Indonesian Journal of Instructional Media and Model
Volume 7, Issue 2 (2025), pp. 130-141 | p-ISSN: 2686-0708, e-ISSN: 2686-0112
http://journal.univetbantara.ac.id/index.php/ijimm

Ontology-Based Recommender Systems for E-Learning and Multimedia: A Systematic Literature Review Across Domains

Suastika Yulia Riska[1], Syaad Patmanthara[2], Triyanna Widiyaningtyas[3]
[1,2,3] Department of Electrical Engineering and Informatics, Universitas Negeri Malang, Indonesia
E-mail: [1]suastika.yulia.2505349@students.um.ac.id*, [2]syaad.ft@um.ac.id, [3]triyannaw.ft@um.ac.id
*Coresponding Author

Article History:
Received: October 22, 2025; Revised: November 25, 2025; Accepted: November 27, 2025;
Published: November 30, 2025

ABSTRACT

The rapid expansion of digital content in e-commerce, healthcare, education, and employment has intensified the need for accurate and explainable recommender systems. Traditional Collaborative Filtering (CF) and Content-Based Filtering (CBF) approaches still suffer from data sparsity and cold-start problems, which are particularly visible in educational and mobile learning environments. This study systematically reviews ontology-based approaches for recommender systems, with a specific emphasis on educational technology and interactive multimedia applications. Using a Systematic Literature Review (SLR) protocol based on PICOC and PRISMA, we initially identified 110 records from Scopus and related databases and finally included 33 primary studies published between 2021 and 2025. The studies were grouped into four domains: e-commerce (N_1), education and e-learning (N_2), healthcare (N_3), and employment (N_4). For each domain, we analyzed ontology construction methods, integration with Knowledge Graphs (KG) and Graph Neural Networks (GNN), and their contributions to recommendation quality. The review shows that ontology-based recommender systems consistently improve recommendation relevance, diversity, and explainability, and they are especially promising for modeling learner profiles, learning resources, and personalized learning paths in educational settings. However, most implementations remain experimental, and face challenges related to ontology engineering effort, scalability, and integration into real-world learning platforms. This study highlights research gaps and future opportunities, including automated ontology construction and hybrid KG and GNN-based models tailored for e-learning and mobile learning contexts.

Keywords: *Educational Technology, E-Learning, Knowledge Graphs, Ontology-Based Approaches, Recommendation Systems*

INTRODUCTION

The rapid expansion of digital content and information across various sectors, such as e-commerce, healthcare, education, and employment, has resulted in an overwhelming influx of data (Xia et al., 2024). This information overload has highlighted the growing importance of recommendation systems, which have evolved from basic tools to essential components of modern digital platforms (Garapati & Chakraborty, 2025). Acting as intelligent curators, these systems predict user preferences and present the most relevant items, products, or information (Rajabi et al., 2024). In doing so, recommendation systems enhance user experience, improve time efficiency, and influence purchasing decisions.

In the education sector, recommender systems increasingly support learning management systems (LMS), mobile learning (m-learning), and large-scale e-learning platforms by suggesting courses, learning objects, assessments, or learning paths that match learner needs and preferences (Dritsas & Trigka, 2025). Ontology-based representations are particularly relevant in this context because they can formally capture pedagogical concepts, competency structures, and learner profiles, enabling more meaningful alignment between learning content, instructional strategies, and student characteristics (Villegas-Ch & García-Ortiz, 2023). Such alignment is central to learning communication, where messages, media, and activities must be adapted to learners' prior knowledge and motivation (Val & Quintas, 2025).

Despite their crucial role, traditional recommendation systems based on methods such as Collaborative Filtering (CF) and Content-Based Filtering (CBF) often face significant limitations, particularly in handling complex and dynamic data typical of real-world scenarios (Alfaifi, 2024). Two major challenges arise with CF methods, which recommend items based on user behavior similarity: data sparsity and the Cold Start problem (Ranjbar Kermany et al., 2023; L.-E. Wang et al., 2024; Zhang et al., 2024). Data sparsity refers to the situation where the interaction matrix between users and items is sparsely populated, making it difficult to identify users with similar preferences (i.e., neighbors) or to generate reliable predictions (Bukhari et al., 2025; Wan et al., 2022). This condition severely impacts the quality of recommendations provided. On the other hand, the Cold Start problem arises when traditional models struggle to function effectively due to a lack of sufficient historical data, either for new items that have not been interacted with or for new users without a history of preferences (Al-Rossais, 2023; Noorian, 2024). In the absence of enough historical data, the system cannot create an accurate representation, leading to recommendations that are either too general or even impossible to generate.

To overcome the fundamental limitations of traditional recommendation system models, research has rapidly progressed toward knowledge-based and semantic approaches (Bazargani et al., 2024; Wan et al., 2022). In this context, ontologies emerge as a powerful architectural solution. An ontology can be defined as a clear formal specification of the division of concepts within a domain, describing entities, attributes, and the complex relationships between those elements (Bernabé et al., 2023).

Ontologies substantially enhance the efficacy of recommendation systems in multiple aspects. Ontologies facilitate enhanced feature representation by integrating supplementary information to augment the comprehension of goods and user profiles (Papadakis et al., 2022). In a movie recommendation system, ontologies document genres and semantic relationships, such as those between director X, the science fiction subgenre, and specific philosophical themes, enabling the system to deliver precise recommendations despite limited user interaction data, thus addressing the cold-start problem (Liang et al., 2023). Moreover, semantic reasoning empowers the system to execute logical deductions; if a user expresses a preference for an item associated with a specific conceptual category, the system can suggest additional items within that category, so enhancing the relevance and diversity of recommendations. Ultimately, ontologies underpin Knowledge Graphs (KG), which, when integrated with Graph Neural Networks (GNN), empower recommendation algorithms to utilize semantic links more extensively. This offers a more scalable approach to enhancing the precision and transparency of suggestions (Gharibi, BagheriFard, Parvïn, et al., 2024; Ma et al., 2025; Yang et al., 2026).

Despite the growing body of work on ontology-based recommender systems, existing surveys and reviews tend to focus either on generic recommendation techniques or on specific technical aspects (e.g., knowledge graph embeddings, GNN architectures) without systematically contrasting educational and non-educational domains. In the e-learning literature, several studies analyze ontology-based recommenders, but they are often limited to pre-2021 publications and do not consider recent advances in KG- and GNN-based hybrid models or cross-domain transfer between e-commerce and education.

This creates three gaps. First, there is limited synthesis of how ontologies are modeled and exploited across domains such as e-commerce, healthcare, employment, and education in the most recent period. Second, the specific role of ontology-based representations in educational and mobile learning settings, where learner modeling and pedagogical structures are central, has not been systematically compared to non-educational applications. Third, there is a lack of consolidated evidence on how ontology-based approaches are being combined with KG and GNN techniques to address cold-start, sparsity, and explainability in educational technology.

To address these gaps, this study conducts a Systematic Literature Review (SLR) of ontology-based recommender systems published between 2021 and 2025, with a particular emphasis on educational and interactive mobile learning contexts. The review (1) maps the application domains in which ontologies are used (RQ1), (2) classifies the computational methods and ontology-integration strategies employed (RQ2), and (3) synthesizes the main contributions of ontology-based approaches, including their impact on cold-start, diversity, and explainability (RQ3). By explicitly contrasting educational and non-educational domains, the study aims to derive implications for instructional designers, educational technologists, and e-learning system developers.

METHODS

This study employs a Systematic Literature Review (SLR) methodology to examine and integrate existing research on the use of ontologies in recommendation systems across various application domains. The aim is to explore the techniques and applications of ontologies within recommendation systems and to evaluate how they improve the quality of knowledge, leading to more relevant, organized, and meaningful recommendations. The research methodology is outlined in Figure 1.

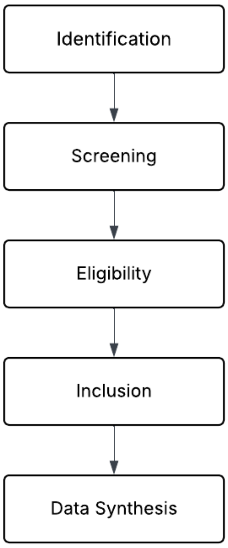

Figure 1. Research Stage

PICOC Protocol

This study followed the PICO/PICOC procedure to develop precise and organized research questions and search criteria. This protocol facilitated the identification of the principal components of the study, including the target population, the methodology that was applied pertinent comparisons, and anticipated outcomes. The elements have been defined as follows:

1. P (Population/Domain): Recommender Systems.
2. I (Intervention/Approach): Ontology, Knowledge-Based Systems, Semantic Web, Knowledge Graph.

3. C (Comparison): A direct comparison with non-ontology approaches is unnecessary.
4. O (Outcome/Results): Applications, Implementation Techniques, Contributions (e.g., enhanced accuracy, cold-start resolution).

Data Sources

A systematic and structured literature search through well-known academic databases, including Scopus, is necessary to investigate the subject of the ontology approach in recommendation systems. The aim of this study is to examine the application of ontology in recommendation systems across four key sectors: e-commerce, education, employment, and healthcare services. The primary objective of this search is to locate recent publications that address the utilization of graph neural networks and knowledge graphs to enhance the relevance and quality of ontology-based recommendations. The objective of the literature search is to identify pertinent and high-quality references that will substantiate the research. Specifically, the search will be restricted to articles published between 2021 and 2025. The search query employed is as follows:

```
TITLE-ABS-KEY(
 (ontolog* OR "knowledge graph*" OR "semantic web" OR "knowledge-based")
 W/3
 ("recommender system*" OR "recommendation system*" OR "recommendation engine*")
)
AND TITLE-ABS-KEY(
 "graph neural network*" OR GNN OR "knowledge graph embedding*" OR TransE OR "semantic similarity" OR OWL OR RDF OR SPARQL
)
AND (
 TITLE-ABS-KEY(e-commerce OR retail OR "product catalog" OR marketplace OR "shopping")
 OR TITLE-ABS-KEY(education OR e-learning OR MOOC OR "learning path" OR curriculum OR pedagogy)
 OR TITLE-ABS-KEY(job OR recruitment OR hiring OR "talent matching" OR "career")
 OR TITLE-ABS-KEY(health* OR medical OR "clinical system*" OR "electronic health record" OR "patient recommendation")
)
AND PUBYEAR > 2021 AND PUBYEAR < 2025
AND (LIMIT-TO(SRCTYPE,"j"))
AND (LIMIT-TO(DOCTYPE,"ar") OR LIMIT-TO(DOCTYPE,"re"))
AND (LIMIT-TO(LANGUAGE,"English") OR LIMIT-TO(LANGUAGE,"Indonesian"))
```

Criteria for Selection

Clear selection criteria have been created to assure the quality and relevance of the papers included in this literature review. The criteria are categorized into two primary types: inclusion criteria and exclusion criteria, designed to determine articles most pertinent to the study's subject. The criteria for selection are delineated as follows:

1. Inclusion criteria are as follows:
    - The inclusion criteria include articles that discuss the application or formulation of ontology/knowledge graphs in recommendation systems.
    - Document type: Relevant journals, conferences, or systematic reviews.

- Publication period: 2021–2025.
- Included in Quartile: Q1 to Q4.

2. Exclusion criteria are as follows:
    - Articles that exclusively address ontology without reference to recommendation systems, or the reverse
    - Surveys and reviews that do not cover the topic of ontology are also excluded.

Article Selection Process

The article selection process follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) principles to guarantee transparency and objectivity. The method comprises four primary stages: identification, screening, eligibility, and inclusion.

1. Identification: Performing a preliminary search with search strings in designated databases. The general count of articles identified is documented.
2. Screening:
    - Duplicate Removal: Eliminate all articles classified as duplicates.
    - Title and Abstract Screening: Evaluate articles based on their titles and abstracts to determine their relevance to Ontology and Recommendation Systems. Articles that are clearly unrelated should be excluded.
3. Eligibility: Evaluate articles that pass the initial screening phase through a detailed full-text review. Articles are assessed based on inclusion criteria (e.g., publication period from 2021 to 2025) and exclusion criteria.
4. Inclusion: Articles that meet all eligibility criteria are classified as the final set for data synthesis in this study.

In accordance with the PRISMA guidelines, the study selection process consisted of four stages: identification, screening, eligibility, and inclusion. In the identification stage, 110 records were identified from Scopus and complementary databases using the search query described above. After removing 7 duplicates, 103 unique records remained for title and abstract screening. At this stage, 73 records were excluded because they did not discuss ontology-based recommendation systems or were outside the target domain. The full text of 30 potentially relevant articles was then evaluated for eligibility based on inclusion and exclusion criteria. Finally, 33 primary studies met all criteria and were included in the qualitative synthesis and domain-specific analysis. A PRISMA flow diagram summarizing these steps is provided to ensure transparency of the SLR process, as shown in Figure 2.

Data Analysis

Following the selection of publications, data synthesis was conducted in three phases:

1. Data Extraction: Extract crucial information, including author, year, application domain, ontology technique employed, and results/contributions.
2. Thematic Synthesis: Categorizing articles according to application domain (RQ1) and implementation technique (RQ2) to identify patterns and trends.
3. Critical Analysis: evaluating the impact of the Ontology method (RQ3) and identifying research gaps.

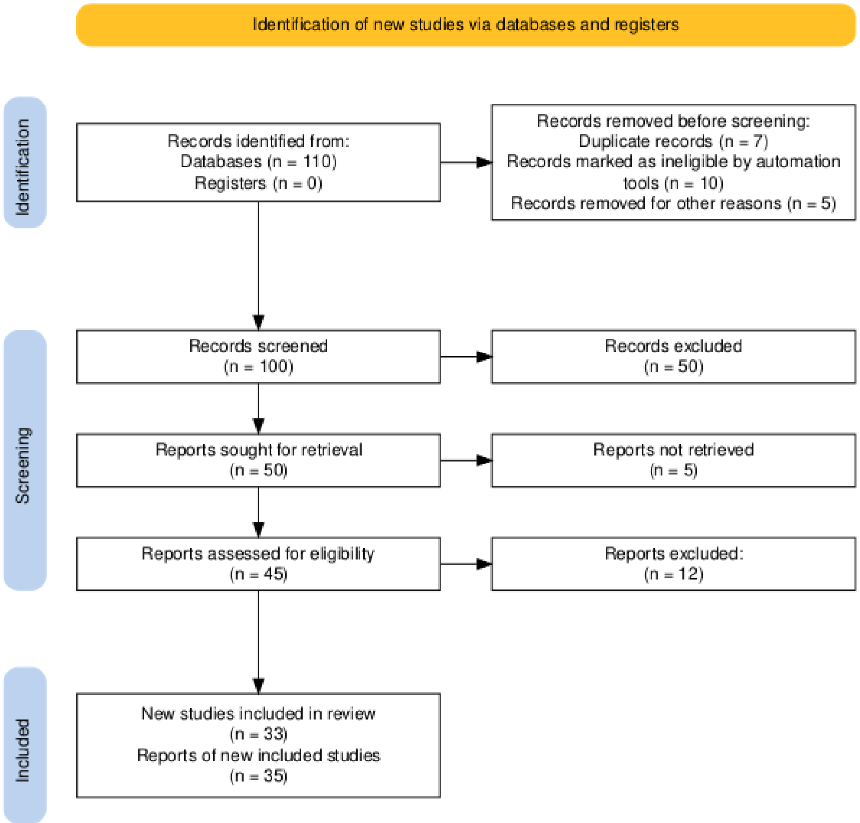

Figure 2. PRISMA Flowchart of the Study Selection Process

Domain Grouping and Educational Focus

For analysis, the studies included were grouped into four application domains: e-commerce, education and e-learning, healthcare, and employment. This multi-domain perspective is intentional. Educational recommended systems frequently reuse modeling patterns, ontology design choices, and KG- or GNN-based architectures that were first developed in non-educational contexts such as product recommendation or healthcare decision support. By treating non-educational domains as comparative baselines rather than primary targets, this review highlights how ontology-based techniques can be transferred and adapted to educational and mobile learning scenarios, and where domain-specific constraints (e.g., pedagogical structure, learner privacy) require different design decisions.

RESULTS AND DISCUSSION

Application of Ontology in Recommendation Systems

The ontology technique has shown effectiveness in modeling complex domains, resulting in its common use across various domains, as illustrated in Table 1.

Table 1. Ontology Applications in Recommendation Systems

Application Domain	Ontology Implementation Objectives	Example of implementation
Employment	Analyze the correlation between skills, employment positions, and applicants to enhance matching precision. This is beneficial for job recommendation systems that can suggest more pertinent positions depending on the skills of candidates.	The use of ontologies in job search systems is widely applied in Job Recommender Systems (Kwieciński et al., 2023; Saito & Sugiyama, 2022; C. Wang et al., 2022).

Application Domain	Ontology Implementation Objectives	Example of implementation
Healthcare services	Building a structured knowledge base to support data visualization recommendations or medical services. This enables the system to recommend medical services based on existing patient data or medical information.	The use of ontology in medical services to organize knowledge and relationships between medical concepts (Rostami et al., 2023; Sangaiah et al., 2023; Yu et al., 2022).
E-commerce	Developing a product ontology model that mitigates data sparsity issues and enhances user preference predictions by enriching product feature information through semantic relationships, thereby enabling more accurate recommendations	The use of CNN (Convolutional Neural Network) for product ontology and OWL (Web Ontology Language) for user behavior ontology, which enables the system to better understand user preferences and behavior (Bukhari et al., 2025; Deng et al., 2023; Gharibi, BagheriFard, Parvin, et al., 2024).
Education	Modeling learning resources, curriculum, and learner profiles to provide more personalized learning path recommendations. This enhances the learning experience by providing recommendations tailored to the learner's needs and learning style.	The use of Knowledge Graph (KG) and ontology for semantic representation in recommended learning content (Alatrash et al., 2024; Amin et al., 2023; Kaur et al., 2025)

Across the 33 primary studies, ontology-based recommender systems were most frequently applied in e-commerce (15 studies), followed by healthcare (7 studies), education and e-learning (5 studies), and employment (6 studies). Although the number of educational studies is smaller than in e-commerce, educational applications typically employ richer domain ontologies that explicitly encode learning objectives, prerequisite relationships, and learner characteristics. In contrast, e-commerce and healthcare systems more often focus on item attributes and contextual factors (e.g., time, location, physiological signals), reflecting differences in the underlying communication goals and decision-making processes.

Ontology Implementation Methods

The methods used to integrate Ontology into recommendation systems can be divided into two categories, namely:

1. Ontology Creation and Utilization
   - Product/Item Ontology Creation: At this stage, techniques such as Convolutional Neural Network (CNN) are used in the preprocessing phase to support the creation of ontology models for products. This process enables the system to map product relationships and attributes in a more structured manner (Shi et al., 2024).
   - User Behavior Modeling: Using libraries such as OWL libraries, ontology models are explicitly created to map user behavior based on predetermined criteria and user interaction history. This helps in understanding user preference patterns and interactions with the system (Razzaq et al., 2024; Shi et al., 2024).
   - Integration with Classical Algorithms: Ontologies serve as a source of knowledge that is integrated into a Knowledge-Based or Hybrid-based recommendation system,

which allows for the calculation of semantic proximity between items or users on a larger scale (Huang et al., 2024; Yap et al., 2024)

2. Knowledge Graph (KG)-Based Approach
   Knowledge Graph-Enhanced Graph Neural Network: Modern research often combines Ontology as the basis of Knowledge Graph with Graph Neural Network to capture deep semantic relationships between items(Lyu et al., 2022). This approach combines Knowledge Graph with Graph Neural Network and multimodal information (visual and textual) to enrich feature representation, improve accuracy, and expand the scope of recommendations provided to users (Han & Dou, 2025).

Comparative Patterns in Educational vs Non-Educational Domains

When comparing educational and non-educational implementations, several patterns emerge. Educational and mobile learning systems more frequently combine ontologies with learner modeling and curriculum structures, resulting in fine-grained representations of competencies, learning objects, and learning paths. These systems often exploit ontology reasoning to ensure that recommended activities respect prerequisite relationships and support personalized remedial or enrichment paths (Amane et al., 2022).

In e-commerce and healthcare, ontology-based recommenders prioritize coverage of large, heterogeneous item or service catalogs (Tiryaki & Yücebaş, 2023). Here, ontologies and knowledge graphs mainly serve to enrich sparse item features and enable cross-domain inferences (e.g., from symptoms to treatments or from product attributes to user interests). Employment-oriented systems focus on aligning skill ontologies with job profiles and training resources, sometimes integrating Bayesian or probabilistic models to capture uncertainty in skill assessment (Baig et al., 2024).

For educational technology, this comparison suggests that ontology design must explicitly capture pedagogical intent and didactic constraints, not only semantic similarity between items. Recommendation quality is therefore determined not only by accuracy metrics but also by how well the recommended learning sequence supports instructional goals and learner autonomy.

Contributions and Challenges of Ontology in Recommendation Systems

The main contributions of the ontology approach to recommendation systems and the challenges still faced in its application are shown in Table 2.

Table 2. Ontology Applications in Recommendation Systems

Key Contributions	Challenges/Open Issues
Resolving Cold-Start	The use of Knowledge Graphs has proven effective in overcoming cold-start problems, both for new users and new items, by providing a deeper understanding of user interests.
Improving Feature Representation	Ontologies provide additional information that helps enrich the representation of user and item features, thereby improving prediction accuracy in recommendation systems.
Improving Explainability	Because ontologies provide an explicit knowledge structure, ontology-based recommendation models tend to be easier to explain than black-box models such as pure Deep Learning.

The implementation of ontologies has proven to provide significant solutions to common problems in recommendation systems, such as cold-start and better feature representation, but it also faces challenges related to implementation and interpretation.

Research Trends and Methodological Shifts

The temporal distribution of studies indicates a shift from purely ontology-based recommenders to hybrid architectures that integrate KG embeddings and GNN models. In educational contexts, these hybrids are used to capture complex relations between learners, learning resources, and assessment data, while still leveraging ontologies for semantic consistency and explainability. In non-educational domains, similar hybrids are adopted primarily to handle large-scale graphs and alleviate sparsity. This suggests that future educational systems can selectively reuse graph-based techniques developed in other domains, provided that pedagogical constraints are encoded at the ontology level.

Implications for Metrics in Educational Recommenders

Most studies report standard recommendation metrics such as precision, recall, NDCG, or MAE, with only a minority of educational systems evaluating learning outcomes or engagement indicators. This creates a methodological gap: ontology-based models are designed to improve conceptual alignment and learning communication, but their evaluation is still dominated by accuracy-oriented metrics inherited from e-commerce. Future research should combine traditional ranking metrics with educational indicators such as learning gain, task completion, or time-on-task, to better assess the instructional value of ontology-based recommendations

CONCLUSION

This systematic review establishes that ontology-based methodologies are pivotal in modern recommender systems, especially in tackling cold-start issues and data sparsity, as well as enhancing the semantic depth and explicability of recommendations in e-commerce, healthcare, employment, and education. In educational and mobile learning environments, ontologies and knowledge graphs are employed to represent learning materials, curricula, and learner profiles, facilitating more tailored and pedagogically coherent learning trajectories than those provided by only collaborative or content-based approaches.

Recent studies at the methodological level increasingly link ontologies with Knowledge Graph (KG) embeddings and Graph Neural Networks (GNN), resulting in hybrid designs that leverage both symbolic and distributed representations. These hybrids have potential for improving recommendation precision and diversity, while maintaining interpretable frameworks that can be examined by instructional designers and educators.

The findings indicate many implications for educational practitioners, instructional designers, and e-learning system developers. Ontology engineering must connect with pedagogical models to ensure that learning objectives, prerequisite frameworks, and assessment methodologies are well articulated. Secondly, incorporating ontology-based recommenders into current LMS or mobile learning platforms can facilitate adaptive material sequencing, remedial education, and competency-based advancement. Third, explainable ontology-driven suggestions may enhance educational communication by elucidating to teachers and students the rationale behind the suggested resources or activities.

This review possesses multiple restrictions. This analysis concentrates on studies published from 2021 to 2025, predominantly indexed in prominent academic databases, hence potentially overlooking older, non-indexed research and grey literature. The investigation is confined to four domains and does not conduct a quantitative meta-analysis of effect sizes. The variability of evaluation methodologies complicates direct comparisons between systems. Subsequent research must rectify these limitations by broadening database scope, standardizing evaluation metrics that integrate recommendation precision with educational results, and investigating automated or semi-automated ontology development techniques suited for extensive e-learning and mobile learning contexts.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

REFERENCES

Alatrash, R., Priyadarshini, R., & Ezaldeen, H. (2024). Collaborative filtering integrated fine-grained sentiment for hybrid recommender system. *Journal of Supercomputing*, *80*(4), 4760–4807. Scopus. https://doi.org/10.1007/s11227-023-05600-w

Alfaifi, Y. H. (2024). Recommender systems applications: Data sources, features, and challenges. *Information*, *15*(10), 660.

Al-Rossais, N. A. (2023). Improving Cold Start Stereotype-Based Recommendation Using Deep Learning. *IEEE Access*, *11*, 145781–145791. Scopus. https://doi.org/10.1109/ACCESS.2023.3343522

Amane, M., Aissaoui, K., & Berrada, M. (2022). ERSDO: E-learning Recommender System based on Dynamic Ontology. *Education and Information Technologies*, *27*(6), 7549–7561. https://doi.org/10.1007/s10639-022-10914-y

Amin, S., Uddin, M. I., Khan Mashwani, W. K., Abdulsalam Alarood, A. A., Alzahrani, A., & Alzahrani, A. O. (2023). Developing a Personalized E-Learning and MOOC Recommender System in IoT-Enabled Smart Education. *IEEE Access*, *11*, 136437–136455. Scopus. https://doi.org/10.1109/ACCESS.2023.3336676

Baig, D., Nurbakova, D., Mbaye, B., & Calabretto, S. (2024). Knowledge Graph-Based Recommendation System for Personalized E-Learning. *Adjunct Proceedings of the 32nd ACM Conference on User Modeling, Adaptation and Personalization*, 561–566. https://doi.org/10.1145/3631700.3665229

Bazargani, M., H.Alizadeh, S., & Masoumi, B. (2024). Group deep neural network approach in semantic recommendation system for movie recommendation in networks online. *Electronic Commerce Research*. Scopus. https://doi.org/10.1007/s10660-024-09897-4

Bernabé, C. H., Queralt-Rosinach, N., Silva Souza, V. E., Bonino Da Silva Santos, L. O., Mons, B., Jacobsen, A., & Roos, M. (2023). The use of foundational ontologies in biomedical research. *Journal of Biomedical Semantics*, *14*(1), 21. https://doi.org/10.1186/s13326-023-00300-z

Bukhari, M., Maqsood, M., Ghazanfar, M. A., & Sattar, A. (2025). Sentiment aware kernel mapping recommender system for Amazon product recommendations. *Pattern Analysis and Applications*, *28*(3). Scopus. https://doi.org/10.1007/s10044-025-01521-x

Deng, Y., Li, Y., Ding, B., & Lam, W. (2023). Leveraging Long Short-Term User Preference in Conversational Recommendation via Multi-agent Reinforcement Learning. *IEEE Transactions on Knowledge and Data Engineering*, *35*(11), 11541–11555. Scopus. https://doi.org/10.1109/TKDE.2022.3225109

Dritsas, E., & Trigka, M. (2025). Methodological and technological advancements in E-learning. *Information*, *16*(1), 56.

Garapati, R., & Chakraborty, M. (2025). Recommender systems in the digital age: A comprehensive review of methods, challenges, and applications. *Knowledge and Information Systems*, *67*(8), 6367–6411. https://doi.org/10.1007/s10115-025-02453-y

Gharibi, S. J., BagheriFard, K., Parvïn, H., Nejatian, S., & Yaghoubyan, S. H. (2024). Ontology-based recommender system: A deep learning approach. *Journal of Supercomputing*, *80*(9), 12102–12122. Scopus. https://doi.org/10.1007/s11227-023-05874-0

Gharibi, S. J., BagheriFard, K., Parvin, H., Nejatian, S., & Yaghoubyan, S. H. (2024). Ontology-based recommender system: A deep learning approach. *The Journal of Supercomputing*, *80*(9), 12102–12122. https://doi.org/10.1007/s11227-023-05874-0

Han, X., & Dou, X. (2025). User recommendation method integrating hierarchical graph attention network with multimodal knowledge graph. *Frontiers in Neurorobotics*, *19*, 1587973.

Huang, J., Xie, Z., Zhang, H., Yang, B., Di, C., & Huang, R. (2024). Enhancing Knowledge-Aware Recommendation with Dual-Graph Contrastive Learning. *Information (Switzerland)*, *15*(9). Scopus. https://doi.org/10.3390/info15090534

Kaur, H., Kaur, T., Dr, M., & Bhardwaj, V. (2025). SLDERCLC: Improving Smart Learning Frameworks Through Deep Learning Enhanced Recommender Systems Using an Efficient Cross-Layer Collaborative Approach. *SN Computer Science*, *6*(2). Scopus. https://doi.org/10.1007/s42979-025-03700-3

Kwieciński, R., Melniczak, G., & Górecki, T. (2023). Comparison of real-time and batch job recommendations. *Ieee Access*, *11*, 20553–20559.

Liang, Z., Yang, Z., & Cheng, J. (2023). Weight normalization optimization movie recommendation algorithm based on three-way neural interaction networks. *Complex and Intelligent Systems*, *9*(6), 6241–6254. Scopus. https://doi.org/10.1007/s40747-023-01066-8

Lyu, Z., Wu, Y., Lai, J., Yang, M., Li, C., & Zhou, W. (2022). Knowledge enhanced graph neural networks for explainable recommendation. *IEEE Transactions on Knowledge and Data Engineering*, *35*(5), 4954–4968.

Ma, R., Lian, Y., Qi, R., Song, C., & Ge, T. (2025). Valid Coverage Oriented Item Perspective Recommendation. *IEEE Transactions on Knowledge and Data Engineering*, *37*(6), 3810–3823. Scopus. https://doi.org/10.1109/TKDE.2025.3547968

Noorian, A. (2024). A BERT-Based Sequential POI Recommender system in Social Media. *Computer Standards and Interfaces*, *87*. Scopus. https://doi.org/10.1016/j.csi.2023.103766

Papadakis, H., Papagrigoriou, A., Panagiotakis, C., Kosmas, E., & Fragopoulou, P. (2022). Collaborative filtering recommender systems taxonomy. *Knowledge and Information Systems*, *64*(1), 35–74. https://doi.org/10.1007/s10115-021-01628-7

Rajabi, E., George, A. N., & Kumar, K. (2024). The role of knowledge graphs in chatbots. *The Electronic Library*, *42*(3), 483–497.

Ranjbar Kermany, N. R., Zhao, W., Batsuuri, T., Yang, J., & Wu, J. (2023). Incorporating user rating credibility in recommender systems. *Future Generation Computer Systems*, *147*, 30–43. Scopus. https://doi.org/10.1016/j.future.2023.04.029

Razzaq, A. M., Abbas, S. S., Ikhlaq, M., Shafique, P. H., & Shahzad, I. (2024). Development of OWL Structure for Recommending Database Management Systems (DBMS). *Journal of Computing & Biomedical Informatics*, *7*(02). https://jcbi.org/index.php/Main/article/view/618

Rostami, M., Farrahi, V., Ahmadian, S., Mohammad Jafar Jalali, S., & Oussalah, M. (2023). A novel healthy and time-aware food recommender system using attributed community detection. *Expert Systems with Applications*, *221*. Scopus. https://doi.org/10.1016/j.eswa.2023.119719

Saito, Y., & Sugiyama, K. (2022). Job recommendation based on multiple behaviors and explicit preferences. *2022 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)*, 1–8. https://ieeexplore.ieee.org/abstract/document/10101899/

Sangaiah, A. K., Rezaei, S., Javadpour, A., & Zhang, W. (2023). Explainable AI in big data intelligence of community detection for digitalization e-healthcare services. *Applied Soft Computing*, *136*. Scopus. https://doi.org/10.1016/j.asoc.2023.110119

Shi, D., Li, Z., Zurada, J., Manikas, A., Guan, J., & Weichbroth, P. (2024). Ontology-based text convolution neural network (TextCNN) for prediction of construction accidents. *Knowledge and Information Systems*, *66*(4), 2651–2681. https://doi.org/10.1007/s10115-023-02036-9

Tiryaki, A. M., & Yücebaş, S. C. (2023). AN ONTOLOGY BASED PRODUCT RECOMMENDATION SYSTEM FOR NEXT GENERATION E-RETAIL. *Journal of Organizational Computing and Electronic Commerce*, *33*(1–2), 1–21. https://doi.org/10.1080/10919392.2023.2226542

Val, S., & Quintas, A. (2025). Key performance indicators for optimizing academic performance and course design in online educational platforms. *Cogent Education*, *12*(1), 2529420. https://doi.org/10.1080/2331186X.2025.2529420

Villegas-Ch, W., & García-Ortiz, J. (2023). Enhancing learning personalization in educational environments through ontology-based knowledge representation. *Computers*, *12*(10), 199.

Wan, S., Liu, Y., Qiu, D., Chambua, J., & Niu, Z. (2022). A dual learning-based recommendation approach. *Knowledge-Based Systems*, *254*. Scopus. https://doi.org/10.1016/j.knosys.2022.109551

Wang, C., Zhu, H., Wang, P., Zhu, C., Zhang, X., Chen, E., & Xiong, H. (2022). Personalized and Explainable Employee Training Course Recommendations: A Bayesian Variational Approach. *ACM Transactions on Information Systems*, *40*(4). Scopus. https://doi.org/10.1145/3490476

Wang, L.-E., Qi, Y., Sun, Z., & Li, X. (2024). MKNBL: Joint multi-channel knowledge-aware network and broad learning for sparse knowledge graph-based recommendation. *Neurocomputing*, *575*. Scopus. https://doi.org/10.1016/j.neucom.2024.127277

Xia, L., Baghaie, S., & Sajadi, S. M. (2024). The digital economy: Challenges and opportunities in the new era of technology and electronic communications. *Ain Shams Engineering Journal*, *15*(2), 102411.

Yang, H., Zhang, R., Cai, J., Wang, J., Wang, Y., Li, Y., Xun, Y., & Zhao, X. (2026). Content suppression mechanisms-based recommendation systems. *Expert Systems with Applications*, *296*. Scopus. https://doi.org/10.1016/j.eswa.2025.128928

Yap, Z.-T., Haw, S.-C., & Binti Ruslan, N. E. (2024). Hybrid-based food recommender system utilizing KNN and SVD approaches. *Cogent Engineering*, *11*(1), 2436125. https://doi.org/10.1080/23311916.2024.2436125

Yu, X., Zhan, D., Liu, L., Lv, H., Xu, L., & Du, J. (2022). A Privacy-Preserving Cross-Domain Healthcare Wearables Recommendation Algorithm Based on Domain-Dependent and Domain-Independent Feature Fusion. *IEEE Journal of Biomedical and Health Informatics*, *26*(5), 1928–1936. Scopus. https://doi.org/10.1109/JBHI.2021.3069629

Zhang, H., Wang, L., Sun, Z., & Li, X. (2024). Knowledge-Aware Dual-Channel Graph Neural Networks For Denoising Recommendation. *Computer Journal*, *67*(5), 1607–1618. Scopus. https://doi.org/10.1093/comjnl/bxad085