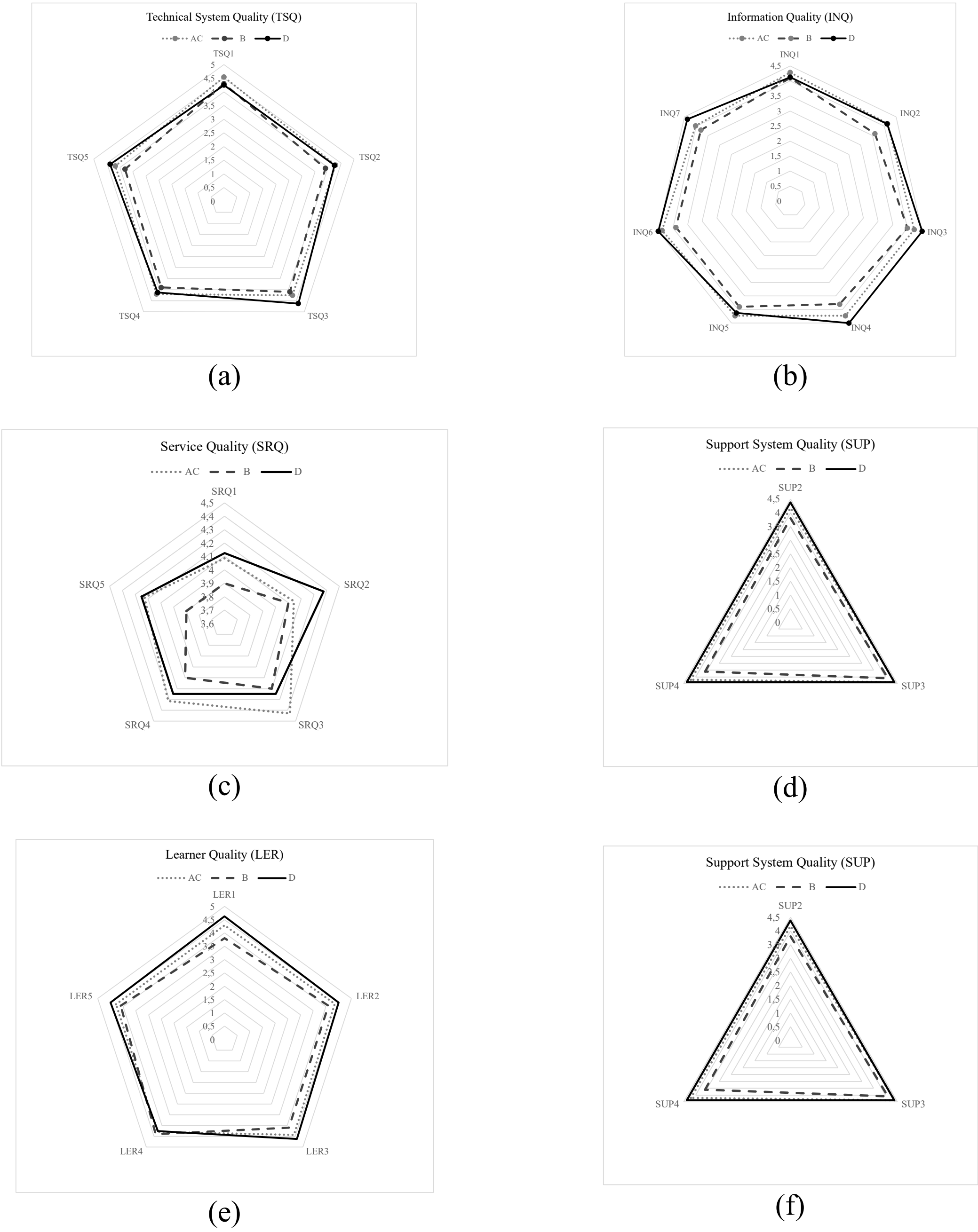
4. Satisfaction perceptions of the hybrid recommender group and the comparison group regarding SUP were relatively similar (Figure 7d).

5. The hybrid recommender group provided the highest satisfaction perception for four out of five variables in the LER construct (Figure 7e), namely, learner behavior (M = 4.63), learner attitude (M = 4.50), learner anxiety (M =4.63), and self-efficacy (M =4.50).

6. The hybrid recommender group (Figure 7f) excelled in the INS construct.

Figure 7

Radar Charts of General E-Learning Satisfaction Constructs: (a) TSQ, (b) INQ, (c) SRQ, (d) SUP, (e) LER, (f) INS



The results in Table 6 and the radar chart in Figure 7 indicate that the hybrid recommender group achieved higher average satisfaction compared to the ontology-based recommender group. However, most of the satisfaction comparisons between three groups did not show significant differences, except for:

1. A significant difference was found between Class D (hybrid recommender group) and Class B (ontology-based recommender group) in the following variables:

INQ3 (usability of e-learning; t = 2.431, p = .049), SUP4 (preference for Moodle; t = 2.885, p =.016), and LER1 (learner behavior; t = 2.902, p = .016).

2. Class B (ontology-based recommender group) significantly differed from Class AC (comparison group) in the SUP4 variable (preference for Moodle; $t = -2.857$; $p = .018$).

Several variables also influenced learners' satisfaction with the recommender system:

- Gender had a significant effect on TSQ1 (ease of use; $p = .038$; $\eta p^2 = .094$) and INQ2 (accessibility of e-learning; $p = .023$; $\eta p^2 = .112$).
- The participation period had a significant effect ($p = .033$; $\eta p^2 = .099$) on the usability of e-learning (INQ3).
- Field of study had a significant effect ($p = .035$; $\eta p^2 = .097$) on content design quality (INQ7).
- Learners' activity or employment status had a significant effect ($p < .001$; $\eta p^2 = 0.222$) on IT team readiness (SRQ3).

Figure 8 shows a radar chart comparing the hybrid and ontology-based groups across the REC construct. Satisfaction specific to the recommender-assisted groups was measured using the Recommender System (REC) construct, with 80% of learners in Class B and 100% in Class D willing to respond. All learners also provided positive feedback to the essay question "Does non-sequential learning align with your expectations?" although the wording of the responses varied (Table 7).

Figure 8

Radar Chart of Perceived Satisfaction Across REC Constructs

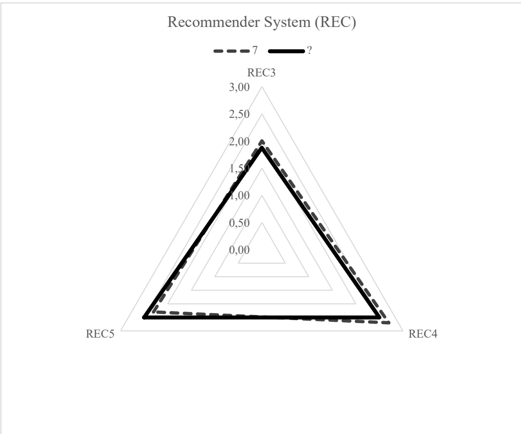


Table 7

Alignment with Learners' Learning Expectations (REC2)

No	Category	Number of learners	Responses
1.	Agree	14	• Satisfactory

			• Effective enough as I don't really like learning in a sequential manner. • In general, satisfactory. • Overall, it matches my expectation. • Yes, I can start with the easiest tasks first, and it's more enjoyable.
2.	Strongly agree	2	• Perfectly meets my expectations because I can access it anytime and anywhere. • Perfectly matches my expectations as the recommendations are helpful.

Based on the above data, the hypothesis addressing RQ3 ("Do learners using the hybrid recommender system report higher satisfaction levels compared to those using the ontology-based system or no recommender system?") is supported by the INQ3, SUP4, and LER1 variables in comparisons between the recommender groups, but not by other variables. Additionally, in comparisons between the ontology-based recommender group and the comparison group, the hypothesis is only supported by the SUP4 variable but not by others.

RQ4: How do learners navigate the learning paths when accessing materials and completing assessments?

Graph-based analysis was conducted to identify patterns in learners' paths. These learning path graphs were generated from navigation log data for materials and assessments. While material navigation logs were readily available in Moodle, assessment logs required a custom plugin specifically developed for this experiment.

A complete set of normalized frequency matrices for all classes is shown in Figure 9. Class A and Class C served as comparison groups for Periods I and II, respectively, while Class B and Class D represented the ontology-based and hybrid recommender groups. Navigation graphs for materials in each class are shown in Figure 10.

Figure 9

Navigation Data: (a) Class A and (b) Class C (comparison groups); (c) Class B and (d) Class D (recommender groups).

Modul	A	B	C	D	E	F	G	H	I	J	K
A	**85**	**62**	6	7	0	2	1	0	0	0	1
B	**27**	**53**	**36**	4	2	0	1	2	0	1	0
C	7	7	**40**	**29**	1	2	1	1	0	0	1
D	3	4	7	**38**	**25**	1	1	0	0	0	1
E	1	2	1	1	**28**	**26**	2	0	0	0	0
F	2	2	1	1	4	**24**	**25**	0	0	1	0
G	1	1	0	1	0	3	**27**	**22**	2	2	2
H	0	1	1	0	1	0	1	**24**	**23**	0	0
I	1	0	0	0	0	1	1	1	**24**	**20**	3
J	1	0	0	1	0	1	1	1	1	**27**	**20**
K	2	1	3	1	1	0	0	3	2	5	**21**

(a)

Modul	A	B	C	D	E	F	G	H	I	J	K
A	**64**	**60**	5	3	1	0	2	1	0	3	0
B	**19**	**56**	**43**	5	3	2	2	1	6	1	1
C	6	**11**	**37**	**33**	0	0	0	1	0	1	1
D	1	2	3	**45**	**34**	3	1	1	0	0	0
E	1	3	0	2	**36**	**32**	1	2	0	1	1
F	2	3	1	1	3	**31**	**28**	0	0	0	2
G	2	1	0	1	0	2	**35**	**35**	0	0	0
H	1	1	0	0	1	1	6	**35**	**30**	0	2
I	1	6	0	1	0	0	0	1	**33**	**32**	0
J	0	1	0	0	0	0	0	0	2	**37**	**36**
K	2	3	1	0	1	0	2	0	6	4	**34**

(b)

Modul	A	B	C	D	E	F	G	H	I	J	K
A	**32**	**18**	3	0	0	0	0	0	2	0	1
B	4	**19**	**13**	5	2	0	1	0	0	1	1
C	2	4	**15**	**10**	3	0	0	0	0	0	1
D	1	3	0	**20**	**11**	1	0	0	0	0	1
E	0	3	1	1	**18**	**10**	0	1	0	1	1
F	0	0	0	0	0	**16**	**10**	1	4	1	2
G	0	0	0	0	0	1	**15**	**11**	2	0	1
H	0	0	0	1	0	2	2	**12**	8	1	0
I	1	0	0	0	0	2	1	0	**13**	**12**	3
J	0	1	0	0	1	0	0	1	0	**16**	**11**
K	2	3	3	0	2	3	1	0	3	1	**10**

(c)

Modul	A	B	C	D	E	F	G	H	I	J	K
A	**28**	**22**	2	3	0	0	0	0	1	0	0
B	4	**22**	**18**	3	0	0	0	0	0	0	0
C	2	4	**14**	**11**	2	0	0	0	0	2	1
D	2	1	1	**17**	9	0	4	0	1	0	0
E	1	0	1	0	**13**	8	2	0	0	0	0
F	0	1	0	0	1	**16**	8	0	0	0	2
G	1	1	0	1	1	1	**16**	**11**	3	1	0
H	0	0	0	0	0	1	1	**15**	**10**	0	0
I	2	0	0	1	0	1	2	1	**12**	**10**	2
J	2	0	0	0	0	1	0	0	1	**13**	**10**
K	2	1	1	0	0	0	1	0	4	1	**11**

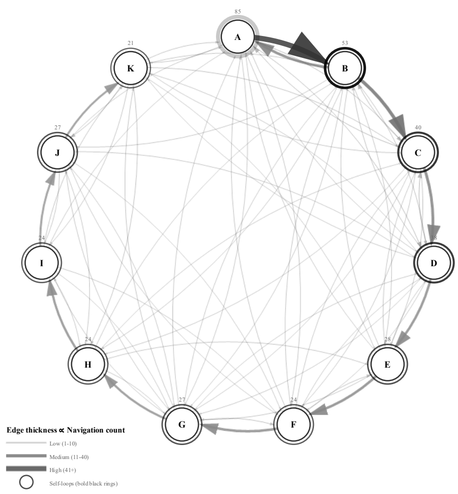
(d)

Learning path patterns in the recommender groups slightly differed from those in the comparison group. This indicates that, besides frequently accessing materials within the same module, learners in the comparison group navigated both forward (e.g., from Module A to Module B) and backward (e.g., from Module B to Module A) between modules. Some learners even alternated directions; for example, after reading Module B, many moved forward to Module C, while others returned to Module A.

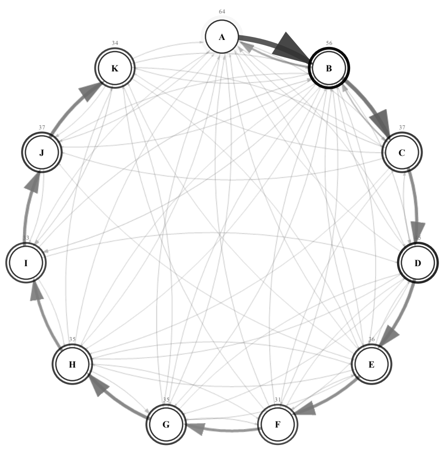
Learning path graphs for the recommender groups show that, in general, learners moved forward to other modules in alphabetical order (referred to as linear forward). For example, learners in the ontology-based recommender group typically progressed from Module A to Module B and read Module J after Module I. Similarly, learners in the hybrid recommender group exhibited a similar pattern. This visualization (Figure 10) also shows that the graph of the ontology-based recommender group appears slightly more complex. However, both recommender groups followed the same linear progression: Module A to Module B to Module C, and so on. Overall, navigation data and graphs show similar linear forward learning paths across all four classes, except for the first three modules in the comparison group.

Figure 10

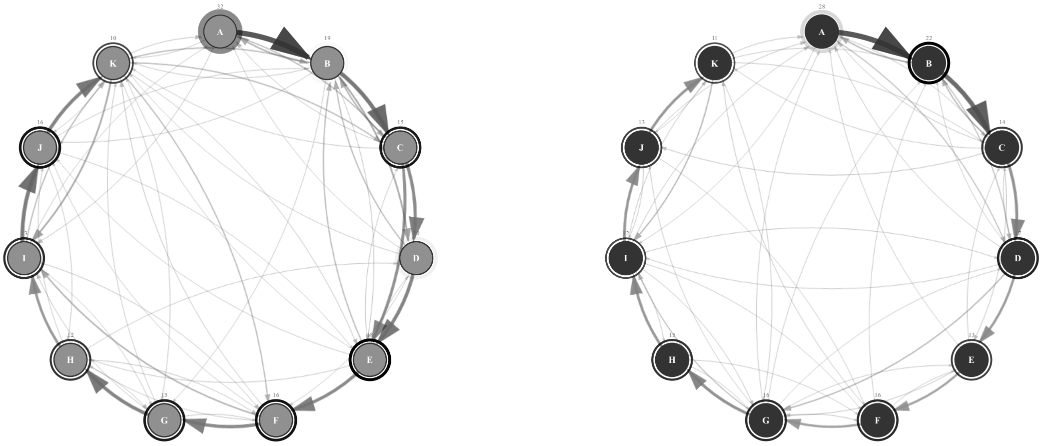
Learning Path of Accessed Materials: (a) Class A and (b) Class C (comparison groups); (c) Class B and (d) Class D (recommender groups).



(a)



(b)



(c) (d)

Note: Edge thickness represents navigation frequency between modules, with arrows indicating direction. Bold black rings indicate within-module navigation (self-loops). Legend shown in (a) applies to all subplots.

This study presents matrices for the two experimental classes, with learning paths recorded using the recommender system plugin. Navigation matrix data (Figure 11a and 11b) highlight frequencies in specific table cells, where cells with more than five assessment attempts are marked in orange. These orange cells indicate repeated attempts on the same assessment. For instance, cell [B, B] in Class B has a value of 6, showing that six learners repeatedly attempted Module B's assessment. Overall, Class B and Class D differ in repetition patterns: assessments for Modules B, C, and K are frequently repeated in Class B, while Modules B, C, F, H, I, J, and K are popular for repetitions in Class D.

Figure 11

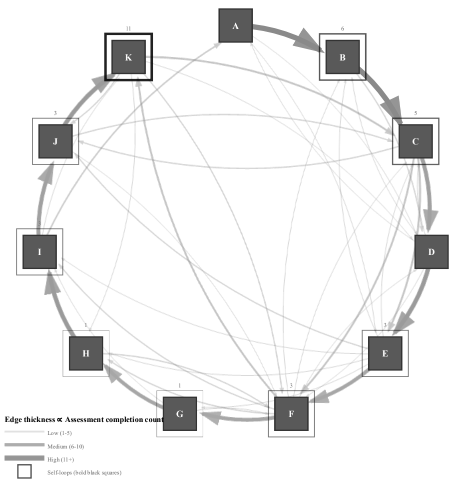
Assessment Completion and Learning Patterns for Classes B and D (recommender groups).

Modul	A	B	C	D	E	F	G	H	I	J	K
A	0	14	0	1	1	0	0	0	0	0	0
B	0	6	14	2	0	0	0	0	0	0	0
C	0	0	5	10	4	4	0	0	0	2	0
D	1	1	1	0	11	1	0	0	0	0	0
E	0	1	1	0	3	9	1	1	1	2	0
F	0	1	1	1	0	3	9	2	2	0	4
G	0	0	0	0	0	1	1	9	1	0	0
H	0	0	0	0	0	2	0	1	11	0	0
I	3	0	0	0	0	0	0	0	3	10	1
J	0	0	2	0	0	1	0	0	0	3	11
K	0	0	4	1	0	2	0	1	0	2	11

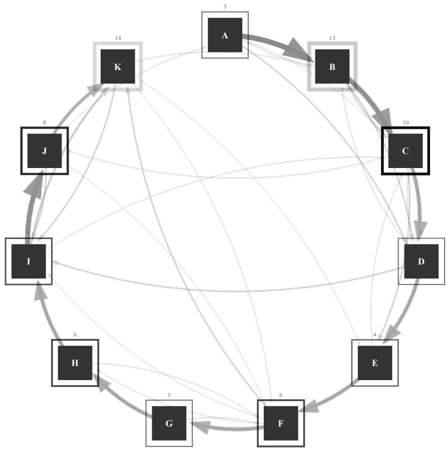
(a)

Modul	A	B	C	D	E	F	G	H	I	J	K
A	3	11	1	2	0	0	0	0	0	0	0
B	1	15	10	2	0	0	0	0	0	0	0
C	0	2	10	7	2	0	0	0	0	1	0
D	0	1	1	3	7	0	0	0	2	0	0
E	0	0	1	0	4	7	0	0	0	0	0
F	0	0	0	0	0	6	7	1	1	0	2
G	0	0	0	0	0	1	3	7	0	0	0
H	0	0	0	0	0	1	0	6	7	0	0
I	0	0	1	0	0	0	0	0	5	10	3
J	1	0	0	0	0	1	0	0	2	8	6
K	0	1	0	0	1	1	0	0	2	0	14

(b)



(c)



(d)

Note: (a,c) Class B; (b,d) Class D. (a,b) Assessment completion matrices; (c,d) assessment navigation graphs. Edge thickness indicates completion frequency; arrows indicate direction; bold black squares = self-loops. Legend shown in (c) applies to all subplots.

Visualization of assessment learning paths (Figure 11c and 11d) shows that assessment completion patterns in Classes B and D resemble material access navigation, following a linear forward order. The result shows that learners in the recommender groups generally completed assessments for Module A, then proceeded sequentially to Module B, C, and so on, until reaching Module K. However, matrix data indicate that learners in the ontology recommender group completed assessments 5% more frequently by using 15.2% more varied paths. Thus, the conclusions are:

1. Most learners in the recommender groups accessed materials and completed assessments in a linear forward path.
2. The ontology-based recommender group completed assessments with more varied nonlinear paths.
3. The hybrid recommender group more frequently repeated assessments for the same module, resulting in a 21% shorter average assessment completion duration.

Discussion

Evaluating recommender systems is a complex domain (Erdt et al., 2015), and the performance of different recommender systems in e-learning is difficult to compare (da Silva et al., 2023; George & Lal, 2019). Therefore, this study has aimed to employ more detailed evaluation metrics than previous studies by specifying measurement constructs, utilizing learner performance data recorded in the system, and adopting a more comprehensive e-learning evaluation framework (Al-Fraihat et al., 2020).

Recommender systems can be evaluated through offline experiments with datasets, user studies in controlled settings, or online experiments (real-life testing) involving real learners. Previous studies indicate that most recommender systems are assessed using offline methods and user studies (da Silva et al., 2023; Erdt et al., 2015; Rahayu et al., 2023). This study, evaluated through online experiments and employing a quasi-experimental design, contributes to understanding system performance in real-life conditions.

The experiments measured the recommender system's performance in terms of efficiency, effectiveness, and satisfaction. These metrics were analyzed using descriptive statistics and hypothesis tests (ANCOVA or Kruskal-Wallis), depending on data distribution. The diverse evaluation approaches, variable dimensions (Erdt et al., 2015), and different statistical techniques compared to previous studies (e.g., *t* tests (Jevremovic et al., 2017), ANOVA (Jeng & Huang, 2019)) provide a comprehensive perspective on recommender system performance.

Descriptive statistics revealed that the hybrid recommender group had the second-highest efficiency after the comparison group. However, hypothesis testing after controlling for covariates showed no significant differences among the three groups. In the assessmentDuration variable, the hybrid group completed assessments 21% faster than the ontology recommender group, likely due to improved assessment layouts based on feedback from Period I. Clearer assessment questions facilitated easier retakes for the hybrid group, aligning with findings that unclear instructions hinder online learners (Kelly et al., 2024; Roy et al., 2020).

The results show no support for H1 (efficiency) and partial support for H2 (effectiveness). The hybrid group accessed significantly fewer materials (p = .023) but achieved equivalent assessment scores, indicating the system influenced learning behavior without improving outcomes. These findings partially contradict research showing hybrid recommender systems enhance learning effectiveness outcomes (Colace & De Santo, 2010; Deschênes, 2020; Jevremovic et al., 2017; Vesin et al., 2013), while aligning with studies showing varied outcomes (Murad et al., 2020). Factors such as short course duration and small sample size may have influenced results. The findings suggest that advantages of the hybrid approach are contextual and depend on measured variables; thus, the hybrid approach is not universally superior to single-method approaches (ontology-based).

The satisfaction evaluation showed the hybrid recommender group scored highest in 22 out of 30 e-learning satisfaction variables. This may be attributed to learning path suggestions and progress tracking features, which reduce extraneous cognitive load by simplifying module selection (Premlatha & Geetha, 2015; Sweller et al., 2011) and visually clarifying learning progress. These features likely made learners feel their progress was important and navigable, leading to higher satisfaction (Sartor et al., 2020; Smith, 2018). Specifically, the hybrid group scored an average of 2.5 out of 3 on benefits (REC4) and overall satisfaction (REC5) in the recommender system variables (REC2 - REC5).

Additionally, 89% of learners in both recommender groups reported that the system met or exceeded their expectations, surpassing 65–65.6% satisfaction rates in other studies (Colace et al., 2020; Vesin et al., 2013). The hybrid recommender group also achieved higher overall satisfaction scores (REC5), though perceptions of frequency and benefits were lower than the ontology-based recommender group. This suggests that satisfaction may be influenced by other factors, such as cognitive styles (Betoret, 2007) or learner needs (Al-Azawei et al., 2016).

The analysis of the learning path graph for course materials reveals that the patterns across the three groups are similar, exhibiting a forward linear path, except for the first three modules in the comparison group. Consequently, although the system provides the option to select materials nonlinearly, learners in the experimental groups accessed the materials in an order comparable to that of the comparison group. One possible explanation for this phenomenon is B.F. Skinner's theory of operant conditioning (Huang et al., 2019). This theory suggests that learners, all over 18 years old, have previously experienced sequential learning processes during their primary and secondary education years (Rohman & Muhtamiroh, 2022). This established condition makes it difficult to alter such habitual behaviors.

Another significant finding is the presence of several confounding variables that influenced the measurement results:

1. Period of Participation: significantly affects access duration (efficiency dimension), the percentage of materials accessed (effectiveness dimension), and e-learning usability (satisfaction dimension).
2. Participant Age: significantly influences the score of sub-learning outcome II (effectiveness dimension).
3. Gender: impacts the ease of use and accessibility of e-learning (satisfaction dimension).
4. Field of Study: affects the quality of content design (satisfaction dimension).
5. Participant Activity or Occupation: influences the IT team's readiness (satisfaction dimension).

These findings align with previous research on the effects of participation period (Sibanda & Donnelly, 2014), age (Kintu et al., 2017), gender (Aliyu et al., 2019), field of study (Li et al., 2018), and learner activity (Alnaji & Karsu, 2016) on learning outcomes. However, it is noteworthy that these five confounding variables only influenced 1–3 out of the 40 dependent variables measured in this study. As a result, the overall impact of these confounding factors on the research outcomes remains inconclusive.

Implications

This study highlights important insights into designing and applying hybrid recommender systems in e-learning environments. While the collaboration between ontology and sequential pattern mining did not deliver the expected performance gains, the findings reveal practical considerations for educators and system designers. Specifically, aligning recommender systems with specific learning approaches, selecting appropriate artificial intelligence techniques, and ensuring robust experimental setups are critical for improving system efficacy. These results offer actionable guidance for personalizing learning paths.

The observed similarity in learning path patterns despite the availability of nonlinear material selection options suggests that habitual learning behaviors, as explained by operant conditioning, may persist even in more flexible learning environments. This has important implications for the design of e-learning recommender systems, indicating that merely providing nonlinear options may not be sufficient to change established learning behaviors. Future systems should consider incorporating strategies that actively encourage exploration and deviation from linear paths to fully utilize the potential of nonlinear learning environments.

The identification of confounding variables highlights the complexity of evaluating e-learning recommender systems. The significant impact of participation period, age, gender, field of study, and learner activity or occupation suggests that these factors should be carefully controlled or accounted for in future studies to isolate the effects of the recommender systems themselves. Additionally, understanding how these variables interact with system performance can inform more personalized and adaptive recommender strategies that cater to diverse learner profiles.

Limitations and Future Directions

This study was limited by several factors, including a small sample size, the presence of confounding variables, and a constrained experimental duration. These limitations affected the hybrid system's performance and the generalizability of the findings. To address these challenges, future research should investigate larger learner cohorts, test diverse combinations of recommender techniques, and extend the duration of experiments. Reducing confounding variables and improving the experimental setup will also enhance the reliability of results and provide deeper insights into hybrid recommender systems' effectiveness in real-world e-learning contexts.

Prior knowledge data were not systematically collected across all experimental groups, limiting our ability to control for this factor in the main three-group comparisons. Supplementary analyses with the two recommender groups ($n = 24$) showed no significant effect of prior knowledge, though the reduced sample size limits generalizability. Additionally, satisfaction surveys were administered anonymously to protect privacy, preventing linkage with prior knowledge or demographic data and limiting examination of individual-level factors. Future studies should implement systematic prior knowledge collection across all conditions while maintaining privacy protections through alternative means such as secure linking codes.

This study involved learners aged over 18 years, based on the assumption that individuals at this age generally possess self-regulated learning skills (Lowe et al., 2013). However, not all learners in this experiment exhibited strong self-regulation levels, which may have affected the performance of the recommender system. Initial screening could be conducted to ensure learners have sufficient self-regulation abilities. This step is expected to enhance the relevance and accuracy of experimental results regarding nonlinear learning path recommender systems.

The hybrid recommender systems combine learning path suggestion and progress tracking features. To increase learner engagement and completion rates, progress tracking features can be developed into gamification elements in e-learning (Meşe & Sevilen, 2021; Strmečki et al., 2015), as gamification has been shown to enhance motivation and sustained participation. Additionally, these features can be expanded into knowledge tracing to measure learners' knowledge status as it evolves over time (Huang et al., 2019; Shen et al., 2022).

Conclusion

This study assessed the effectiveness of e-learning recommender systems within a Database MOOC, comparing a comparison group, a single-method ontology-based recommender group, and a hybrid recommender group combining ontology and sequential pattern mining. The experimental results demonstrate that the hybrid recommender system surpassed the ontology-based system in efficiency, achieved the highest effectiveness in several sub-learning outcomes, and obtained the best scores in 22 out of 30 general e-learning satisfaction variables. Furthermore, ANCOVA revealed significant differences in user satisfaction across three variables: e-learning usability (INQ3), Moodle preference (SUP4), and learner behavior (LER1), providing partial support for the satisfaction hypothesis. The effectiveness hypothesis was also partially supported, with the hybrid group accessing significantly fewer materials (p =.023), though this behavioral difference did not translate into superior assessment scores. No significant differences were observed in efficiency. These findings suggest that while hybrid recommender systems can influence learning behaviors and enhance specific aspects of user satisfaction, their impact on learning outcomes may be limited or contextual. The results emphasize the importance of tailoring recommender systems to specific learning environments and learner profiles, and distinguishing between process-level improvements and outcome-level effectiveness in evaluating recommender system performance. Future research should consider the identified confounding variables and explore alternative configurations for hybrid recommender systems to maximize their benefits across various educational settings.

Furthermore, the study identified five confounding variables (period of participation, age, gender, field of study,and learner activity or occupation) that affected a subset of the dependent variables. This highlights the complexity of evaluating e-learning systems and the need to account for diverse learners' characteristics in future research.

List of Abbreviations

ACM	Association for Computing Machinery
ANCOVA	Analysis of Covariance
ANOVA	Analysis of Variance
EESS	Evaluating E-learning System Success
IEEE	Institute of Electrical and Electronics Engineers
INS	Instructor Quality
INQ	Information Quality
LER	Learner Quality
LMS	Learning Management System
MOOC	Massive Open Online Course
SQL	Structured Query Language
SRQ	Service Quality
SUP	Support System Quality
TSQ	Technical System Quality

Declarations

Ethics Statement
Formal ethics board approval was not obtained prior to data collection. All participants provided informed consent to participate and for their anonymized data to be used for research purposes. All data were anonymized and handled to protect participant privacy.

Availability of Data and Materials
The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Conflict of Interests
The authors declare that they have no competing interests.

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Authors' Contributions
NW: Methodology, formal analysis, investigation, writing - original draft, writing - review & editing. IN: Resources. IH: Validation. RF: Funding acquisition. SS: Conceptualization, Methodology, Supervision.

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References

Aggarwal, C. C. (2016). *Recommender Systems*. Springer International Publishing Switzerland. https://doi.org/10.1007/978-3-319-29659-3

Alatrash, R., Chatti, M. A., Ain, Q. U., Fang, Y., Joarder, S., & Siepmann, C. (2024). ConceptGCN: Knowledge concept recommendation in MOOCs based on knowledge graph convolutional networks and SBERT. *Computers and Education: Artificial Intelligence*, *6*, 100193. https://doi.org/10.1016/j.caeai.2023.100193

Al-Azawei, A., Parslow, P., & Lundqvist, K. (2016). Investigating the effect of learning styles in a blended e-learning system: An extension of the technology acceptance model (TAM). *Australasian Journal of Educational Technology*. https://doi.org/10.14742/ajet.2741

Al-Fraihat, D., Joy, M., Masa'deh, R., & Sinclair, J. (2020). Evaluating E-learning systems success: An empirical study. *Computers in Human Behavior*, *102*, 67–86. https://doi.org/10.1016/j.chb.2019.08.004

Aliyu, O. A., Arasanmi, C., & Ekundayo, S. (2019). Do demographic characteristics moderate the acceptance and use of the Moodle learning system among business students? *International Journal of Education and Development Using ICT*, *15*(1). https://www.learntechlib.org/p/209741/

Alnaji, L., & Karsu, Y. (2016). Effect of work status, experience and job sector on e-learning style in hybrid classrooms: GCC case study. *European Journal of Business and Management*, *8*(12), 31–36.

Amin, S., Uddin, M. I., Alarood, A. A., Mashwani, W. K., Alzahrani, A., & Alzahrani, A. O. (2023). Smart e-learning framework for personalized adaptive learning and sequential path recommendations using reinforcement learning. *IEEE Access*, *11*, 89769–89790. https://doi.org/10.1109/ACCESS.2023.3305584

Betoret, F. D. (2007). The influence of students' and teachers' thinking styles on student course satisfaction and on their learning process. *Educational Psychology*, *27*(2), 219–234. https://doi.org/10.1080/01443410601066701

Blaschke, L. M., & Hase, S. (2016). *Heutagogy: a holistic framework for creating twenty-first-century self-determined learners.* In B. Gros, Kinshuk, & M. Maina (Eds.), *The Future of ubiquitous learning: learning designs for emerging pedagogies* (pp. 25–40). https://doi.org/10.1007/978-3-662-47724-3_2

Buchner, A. (2022). *Understanding Moodle plugins*. In *Moodle 4 Administration* (4th ed.). Packt Publishing. https://subscription.packtpub.com/book/web-development/9781801816724/2/ch02lvl1sec08/understanding-the-moodle-architecture

Cagiltay, N. E., Cagiltay, K., & Celik, B. (2020). An analysis of course characteristics, learner characteristics, and certification rates in MITx MOOCs. *The International Review of Research in Open and Distributed Learning*, *21*(3), 121–139. https://doi.org/10.19173/irrodl.v21i3.4698

Capuano, N., & Toti, D. (2019). Experimentation of a smart learning system for law based on knowledge discovery and cognitive computing. *Computers in Human Behavior*, *92*, 459–467. https://doi.org/10.1016/j.chb.2018.03.034

Colace, F., & De Santo, M. (2010). Ontology for e-learning: A Bayesian approach. *IEEE Transactions on Education*, *53*(2), 223–233. https://doi.org/10.1109/TE.2009.2012537

Colace, F., De Santo, M., Lombardi, M., Mosca, R., & Santaniello, D. (2020). A multilayer approach for recommending contextual learning paths. *Journal of Internet Services and Information Security (JISIS)*, *10*(2), 91–102. https://doi.org/10.22667/JISIS.2020.05.31.091

Correa, M. I. (2017). *Visual maps to navigate non-linear learning environments*. https://static1.squarespace.com/static/58856d643a0411d1d209ba6f/t/59a075c9f14aa16f879c3b86/1503688141364/Visual+Maps+to+navigate+Non-Linear+Learning+Environments+.pdf

Coursera. (2021). *Course Certificates*. Learner Help Center. https://www.coursera.support/s/article/208280196-Course-Certificates?language=en_US

da Silva, F. L., Slodkowski, B. K., da Silva, K. K. A., & Cazella, S. C. (2023). A systematic literature review on educational recommender systems for teaching and learning: research trends, limitations and opportunities. *Education and Information Technologies*, *28*(3), 3289–3328. https://doi.org/10.1007/s10639-022-11341-9

Deschênes, M. (2020). Recommender systems to support learners' agency in a learning context: a systematic review. *International Journal of Educational Technology in Higher Education*, *17*(1). https://doi.org/10.1186/s41239-020-00219-w

El-Bouhdidi, J., Ghailani, M., & Fennan, A. (2013). An intelligent architecture for generating evolutionary personalized learning paths based on learner profiles. *Journal of Theoretical and Applied Information Technology*, *57*(2), 294–304.

Erdt, M., Fernandez, A., & Rensing, C. (2015). Evaluating recommender systems for technology enhanced learning: A quantitative survey. *IEEE Transactions on Learning Technologies*, *8*(4), 326–344. https://doi.org/10.1109/TLT.2015.2438867

Fernando, W. (2020). Moodle quizzes and their usability for formative assessment of academic writing. *Assessing Writing*, *46*(July), 100485. https://doi.org/10.1016/j.asw.2020.100485

Field, A., & Hole, G. (2002). *How to design and report experiments*. SAGE Publications Ltd.

George, G., & Lal, A. M. (2019). Review of ontology-based recommender systems in e-learning. *Computers & Education*, *142*, 1–18. https://doi.org/10.1016/j.compedu.2019.103642

Gong, J., Liu, T. X., & Tang, J. (2021). How monetary incentives improve outcomes in MOOCs: Evidence from a field experiment. *Journal of Economic Behavior & Organization*, *190*, 905–921. https://doi.org/10.1016/j.jebo.2021.06.029

Harley, J. M., Taub, M., Azevedo, R., & Bouchet, F. (2018). “Let’s set up some subgoals”: Understanding human-pedagogical agent collaborations and their implications for learning and prompt and feedback compliance. *IEEE Transactions on Learning Technologies*, *11*(1), 54–66. https://doi.org/10.1109/TLT.2017.2756629

Hase, S. (2016). *Self-determined Learning (heutagogy): Where Have We Come Since 2000 ?*

Hasso Plattner Institute. (2023). *Records on openHPI*. https://open.hpi.de/pages/document_types

He, J., Liu, Z., & Kong, X. (2023). A novel link prediction approach for MOOC forum thread recommendation using personalized PageRank and machine learning. *2023 3rd International Conference on Educational Technology (ICET)*, 37–41. https://doi.org/10.1109/ICET59358.2023.10424086

Hnida, M., Idrissi, M. K., & Bennani, S. (2014). A formalism of the competency-based approach in adaptive learning systems. *WSEAS Transactions on Information Science and Applications*, *11*, 83–93.

Huang, R., Spector, J. M., & Yang, J. (2019). *Lecture notes in educational technology*. Springer Nature Singapore. https://doi.org/https://doi.org/10.1007/978-981-13-6643-7

Ishaq, M., Abid, A., Farooq, M. S., Manzoor, M. F., Farooq, U., Abid, K., & Helou, M. A. (2023). Advances in database systems education: Methods, tools, curricula, and way forward. *Education and Information Technologies*, *28*(3), 2681–2725. https://doi.org/https://doi.org/10.1007/s10639-022-11293-0

Isnawan, M. G. (2020). *Kuasi-Eksperimen* (Sudirman, Ed.). Nashir Al-Kutub Indonesia.

Jeng, Y., & Huang, Y.-M. (2019). Dynamic learning paths framework based on collective intelligence from learners. *Computers in Human Behavior*, *100*, 242–251. https://doi.org/10.1016/j.chb.2018.09.012

Jerz, R. (2018, January 19). *Amount of time spent in course*. Moodle Forum. https://moodle.org/mod/forum/discuss.php?d=364261

Jevremovic, A., Shimic, G., Veinovic, M., & Ristic, N. (2017). IP addressing: Problem-based learning approach on computer networks. *IEEE Transactions on Learning Technologies*, *10*(3), 367–378. https://doi.org/10.1109/TLT.2016.2583432

Jing, X., Patel, V. L., Cimino, J. J., Shubrook, J. H., Zhou, Y., Liu, C., & De Lacalle, S. (2022). The roles of a secondary data analytics tool and experience in scientific hypothesis generation in clinical research: Protocol for a mixed methods study. *JMIR Research Protocols*, *11*(7), e39414. https://doi.org/10.2196/39414

Kaplan, H., Bar-Tov, I., Glassner, A., & Back, S. (2021). Promoting agentic engagement and heutagogy in Tomer elementary school in Beer Sheva, Israel. In S. Hase & L. M. Blaschke (Eds.), *Unleashing the Power of Learner Agency* (pp. 112–123). EdTech Books. https://edtechbooks.org/up

Kelly, E., Colella, J., & Sottosanti-Kusnir, A. (2024). Student perceptions of effective educators in online learning. *Online Learning*, *28*(3). https://doi.org/10.24059/olj.v28i3.3534

Kintu, M. J., Zhu, C., & Kagambe, E. (2017). Blended learning effectiveness: the relationship between student characteristics, design features and outcomes. *International Journal of Educational Technology in Higher Education*, *14*(1), 7. https://doi.org/10.1186/s41239-017-0043-4

Klašnja-Milićević, A., Ivanović, M., & Nanopoulos, A. (2015). Recommender systems in e-learning environments: a survey of the state-of-the-art and possible extensions. *Artificial Intelligence Review*, *44*(4), 571–604. https://doi.org/10.1007/s10462-015-9440-z

Leroux, J. S., de Lannoy, L., & Baillie, C. P. T. (2024). Disorientation in community service-learning: A phenomenological inquiry. *Pedagogy in Health Promotion*, *10*(1), 16–24. https://doi.org/10.1177/23733799231204023

Li, J., Tang, Y., Cao, M., & Hu, X. (2018). The moderating effects of discipline on the relationship between asynchronous discussion and satisfaction with MOOCs. *Journal of Computers in Education*, *5*(3), 279–296. https://doi.org/10.1007/s40692-018-0112-2

Lowe, S. R., Dillon, C. O., Rhodes, J. E., & Zwiebach, L. (2013). Defining adult experiences. *Journal of Adolescent Research*, *28*(1), 31–68. https://doi.org/10.1177/0743558411435854

Lowenthal, P., Bauer, C., & Chen, K.-Z. (2015). Student perceptions of online learning: An analysis of online course evaluations. *American Journal of Distance Education*, *29*(2), 85–97. https://doi.org/10.1080/08923647.2015.1023621

Mamun, M. A. Al, Lawrie, G., & Wright, T. (2020). Instructional design of scaffolded online learning modules for self-directed and inquiry-based learning environments. *Computers & Education*, *144*, 103695. https://doi.org/10.1016/j.compedu.2019.103695

Meşe, E., & Sevilen, Ç. (2021). Factors influencing EFL students' motivation in online learning: A qualitative case study. *Journal of Educational Technology and Online Learning*, *4*(1), 11–22. https://dergipark.org.tr/en/pub/jetol/issue/60134/817680

Moodle. (2024, March 4). *Plugins FAQ*. Installation. https://docs.moodle.org/403/en/Plugins_FAQ

Moore, R. L. (2020). Developing lifelong learning with heutagogy contexts critiques and challenges. *Distance Education*, *41*(3), 381–401. https://doi.org/https://doi.org/10.1080/01587919.2020.1766949

Murad, D. F., Heryadi, Y., Isa, S. M., & Budiharto, W. (2020). Personalization of study material based on predicted final grades using multi-criteria user-collaborative filtering recommender system. *Education and Information Technologies*, *25*(6), 5655–5668. https://doi.org/10.1007/s10639-020-10238-9

O'Brien, E., & Reale, J. (2021). Supporting learner agency using the pedagogy of choice. In S. Hase & L. M. Blaschke (Eds.), *Unleashing the Power of Learner Agency* (pp. 73–82). EdTech Books. https://edtechbooks.org/up

Oliveira, R. J. M. (2016). *Recommender system for an e-learning platform* [Master thesis]. University of Porto. https://sigarra.up.pt/fcup/pt/pub_geral.show_file?pi_doc_id=90364b

Peters, O. (2002). *Distance education in transition: New trends and challenges*. Bibliotheks- und Informationssystem der Carl von Ossietzky Universität Oldenburg (BIS). http://oops.uni-oldenburg.de/550/2/petdis02.pdf

Premlatha, K. R., & Geetha, T. V. (2015). Learning content design and learner adaptation for adaptive e-learning environment: A survey. *Artificial Intelligence Review*, *44*(4), 443–465. https://doi.org/10.1007/s10462-015-9432-z

Rahayu, N. W., Adi, A. N., Ferdiana, R., & Kusumawardani, S. S. (2024). Nonlinear learning path: A systematic review. *Turkish Online Journal of Distance Education*, *25*(4), 143–161. https://doi.org/10.17718/tojde.1349356

Rahayu, N. W., Ferdiana, R., & Kusumawardani, S. S. (2022). A systematic review of ontology use in E-Learning recommender system. *Computers and Education: Artificial Intelligence*, *3*(6), 100047. https://doi.org/https://dx.doi.org/10.1016/j.caeai.2022.100047

Rahayu, N. W., Ferdiana, R., & Kusumawardani, S. S. (2023). A systematic review of learning path recommender systems. *Education and Information Technologies*, *28*(6), 7437–7460. https://doi.org/10.1007/s10639-022-11460-3

Reichardt, C. S. (2019). *Quasi-experimentation: a guide to design and analysis*. The Guilford Press.

Robberecht, R. (2007). Interactive nonlinear learning environments. *The Electronic Journal of E-Learning*, *5*(1), 59–68. https://academic-publishing.org/index.php/ejel/article/view/1503/1466

Rogers, J., & Révész, A. (2019). *Experimental and quasi-experimental designs.* In J. McKinley & H. Rose (Eds.), *The Routledge Handbook of Research Methods in Applied Linguistics*. Routledge. https://doi.org/10.4324/9780367824471

Rohman, A., & Muhtamiroh, S. (2022). Shaping the santri's inclusive attitudes through learning in pesantren: A case study of pesantren Al-Anwar Sarang Rembang Indonesia. *Journal of Educational and Social Research*, *12*(2), 367. https://doi.org/10.36941/jesr-2022-0058

Romero, L., Saucedo, C., Caliusco, Ma. L., & Gutiérrez, M. (2019). Supporting self-regulated learning and personalization using ePortfolios: a semantic approach based on learning paths. *International Journal of Educational Technology in Higher Education*, *16*(1), 16. https://doi.org/10.1186/s41239-019-0146-1

Rootzén, H. (2015). Individualized learning through non-linear use of learning objects: With examples from math and stat. *Proceedings of the 14th European Conference on E-Learning (ECEL 2015)*, 500–506. https://core.ac.uk/download/pdf/43254856.pdf

Roy, S., Beer, C., & Lawson, C. (2020). The importance of clarity in written assessment instructions. *Journal of Further and Higher Education*, *44*(2), 143–155. https://doi.org/10.1080/0309877X.2018.1526259

Salehi, M., Kamalabadi, I. N., & Ghoushchi, M. B. G. (2013). An effective recommendation framework for personal learning environments using a learner preference tree and a GA. *IEEE Transactions on Learning Technologies*, *6*(4), 350–363. https://doi.org/10.1109/TLT.2013.28

Sartor, L. B., Rosa, L. L. da, Madeira, K., Uggioni, M. L. R., Ferreira Filho, O. F., & Rosa, M. I. da. (2020). Undergraduate medical student's perception about the progress testing. *Revista Brasileira de Educação Médica*, *44*(2). https://doi.org/10.1590/1981-5271v44.2-20190286.ing

Shen, S., Chen, E., Liu, Q., Huang, Z., Huang, W., Yin, Y., Su, Y., & Wang, S. (2022). Monitoring student progress for learning process-consistent knowledge tracing. *IEEE Transactions on Knowledge and Data Engineering*, 1–15. https://doi.org/10.1109/TKDE.2022.3221985

Shih, Y.-C., Huang, P.-R., Hsu, Y.-C., & Chen, S. Y. (2012). A complete understanding of disorientation problems in web-based learning. *Turkish Online Journal of Educational Technology-TOJET*, *11*(3), 1–13.

Sibanda, M., & Donnelly, S. (2014). The impact of e-learning on student performance: A case study of an entry-level module at a South African University. *Mediterranean Journal of Social Sciences*. https://doi.org/10.5901/mjss.2014.v5n9p478

Smith, M. R. (2018). *Student perspectives on satisfaction with learning in Bachelor of Nursing programs in Australia: A constructivist grounded theory study* [Doctoral dissertation, Griffith University]. http://hdl.handle.net/10072/381377

Strmečki, D., Bernik, A., & Radošević, D. (2015). Gamification in e-learning: Introducing gamified design elements into e-learning systems. *Journal of Computer Science*, *11*(12), 1108–1117. https://doi.org/10.3844/jcssp.2015.1108.1117

Sudijono, A. (2015). *Pengantar Evaluasi Pendidikan* (Ed. 1). Rajawali Pers.

Sweller, J., Ayres, P., & Kalyuga, S. (2011). *Cognitive load theory.* Springer Science+Business Media. https://doi.org/10.1007/978-1-4419-8126-4

Tarus, J. K., Niu, Z., & Mustafa, G. (2018). Knowledge-based recommendation: A review of ontology-based recommender systems for e-learning. *Artificial Intelligence Review*, *50*(1), 21–48. https://doi.org/10.1007/s10462-017-9539-5

Tarus, J. K., Niu, Z., & Yousif, A. (2017). A hybrid knowledge-based recommender system for e-learning based on ontology and sequential pattern mining. *Future Generation Computer Systems*, *72*, 37–48. https://doi.org/https://doi.org/10.1016/j.future.2017.02.049

Tazi, K., Azzouzi, S., & Charaf, M. E. H. (2023). An ontology-based recommender system for identifying learners' confusion in MOOCs. *2023 7th IEEE Congress on Information Science and Technology (CiSt)*, 492–496. https://doi.org/10.1109/CiSt56084.2023.10409939

Tedre, M., & Moisseinen, N. (2014). Experiments in computing: A survey. *The Scientific World Journal*, *2014*, 1–11. https://doi.org/10.1155/2014/549398

Tondello, G. F., Orji, R., & Nacke, L. E. (2017). Recommender systems for personalized gamification. *Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*, 425–430. https://doi.org/10.1145/3099023.3099114

Vesin, B., Klasnja-Milicevic, A., Mirjana, I., & Budimac, Z. (2013). Applying recommender systems and adaptive hypermedia for e-learning personalization. *Computing and Informatics*, *32*, 629–659. https://www.cai.sk/ojs/index.php/cai/article/view/1736

Wu, X., Jiang, H., Zhang, J., Wu, Z., Cheng, X., Yang, Q., & Zhou, Y. (2024). *KAMC: Knowledge-aware meta-concept recommendation* [Preprint]. Research Square. https://doi.org/10.21203/rs.3.rs-4521552/v1

Appendix A

Complete List of Analyzed Articles from Systematic Literature Review on MOOC Recommender Systems

No	Year	Authors	Title	Type	In-course recommender	DOI/URL
Part A: Research papers - In-course recommender systems (n=5; 18%)						
1	2023	Alatrash, R., Chatti, M. A., Ain, Q. U., Fang, Y., Joarder, S., & Siepmann, C.	ConceptGCN: Knowledge concept recommendation in MOOCs based on knowledge graph convolutional networks and SBERT	Research	Yes	Link
2	2023	Amin, S., Uddin, M. I., Alarood, A. A., Mashwani, W. K., Alzahrani, A., & Alzahrani, A. O.	Smart E-learning Framework for Personalized Adaptive Learning and Sequential Path Recommendations Using Reinforcement Learning	Research	Yes	Link
3	2023	He, J., Liu, Z., Chen, X., Wang, Y., & Zhang, M.	A novel link prediction approach for MOOC forum thread recommendation using personalized pagerank and machine learning	Research	Yes	Link
4	2023	Tazi, K., Azzouzi, S., & Charaf, M. E. H.	An Ontology-based Recommender System for Identifying Learners' Confusion in MOOCs	Research	Yes	Link
5	2024	Wu, X., Jiang, H., Zhang, R., Wang, Y., & Chen, L.	KAMC: Knowledge-Aware Meta-Concept Recommendation	Research	Yes	Link
Part B: Research papers - Course recommender systems (n=23; 82%)						
6	2023	Amin, S., Uddin, M. I., Mashwani, W. K., Alarood, A. A., Alzahrani, A., & Alzahrani, A. O.	Developing a personalized E-learning and MOOC recommender system in IoT-enabled smart education	Research	No	Link
7	2023	Garcia Cuco, A.	Recommender system for online courses	Research	No	Link
8	2023	Li, Y., Xiong, H., & Zhang, Y.	MHRR: MOOCs Recommender Service With Meta Hierarchical Reinforced Ranking	Research	No	Link
9	2023	Madhavi, A., Nagesh, A., & Kumar, P.	Efficient Course Recommendation using Deep Transformer based Ensembled Attention Model	Research	No	Link
10	2023	Mansouri, N., Soui, M., & Abed, M.	SFS feature selection with decision tree classifier for massive open online courses (MOOCs) recommendation	Research	No	Link
11	2023	Midhun Chakkaravarthy, D. G.	A Quality of Experience-based Recommender System for E-learning Resources	Research	No	Link
12	2023	Mohammad, U., Hamdan, Y., & Al-Masri, A.	A Novel Algorithm for Professor Recommendation in Higher Education	Research	No	Link
13	2023	Murad, D. F., Toha, M., & Rahman, A.	The Impact of Recommendation System Provided Based on Online Learning Readiness in the MOOC Environment	Research	No	Link
14	2023	Ul Haque, M. M., & Kotaiah, B.	A Cluster Based Recommendation System for MOOCs	Research	No	Link
15	2023	Wang, Q., Xiong, A., & Chen, L.	Design and Application of Online Courses under the Threshold of Smart Innovation Education	Research	No	Link

16	2023	Yang, B., & Qi, C.	A Personalized Course Recommendation System has been Developed Using xDeepFM and RoBERTa Models	Research	No	Link
17	2024	Alatrash, R., Chatti, M. A., Ain, Q. U., & Joarder, S.	Transparent Learner Knowledge State Modeling using Personal Knowledge Graphs and Graph Neural Networks	Research	No	Link
18	2024	Gupta, C., Khalaf, O. I., & Kumar, S.	MOOCRec_Sys: An Empirical E-learning Paradigm on Online Open Course using Sentiment Analysis and OWA operator	Research	No	Link
19	2024	Hao, L., Abdipoor, S., & Rahman, M.	Hybrid Graph Neural Networks with LSTM Attention Mechanism for Recommendation Systems in MOOCs	Research	No	Link
20	2024	Khalid, A.	Scalable and Practical Recommender System in Massive Open Online Courses (MOOCs)	Research	No	Link
21	2024	Lowe, D., Galhotra, B., & Smith, A.	Leveraging Recommender Systems to Tailor Moocs for Student Needs: A Data-Driven Approach	Research	No	Link
22	2024	Ma, W., Zhao, Y., & Chen, X.	Cascaded Knowledge-Level Fusion Network for Online Course Recommendation System	Research	No	Link
23	2024	Nurakhmadyavi, S. M. K. H.	Course Recommendation on Online Learning Platforms using Collaborative Filtering and Content-based Filtering with Implicit Feedback	Research	No	Link
24	2024	Rao, J., & Borchers, C.	Coursera-REC: Explainable MOOCs Course Recommendation using RAG-facilitated LLMs	Research	No	Link
25	2024	Rao, J., & Lin, J.	RAMO: Retrieval-Augmented Generation for Enhancing MOOCs Recommendations	Research	No	Link
26	2024	Sun, J., Mei, S., & Liu, H.	Prerequisite-enhanced category-aware graph neural networks for course recommendation	Research	No	Link
27	2024	Zhou, W., Zhou, X., Li, Y., & Wang, H.	Online Course Recommendation by Exploring User Interaction and Course Description	Research	No	Link
28	2024	Ain, Q. U., Chatti, M. A., Meteng Kamdem, P. A., Alatrash, R., Joarder, S., & Siepmann, C.	Learner Modeling and Recommendation of Learning Resources using Personal Knowledge Graphs	Research	Full text N/A	Link
Part C: Review papers (n=7, excluded from percentage analysis)						
29	2023	Asfaw, Z., Alemneh, D. G., & Tefera, B.	Data-Driven Decision-Making and Its Impacts on Education Quality in Developing Countries: A Systematic Review	Review	-	Link
30	2023	Cisel, M. T.	On the Ethical Issues Posed by the Exploitation of Users' Data in MOOC Platforms: Capturing Learners' Perspectives	Review	-	Link
31	2023	El Aouifi, H., El Hajji, M., & Es-Saady, Y.	Video-Based Learning Recommender Systems: A Systematic Literature Review	Review	-	Link
32	2023	Kumar, H., & Kumar, S.	Persistent Technologies Like Modified E-learning and MOOC Recommender System in IoT-Enabled Smart Education	Review	-	Link
33	2023	Maryam, O., Ashraf, H., & Khan, A.	Improved E-learning Based Recommender Systems: A Survey	Review	-	Link

34	2024	Bin, Q., Zuhairi, M. F., & Ahmad, N.	A Comprehensive Study On Personalized Learning Recommendation In e-learning System	Review	-	Link
35	2024	Boufaida, S. O., Benmachiche, A., & Kazar, O.	An Extensive Examination of Varied Approaches in E-learning and MOOC Research: A Thorough Overview	Review	-	Link

Appendix B

Supplementary ANCOVA Results with Prior Knowledge

Variable	N	Group effect			Prior knowledge effect		
		F	p	ηp²	F	p	ηp²
Efficiency							
accessDuration	24	1.453	.242	.010	.214	.648	.010
assessmentDuration	24	.063	.804	.003	.026	.873	.001
Effectiveness							
materialPercentage	24	.960	.338	.044	.666	.424	.031
subLO1Score	24	.254	.619	.012	.954	.340	.043
subLO2Score	18	.836	.375	.053	.016	.901	.001
subLO3Score	17	.003	.954	2.439×10^{-4}	1.457	.247	.094
finalScore	24	.681	.418	.031	.315	.581	.015