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A systematic review of ontology use in E-Learning recommender system

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A R T I C L E I N F O

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Learning object
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Ontology use

A B S T R A C T

Ontology and knowledge-based systems typically provide e-learning recommender systems. However, ontology use in such systems is not well studied in systematic detail. Therefore, this research examines the development and evaluation of ontology-based recommender systems. The study also discusses technical ontology use and the recommendation process. We identified multidisciplinary ontology-based recommender systems in 28 journal articles. These systems combined ontology with artificial intelligence, computing technology, education, education psychology, and social sciences. Student models and learning objects remain the primary ontology use, followed by feedback, assessments, and context data. Currently, the most popular recommendation item is the learning object, but learning path, feedback, and learning device could be the future considerations. This recommendation process is reciprocal and can be initiated either by the system or students. Standard ontology languages are commonly used, but standards for student profiles and learning object metadata are rarely adopted. Moreover, ontology-based recommender systems seldom use the methodology of building ontologies and hardly use other ontology methodologies. Similarly, none of the primary studies described ontology evaluation methodologies, but the systems are evaluated by nonreal students, algorithmic performance tests, statistics, questionnaires, and qualitative observations. In conclusion, the findings support the implementation of ontology methodologies and the integration of ontology-based recommendations into existing learning technologies. The study also promotes the use of recommender systems in social science and humanities courses, non-higher education, and open learning environments.

1. Introduction

Learning technology has grown rapidly and receives significant support from technology development, online learning, and stakeholders with complex needs (Huang et al., 2019). The online learning market is large, so its market potential is estimated to be worth $325 billion in 2025 (a three-fold increase from 2015). Therefore, it is not surprising that many organizations, researchers, and educators are actively developing learning technologies. Numerous innovations such as wearable devices (Huang et al., 2019), social network analysis (SNA) (Cela et al., 2015), learning analytics (Araka et al., 2020; Huang et al., 2019), and adaptive/personalized learning (Hwang et al., 2020; Zhang et al., 2020) have been proposed for technology-based learning.

Several studies related to e-learning recommender systems have discussed personalization techniques, such as ontology (Al-Yahya et al., 2015), collaborative filtering (Bremgartner et al., 2015), software agents (Bremgartner et al., 2015; Schouten et al., 2018), fuzzy logic (Luna-Urquizo, 2019), machine learning (George & Lal, 2019), and hybrids (George & Lal, 2019). Secondary literature (George & Lal, 2019; Tarus et al., 2018) reports that ontology and knowledge-based systems dominate recommendation making because such systems can solve cold-start, diversity rating, and overspecialized recommendation problems (Salehi et al., 2013; Tarus et al., 2018). This aspect is supported by using ontology to simplify the relationship among data so that the accuracy of the profiling process increases by 7%–15% (Middleton et al., 2009).

Owing to the increasing scholarly attention to ontology for recommendation systems, there are several comprehensive reviews of this field. For example (Bhareti et al., 2020), compares recommendation techniques, while (Javed et al., 2021; Tarus et al., 2018) classifies recommender systems based on artificial intelligence techniques. Additionally (George & Lal, 2019; Javed et al., 2021; Tarus et al., 2018), classify ontology-recommender systems according to tool, ontology type, and ontology representation language. Furthermore (Premlatha & Geetha, 2015; Tarus et al., 2018; Truong, 2016), categorize the systems based on the recommendation items. Our research complements the previous studies; we discuss the development and evaluation of

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List of abbreviations

ADL	Advanced Distributed Learning
CAI	Computer-assisted instruction
CSCL	Computer-supported collaborative learning
IMS	Instructional Management Systems
ITS	Intelligent Tutoring Systems
IVET	Intelligent Virtual Environments for Training
KBS	Knowledge Based System
LIP	Learner Information Package
LMS	Learning Management System
OWL	Web Ontology Language
PAPI	Public and Private Information
PLE	Personal Learning Environment
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RDF	Resource Description Framework
RDFS	Resource Description Framework Schema
SNA	Social Network Analysis
W3C	World Wide Web Consortium

ontology-based recommender systems. Second, we detail the ontology components, standards related to ontology models, the ontology collaborators, and the recommendation techniques. Third, we map the variety of recommendation items and the recommendation process that are specifically generated by ontology-based recommendation systems.

Hence, this review addresses the following research questions:

- RQ1 How can we build an ontology-based recommendation system for e-learning?
- RQ2 What are the state-of-the-art recommendation items for ontology-based recommendation systems?
- RQ3 How do e-learning recommender systems work?
- RQ4 What is the role of ontology in the recommendation process?
- RQ5 What are the ontology collaborators in the e-learning recommender systems?
- RQ6 What are the evaluation techniques and the evaluation results of the e-learning recommender systems?

This study discusses and classifies the primary studies related to ontology for recommendation systems. We conducted the research by applying the statement of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et al., 2021). The material was gathered using a broad automated search method from all journal articles published in Institute of Electrical and Electronics Engineers (IEEE) Xplore, JSTOR, Proquest, SAGE Journals, Science Direct, SpringerLink, and Taylor & Francis Online during 2010–2020.

By mapping the latest ontology-based recommender system, this study aims to contribute to the extant body of knowledge on ontology for e-learning. Furthermore, the study findings will provide the research community with a basis to advance the use of ontology and further develop e-learning recommender systems, using a comprehensive methodology.

The remaining sections of this paper continue as follows. Sections 2 highlight literature review related to ontology use, learning technology and e-learning recommender system. Section 3 and 4 present the related work and the review methodology, respectively. In Section 5, we provide the extraction results and analysis to answer RQ1-RQ6. Section 6 is dedicated to discussing implications, research agendas and limitations. Finally, Section 7 concludes the paper.

2. Literature review

2.1. Ontology use in e-learning

An ontology is defined as *a logical structure of terms used to describe a domain of knowledge, including both the definitions of applicable terms and their relationships* ("ISO/IEC/IEEE International Standard - Systems and Software Engineering–Vocabulary," 2017). Ontology has three main components, i.e., class, individual and property (Hebeler et al., 2009; Pollock, 2009). Examples of classes are *Student* and *LearningObject*, while a student or a unit of material is an individual example. Furthermore, the property component describes the individuals (e.g., the student's name and academic level (Gómez et al., 2016)) or the relationship between individuals (e.g., the property *'belongsTo'* of a learning object with respect to its learning level) (Mariño et al., 2018).

In literature, ontology have been classified from various viewpoints (Al-Yahya et al., 2015; Khadir et al., 2021; Tapia-Leon et al., 2018). In the current study, ontologies are categorized based on their use in e-learning environments. Examples of such uses are as follows:

(1) Modeling the curriculum, e.g., mapping the relationships among learning objects, learning goals, and the objectives of the study program (Al-Yahya et al., 2015), and providing a correct curriculum representation that can be understood by educators, students, and computers (Tapia-Leon et al., 2018).
(2) Data integration, for example, by integrating and expanding the ontology domain from one discipline to another (Tapia-Leon et al., 2018).
(3) A description of the domain and learning activities. The domain ontology contains a data model of the course content and learning activities that can be used in many features of the system. Content retrieval (i.e., ontology-based queries on the learning object's metadata and semantics) (Al-Yahya et al., 2015; Tapia-Leon et al., 2018), learning assessment (i.e., mapping student learning outcomes into the ontology domain), and feedback (i.e., student's answer verification and system guidance on the assessment process) (Al-Yahya et al., 2015) are examples of such usage.
(4) Data storage of student profiles (personal data) and learning performance (Al-Yahya et al., 2015). Such performance data stores students' grades and learning progress, and student profiles are stored in either a customized or standardized format. The specification standards are IEEE Public and Private Information (PAPI) for Learner and the IMS[1] Learner Information Package (LIP).
(5) Recommendation tools for personalized learning; for example, recommendation of learning objects (Al-Yahya et al., 2015), learning paths (Premlatha & Geetha, 2015), and learning customization for students with disabilities (Tapia-Leon et al., 2018).

2.2. Learning technology

Digital technology as an e-learning application is also called instructional technology (Huang et al., 2019) or learning technology (Huang et al., 2019; West, 2018). The last term is used in this current study as an umbrella term for a wide range of related technologies (seeAppendix A). Learning technology and nondigital learning tools (e.g., flash cards) have been used to facilitate learning. Numerous learning technology innovations have gained popularity owing to the numerous challenges posed by students' differences in learning capabilities and technological advances.

Some learning technologies do not contain recommendation items (e.g., traditional mind map tools and blogs), but others offer recommendation processes. Students' backgrounds, interests, and

[1] IMS stands for Instructional Management Systems.

expectations appear at different levels and in diverse contexts, while technology develops very rapidly and increasingly needed (Huang et al., 2019; Hwang et al., 2020). (Dron & Anderson, 2021) explicitly stated that learning analytics, artificial intelligence, and collaborative systems will be the most significant innovations.

2.3. Recommender system in e-learning domain

The recommender system is defined as *software tools and techniques that provide suggestions for items to be of use to a user* (Klašnja-Milicevic et al., 2015). The systems choose the best relevant item by using the dependency principle between user-based activities and item-based activities (Aggarwal, 2016). In the e-learning domain, such systems are used for personalization to achieve student engagement (Huang et al., 2019), increase academic achievement (Harley et al., 2018), and help problematic students (Huang et al., 2019).

In the literature, various classifications of recommender systems in the e-learning domain were found. Using technique-based classification (Sinha & Dhanalakshmi, 2019), proposed six categories, namely, content-based, collaborative filtering, knowledge-based systems (KBS), demographic systems, community-based, and hybridized systems (Sinha & Dhanalakshmi, 2019). Similarly (Tarus et al., 2018), described 11, namely, content-based, collaborative filtering, KBS, demographic-based, utility-based, context-aware, trust-aware, fuzzy-based, social network-based, group-based, and hybrid. Focusing on the e-learning domain (Klašnja-Milicevic et al., 2015), described four categories, i.e., content-based, collaborative filtering, matrix and tensor factorization, and association rule mining. The current study adopts the classification given by (Aggarwal, 2016) as below.

(1) The basic model of the recommender system uses interaction or attribute data. Examples are the collaborative filtering recommender, which uses rating data (e.g., ratings of learning objects and shopping items) and the content-based recommender, which uses users' attributes (profiles) or items' attributes (keywords). Additionally, KBS recommenders (i.e., those that use active user specifications of their needs and interests), demographic-based recommenders (i.e., applying user demographics), and hybrid recommenders (i.e., combining various types of recommenders) are also included in this category.
(2) Domain-specific recommender systems. Examples are context-based/context-aware recommenders, which use location, season, and social data; time-sensitive recommenders, which consider changes in ratings/interests over time; location-based recommenders, which use spatial locality; and social recommenders, which use network structures, social cues, and tags.

The KBS has two main components, i.e., systems and knowledge. In contrast to information retrieval systems or content-based recommender systems that rely upon keywords, KBS stores the knowledge component in a knowledge base of relational attributes (Aggarwal, 2016). Then, the system component applies an inference mechanism to the knowledge base to compile recommendations (Ertel, 2017). Fig. 1 shows the simplified hierarchy of the relationships among the learning technologies (digital learning tools), recommender system, and ontology model.

3. Related work

The study of recommender systems and adaptive/personalized learning has grown rapidly. To understand the development of the recommender system in the e-learning domain, we searched for related systematic reviews and mapping studies in the Scopus database. The search was carried out on peer reviewed articles published with the keyword "*review*," "*ontology*," "*recommend**," "*personal**," and "*learning*." We selected articles published between 2015 and 2021 because a study of articles between 2011 and 2015 concluded that e-learning recommendation systems are mostly collaborative filtering, content-based or context-based systems (Klašnja-Milicevic et al., 2015). The search returned 64 articles, and then abstract selection was performed to find related studies. We excluded 30 studies not in the e-learning domain, 25 articles that were not purely systematic reviews, and 3 articles that did not discuss recommender systems nor ontology. Thus, we found six very relevant articles in our study. We also added three other review articles that we knew about before. Hence, we examined nine articles in total. Below is a brief description of each article to find the research gap for our current study, and a summary is presented in Table 1.

(Al-Yahya et al., 2015) has classified ontology by its usage in education. The categories are curriculum modeling, object domain ontology, task-ontology, student data, and e-learning service. The study also found that the ontology was commonly used for learning objects and link/navigation personalization. Likewise (Bremgartner et al., 2015), reviewed the adaptation techniques in virtual learning environments (e.g., distance education and blended courses) by using the constructivist learning theory. The study concluded that ontology is one of the popular artificial techniques, besides software agent and fuzzy logic. Ontology is a well-known technique that uses student profile to form student groups in the context of collaborative learning. Further, these findings are similar to (Mohemad et al., 2017), which found that ontology, multimedia, data mining, and neural networks are popular techniques for supporting students with learning disabilities. However (Bremgartner et al., 2015), suggested that the development of an ontology-based system in the e-learning domain should still consider pedagogical aspects (educational theory) and technological innovations.

Technically, the benefits and drawbacks of each recommendation technique have been discussed in other systematic reviews. For example (Bhareti et al., 2020), compares content-based, collaborative filtering, KBS, ontology-based, neural network, deep learning, random forest, and hybrid techniques (mostly combinations of content-based and collaborative filtering). Similarly (Javed et al., 2021), also classifies context-aware recommender systems based on content-based, collaborative filtering, KBS/ontology-based, and hybrid techniques (mainly combinations of content-based and collaborative filtering). Similar comparison studies were also conducted by (Tarus et al., 2018) but with the addition of context-aware, fuzzy-based, and trust-aware techniques. These studies differ from ours because the scope of our study does not limit ontology collaborators from the field of artificial intelligence only. As a multidisciplinary study, the e-learning recommender system should integrate other disciplines (e.g., education and educational psychology). Moreover, our study discussed the technical details related to the development of the recommender system in various learning technologies and evaluation methods.

Related to ontology, previous systematic reviews grouped ontology-based recommender systems by tool (George & Lal, 2019), ontology type, and ontology representation language (George & Lal, 2019; Javed et al., 2021; Tarus et al., 2018). Furthermore (George & Lal, 2019), also described issues solved by the ontology-based recommender system. Although these studies were similar to ours, we have added details on the ontology components, standards related to the ontology model, and inference engines and recommendation techniques that perform reasoning tasks on the ontology.

Recommendation items were reviewed in previous systematic reviews. For example, recommendations for learning objects in the form of content (Premlatha & Geetha, 2015; Tarus et al., 2018; Truong, 2016), link (Premlatha & Geetha, 2015), format (Premlatha & Geetha, 2015; Truong, 2016), learning path (Premlatha & Geetha, 2015; Tarus et al., 2018), student requirement (Javed et al., 2021), and teaching strategy (Truong, 2016). Because the source data are not yet specific using ontology, our study tries to map the variation of recommendation items

[2] education technology category based on (Huang et al., 2019).
[3] categorization of recommender systems based on (Aggarwal, 2016).

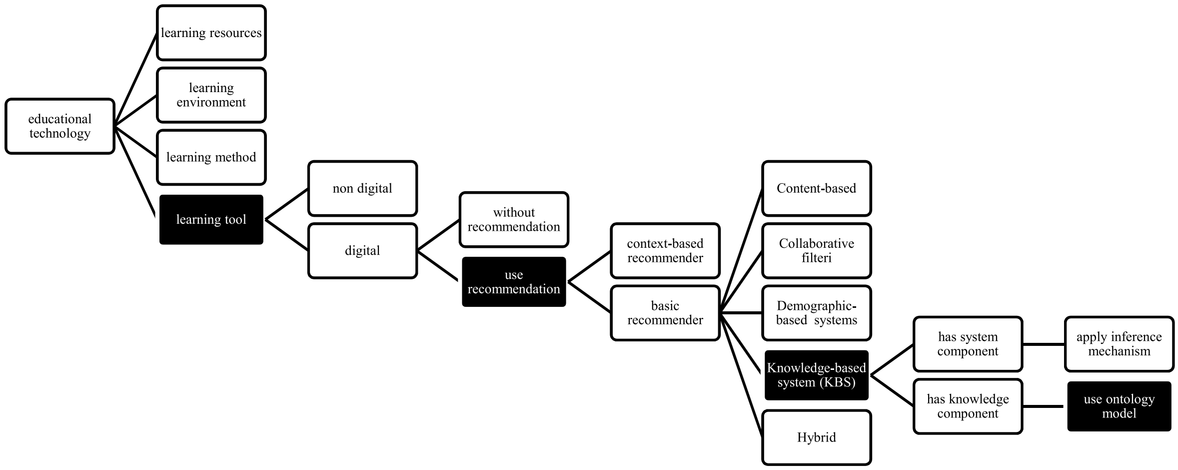

Fig. 1. Relationship among the learning technology,[2] recommender system,[3] and ontology.

generated by ontology-based recommendation systems. Moreover, our research also discusses the recommendation process for each recommendation item.

4. Materials and methods

This research used the PRISMA flow diagram. PRISMA is used to identify, select, appraise, and synthesize studies of the state of knowledge in a field (Page et al., 2021). Since its publication in 2009, PRISMA has been widely adopted in various disciplines, which includes reviews of learning technology in the education domain (Bedenlier et al., 2020; Palalas & Wark, 2020) and reviews of recommender systems/artificial intelligence in education (Chen et al., 2020; Deschênes, 2020). This study uses the latest version of PRISMA ("the PRISMA 2020 statement") as a reference for the criteria. PRISMA includes several checklists, such as eligibility criteria (inclusion and exclusion criteria), search strategy, data collection process, study selection, synthesis method, and synthesis result (Page et al., 2021).

4.1. Literature search

This study searches the primary studies using a broad automated search method. The keyword string[4] applied in the metadata search consisted of three components and included wildcard characters (if applicable). Specifically, we searched for[5] "*(learner OR student) AND (adapt* OR personali* OR recommend* OR intelligent*) AND ontology*" for journal articles published from 2010 to 2020. This initial search retrieved 90,619 articles across 7 databases (i.e., IEEE Xplore, JSTOR, Proquest, SAGE Journals, Science Direct, SpringerLink, and Taylor & Francis Online).

4.2. Article selection

For inclusion in the study, the reviewed papers must fulfill the requirements of being both English journal articles and belong to computer science/artificial intelligence subjects. We believe that ontology utilization is rarely discussed outside the field of computer science and artificial intelligence. Therefore, we concentrated our search on journal publications in these two fields. After screening through these requirements, we found 1,962 articles.

Abstracts were subsequently scanned to select articles of primary studies delivering an e-learning domain with adaptive/personalized content, resulting 72 articles left for full-text exclusion review. Some articles were then excluded for several reasons, such as not containing an ontology, using ontologies as a modelling tool without recommendation, providing prediction only, and discussing personalization outside of the technical perspective. Finally, as the details are shown in Figs. 2 and 28 articles containing ontology-based personalization techniques were ready to be extracted (see details in Appendix B).

4.3. Data extraction

Paper extraction uses the following criteria to obtain comprehensive information:

(1) Article profile: author(s); author(s) affiliation; journal name; publication title; publication year; publisher; and ScimagoJR 2020 quartile.
(2) Technology: disciplines; model/system's name; research output (model, prototype); type of learning technology; and tools used for system development.
(3) Ontology model: learner style; learning object's metadata; ontology methodology; ontology language; ontology models; recommendation item; recommendation technique; semantic web tool; student model; student model's data; and student profile.
(4) Inference mechanism: reasoner method; reasoner tool; reasoner type (OWL,[6] RDFS,[7] rule); rule language (*if any*); sample knowledge; and sample rule.
(5) Performance evaluation: baseline characteristics; case study; control group; country; course/topic/domain; course/experiment duration; evaluation method; evaluation result; number of participants; participant type; and study variables.

5. Result and analysis

All 28 extracted articles were found in the Q1 and Q2 quartiles of fourteen journals: *Computers & Education, Computers in Human Behavior, Data & Knowledge Engineering, Educational Technology & Society, E-*

[4] Except for the IEEE Xplore database, which incorporates keywords into the abstract field, and the ScienceDirect database, which incorporates keywords into the title, abstract, and keyword sections.

[5] ScienceDirect database can recognize spelling variants but does not support wildcards (*); thus, we use the search string: (learner OR student) AND (adaptive OR adaptivity OR personalization OR recommendation OR recommend OR intelligent) AND ontology.

[6] OWL is an abbreviation for Web Ontology Language.

[7] RDFS stands for "Resource Description Framework Schema."

Table 1
Summary of systematic review of ontology use in the e-learning recommender system.

Authors	Database source	Keyword search	Number of articles	Time span	Focus
Al-Yahya et al. (2015)	ACM, IEEE, Science Direct, and Web of Science	ontology, learning	33	2000–2012	Classification of ontology use (curriculum modelling, object-domain ontology, task-ontology, student data and e-learning service)
Bhareti et al. (2020)	–	–	–		Comparison of the advantages and disadvantages of each AI-based recommendation technique
Bremgartner et al. (2015)	IEEE Xplore, ACM Digital Library, Scopus, Elsevier, EI Compendex	profile, profiling, profilling, personalization, personalization, adaptation, adaptive, adaptivity, context-awareness, VLE, virtual learning environments, constructivism, constructivist, CSCL[a], computer-suported-collaborative- learning, collaborative learning	105 out of 951	no time constraint	Adaptation techniques in VLE based on the constructivist approach; the role of artificial intelligence in adaptation
George and Lal (2019)	Springer, Elsevier, IEEE, ACM Digital Library, and Google Scholar	recommender system, e-learning, hybrid recommender system, ontology, ontology-based recommender system, learning management system, knowledge, machine learning	108	2010–2018	Ontology-based recommendation system classification by used tool, language, recommendation item, and ontology type; description of issues and solutions addressed by the ontology-based recommender system
Javed et al. (2021)	–	–	39	2000–2014	Classification of context-aware recommender systems by artificial intelligence techniques; categorization of the ontology-based recommendation system by recommendation technique, ontology type, ontology representation language and recommendation item (student requirement, learning object, learning path)
Mohemad et al. (2017)	ScienceDirect, Scopus, Springer, ACM Digital Library, and IEEE Xplore	education, special education, learning disability, dyslexia, dyscalculia, and dysgraphia	15	2009–2017	Computer techniques to help students with learning disabilities (dyslexia, dyscalculia, and dysgraphia)
Premlatha and Geetha (2015)	–	–	–		Various adaptations of learning objects; use of related ontologies
Tarus et al. (2018)	Web of Science (SCI), Engineering Index (EI), Science Direct, EBSCO Academic Search Premier, Springer, IEEE Xplore, and ACM Digital Library	ontology, recommender, recommendation, learning, education, knowledge e-learning, and online learning	36 out of 229	2005–2014	Recommendation techniques used in ontology-based recommendation system in e-learning; classification of recommended systems based on ontology type and representation language; description of recommendation items
Truong (2016)	Google Scholar, Scopus, and Science Direct.	learning styles (or) style, measurement ∣ classification ∣ prediction ∣ evaluation ∣ modelling ∣ detection ∣ recognition, adaptive ∣ personalized ∣ individualized ∣ personalization, integration ∣ application ∣ using, automatic, learning system ∣ learning management system, intelligent tutoring system, student ∣ user modelling, online ∣ e-learning, computer-assisted learning, adaptive instructions, adaptive hypermedia, artificial intelligent, education data mining	51	2004–2012	Process of integrating learning styles into adaptive e-learning; description of potential data sources for learning style prediction; algorithms for classification of learning styles; recommendation items by using learning styles

[a] CSCL is an abbreviation for Computer-supported collaborative learning.

Learning and Digital Media, Education and Information Technologies, Engineering Applications of Artificial Intelligence, Expert Systems with Applications, Future Generation Computer Systems, Human-centric Computing and Information Sciences, IEEE Access, IEEE Transactions on Learning Technologies, Interactive Learning Environments, and *Knowledge-Based Systems.* The extraction results showed that the articles were written by 78 unique authors. An article was written by three authors on average, but articles written by five authors were also found (Muñoz et al., 2015; Porcel et al., 2018; Sánchez-Vera et al., 2012). The authors belonged to 36 research institutions, most prolifically from the University of Granada and the University of Alcala (both in Spain).

The distribution of the primary studies is dynamic but shows an increasing trend (see Fig. 3). Furthermore, the number of journal publications during 2018–2019 has almost doubled. The exception occurred in 2020 and was possible because the selection process was carried out between October 2020 and February 2021.

5.1. RQ1 how can we build an ontology-based recommendation system for e-learning?

The recommender systems in the primary studies used ontology as a knowledge base. Models or prototypes of recommender systems have been designed or implemented in various learning technologies (West, 2018). The primary studies identified 14 learning technologies, as listed in Table 2. Moreover, the table shows that the number of recommendation prototypes was twice that of the recommendation model. Among these technologies, the most popular prototypes are classified as learning management systems (LMS), intelligent tutoring systems (ITS), computer-assisted instruction (CAI), and personal learning environments (PLE).

Most studies use recommender systems primarily in higher education, with the exception of (Mustafa et al., 2019) in preschool. Most of the studies are computer science courses (eight studies): C++

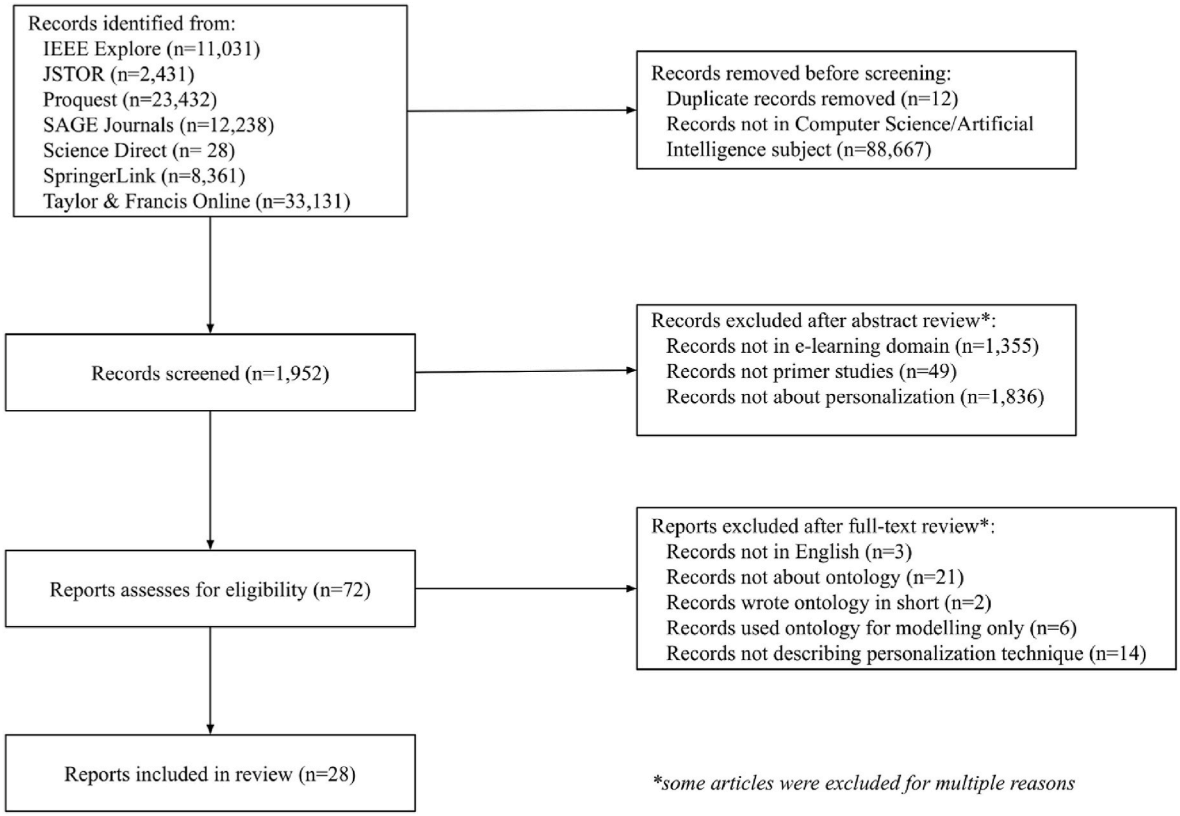

Fig. 2. PRISMA flow diagram for article selection.

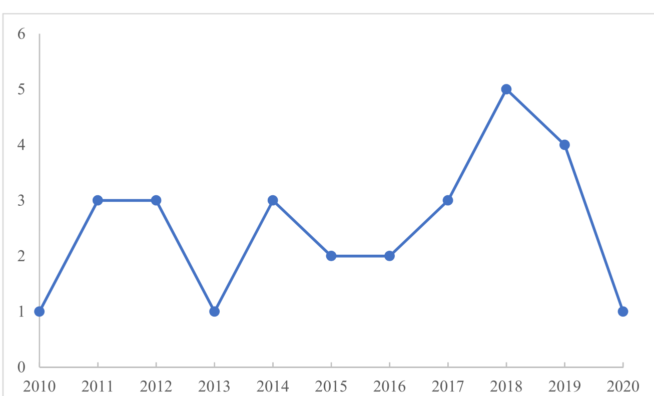

Fig. 3. Year of publication of 28 selected articles.

programming language (Benlamri & Zhang, 2014), computer as a system (Grubišić et al., 2013), computer network (Demaidi et al., 2018; Jevremovic et al., 2017), computer security (AlAgha, 2012), database administration (Muñoz et al., 2015), web technology (Nitchot et al., 2018) and several courses for third year students (Tarus et al., 2017). Other studies use recommender systems in science courses (Ullrich & Melis, 2010), engineering courses (Clemente et al., 2014; Gómez et al., 2016; Sánchez-Vera et al., 2012), and medicine and nursing courses (Gómez et al., 2016). In comparison, we found only one study that utilized recommender systems in the social sciences (Caravantes & Galán, 2011), and none in the humanities.

The whole process of ontology creation utilizes several tools/environments. Protégé is still a popular development environment, while some ontologies have been created using the OWL API (Rani et al., 2015) and designed in Motp (Savard et al., 2020). Moreover (Belcadhi, 2016), displayed graphs and class hierarchies by using a combined OWL Viz

Table 2
Type of learning technology (detail description could be found in Appendix A).

Learning technology	Model	Prototype
Academic advisor	–	EDUC8 (Iatrellis et al., 2019)
Cloud e-learning	Rani et al. (2015)	–
CAI	–	electronic Justice Relationship Management (Capuano & Toti, 2019); (Benlamri & Zhang, 2014)
CSCL	Khaled et al. (2019)	Porcel et al. (2018)
Courseware generator	Labib et al. (2017)	Piagos (Ullrich & Melis, 2010)
E-assessment	Belcadhi (2016)	Ontology eLEarning (Sánchez-Vera et al., 2012)
Instructional design advisor tool	Cultural variables ontology (Savard et al., 2020)	–
ITS	AC-Ware (Grubišić et al., 2013); (Clemente et al., 2011)	Cognitive Ontology of Educational Systems (Caravantes & Galán, 2011); CogSkills2 (Mustafa et al., 2019); IP Addressing: Problem-Based Learning (Jevremovic et al., 2017);
Intelligent Virtual Environments for Training (IVET)	ON-SMMILE (Yago et al., 2018)	Student Modeling Agent (Clemente et al., 2014)
LMS	INES (Fonte et al., 2012); (Demaidi et al., 2018)	OntoPeFeGe (Demaidi et al., 2018); OntoSakai (Muñoz et al., 2015)
PLE	–	KnowledgePuzzle (AlAgha, 2012); MyTeleMap (Nitchot et al., 2018)
Social learning network	–	ILEARN (Khaled et al., 2019), SharingNotes (Porcel et al., 2018)
Ubiquitous learning	Gómez et al. (2016)	–
VLE	–	Kurilovas et al. (2014)

and OntoGraph environment.

Ontology models in the e-learning domain were developed by ontological engineers (Khadir et al., 2021), pedagogues, and domain experts (such as educators and researchers) (Boyce & Pahl, 2007). Furthermore, there are various ontology methodologies available, that is, methodologies for building ontologies, ontology reengineering, ontology learning, ontology evaluation, and ontology merging (Corcho et al., 2003). The review study found that the methodologies of NeOn (Mariño et al., 2018; Yago et al., 2018), On-To-Knowledge (Labib et al., 2017), METHONTOLOGY (Muñoz et al., 2015), and KACTUS (Rani et al., 2015) were used to build ontologies. This finding is intriguing because no other ontology methodologies were explicitly mentioned in the primary studies.

A few ontology models are declared to conform to interoperability standards. For example, two student profiles (as a part of the student ontology) follow IEEE PAPI or IMS LIP standards. Additionally, five learning objects (i.e., domain ontologies) apply the IMS LOM,[8] LRE AP,[9] or ADL SCORM[10] metadata standards. This finding is also interesting because interoperability standards are in line with the spirit of ontology and semantic web technologies that strengthen the internet's role as a web of linked data (Pollock, 2009).

The current study shows that ontology language standards are being widely used. Although the World Wide Web Consortium (W3C) publishes several language standards, almost half of our primary studies used the OWL (Belcadhi, 2016; Benlamri & Zhang, 2014; Clemente et al., 2011; Demaidi et al., 2018; Gómez et al., 2016; Khaled et al., 2019; Labib et al., 2017; Mariño et al., 2018; Muñoz et al., 2015; Rani et al., 2015; Sánchez-Vera et al., 2012; Yaghmaie & Bahreininejad, 2011; Yago et al., 2018).

5.2. RQ2 what are the state-of-the-art recommendation items of ontology-based recommendation systems?

Learning objects, learning paths, feedback, learning devices, and pedagogical scenarios are common recommendation items found in primary studies (see Table 3). In the current study, the term "learning object" is synonymous with "learning resource," "learning materials," and "learning content." The learning object itself is defined as *verified information resources (data, facts, pictures, and videos) related to the learning objectives/goals* (Huang et al., 2019). Examples of learning objects include the subject matter or content to be learned, narrative text, and problem sets.

Table 3
Recommendation items.

Recommendation Items	Related Studies
Learning objects	Learning content (Clemente et al., 2014; Fonte et al., 2012; Gómez et al., 2016; Grubišić et al., 2013; Khaled et al., 2019; Kurilovas et al., 2014; Muñoz et al., 2015; Porcel et al., 2018; Rani et al., 2015; Tarus et al., 2017; Yaghmaie & Bahreininejad, 2011; Yago et al., 2018) Narrative text (Capuano & Toti, 2019) Problem set (Jevremovic et al., 2017)
Learning paths	(AlAgha, 2012; Clemente et al., 2011; Iatrellis et al., 2019; Nitchot et al., 2018)
Feedback	(Belcadhi, 2016; Demaidi et al., 2018; Sánchez-Vera et al., 2012)
Learning devices	Mariño et al. (2018)
Pedagogical scenarios	Savard et al. (2020)

The majority of recommended items help students directly, except for the pedagogical scenario, which benefits educators directly and indirectly benefits students. It is reasonable because a class is commonly attended by many students and taught by one or few educators. Therefore, recommendations are more focused on the students. Furthermore, this study also finds that learning objects are still the most popular recommendation item.

5.3. RQ3 how do e-learning recommender systems work?

Each recommender system has its own recommendation process. According to the category of recommendation items (Table 3), the procedures are summarized below.

(1) Personalized learning objects: The system chooses the learning methods (e.g., blogging) and then provides an alternative learning object (such as textbooks or glossaries) (Gómez et al., 2016; Kurilovas et al., 2014). Alternatively, the system provides exercises according to the user's competency level (Fonte et al., 2012; Jevremovic et al., 2017) or provides learning objects that match the extracted concept (Capuano & Toti, 2019).
(2) Personalized learning paths: The system verifies the student's profile and instructional design before selecting the appropriate activity or procedure. Later, the system selects the sequence of activities and records each activity in the student model (Clemente et al., 2011).
(3) Personalized feedback: Students select their own level of expertise and take a test. Later, the system provides feedback that contains a score, encouragement, and references to a specific learning object (Belcadhi, 2016). Alternatively, the system selects a feedback type that suits the student's knowledge, the difficulty level of the test, and the number of correct answers (Demaidi et al., 2018).
(4) Personalized learning devices: After checking the strengths and weaknesses of the user, the system provides related support and then recommends suitable activities or devices (Mariño et al., 2018).
(5) Personalized pedagogical scenarios: The system analyses the educator's culture and then provides suggestions for learning scenarios that fit the culture of prospective students. The educator can then accept, reject, or change the suggestion, and their response is recorded by the system (Savard et al., 2020).

Personalization initiatives were found either by the system or by the students. Overall, we conclude that the basic recommendation process is that (1) the system checks the student model and then (2) the system provides recommendations according to the student model.

5.3.1. Recommendation technique

The current review found that various AI techniques supported semantic reasoners in making recommendations. Three studies (Belcadhi, 2016; Labib et al., 2017; Sánchez-Vera et al., 2012) employed solely semantic reasoners to make recommendations; the others used different AI techniques as follows:

(1) Software agents (Clemente et al., 2011, 2014; Fonte et al., 2012; Kurilovas et al., 2014; Rani et al., 2015; Savard et al., 2020; Yaghmaie & Bahreininejad, 2011)
(2) Collaborative filtering (Tarus et al., 2017)
(3) Cognitive diagnosis method (Clemente et al., 2014)
(4) Fuzzy linguistics (Porcel et al., 2018)
(5) Generalized sequential pattern algorithm (Tarus et al., 2017)
(6) Hierarchical Task Network Planning (Ullrich & Melis, 2010)

[8] LOM is an abbreviation for Learning Object Metadata.
[9] LRE AP is an abbreviation for European Learning Resource Exchange Application Profile.
[10] ADL SCORM stands for "Advanced Distributed Learning Sharable Content Object Reference Model."

(7) Natural language processing (Capuano & Toti, 2019)

Ontology as a knowledge base for e-learning recommender systems has collaborated with other AI techniques, mostly with software agents. All related primary studies employed multiple agents (as many as 19 agents in one study (Savard et al., 2020)). Typical software agents are tutoring agents, which receive information on learning objectives from the student model (Clemente et al., 2014); conversational agents, which communicate with students in their daily language (Fonte et al., 2012); and advisor agents, which choose the correct instructional design under a set of rules (Savard et al., 2020).

For example (Clemente et al., 2014), stored the student model data in an ontology and used a software agent to receive information about learning objectives from the student model. Due to this collaboration, the recommender system becomes a hybrid system. This finding is consistent with the findings of a previous review of the literature, which concluded that recent recommender systems employ hybrid techniques, including collaborative filtering and other techniques. (George & Lal, 2019). Unfortunately, performance comparison among hybrid techniques is rarely studied. Only one primary study evaluated performance of three techniques: (1) collaborative filtering alone; (2) collaborative filtering and ontology; and (3) a combination of collaborative filtering, ontology, and sequential pattern mining (Tarus et al., 2017).

5.4. RQ4 what is the role of ontology in the recommendation process?

5.4.1. Ontology component

The ontology is used to store data from learning objects, activities, cognitive, emotional states, and student data models in primary studies. Ontology models could consist of several classes or subontologies (Clemente et al., 2011; Yago et al., 2018) from various data sources. The data sources were either ontological resources (e.g., existing ontologies) or non-ontological resources (e.g., a relational database, thesauri). To build an ontology, the resources were then extracted (Santoso et al., 2011) or reengineered using some techniques (e.g., ontology similarity (Zhao et al., 2012)).

A student model itself usually contains students' profiles, learning styles, student knowledge, and socio-technical contexts (Kurilovas et al., 2014). Although student models are tailored to each study, such models typically contain fixed data. However (Grubišić et al., 2013), used a Bayesian model to deal with uncertainty in students' knowledge. For example (Tarus et al., 2017), built an ontology that stores student models. The model stores the student's profile (i.e., name, sex, and age), learning style (active or reflective, sensing or intuitive, visual or verbal, sequential or global), and level of student's knowledge (beginner, intermedia, advanced).

Two primary studies used student profile standards as part of the student model, while the rest did not. IEEE PAPI and IMS LIP were used in studies (Belcadhi, 2016) and (Fonte et al., 2012), respectively. Furthermore, four articles declared specific learning styles, i.e., the Felder–Silverman Index of Learning Styles (Rani et al., 2015; Tarus et al., 2017), Honey and Mumford Learning Styles (Kurilovas et al., 2014), and the Kolb Learning Style Inventory (Yaghmaie & Bahreininejad, 2011).

To build domain ontologies of learning objects, two studies reused ontologies (Mariño et al., 2018; Muñoz et al., 2015) and others reused or re-engineered non-ontological resources from textbooks (Demaidi et al., 2018; Jevremovic et al., 2017) or thesauri (Capuano & Toti, 2019). Five studies used metadata standards explicitly, while the remainder did not. The most used standards are IMS LOM (Benlamri & Zhang, 2014; Fonte et al., 2012; Yago et al., 2018), followed by the LRE AP (Kurilovas et al., 2014) and the ADL SCORM (Yaghmaie & Bahreininejad, 2011). For example (Capuano & Toti, 2019), created a domain ontology in the legal domain. The ontology contains thousands of concepts (e.g., legal mediation, mediation process, and mediator obligations) that are connected through informative relationships (e.g., narrower terms, broader terms, and related terms) and educational relationships (e.g., "requires," "has part," and "teaching order").

Furthermore, ontology models in reviewed articles could be more specific, such as:

(1) Ontology of the assessment rubric which stores assessment criteria, categories, and assessments (Yago et al., 2018).
(2) Cognitive ontology which collects information about the learning target (Zhong et al., 2015) or the activation states of learning objects for a student (e.g., repeated, read, viewed, known, evaluated, and learned) (Caravantes & Galán, 2011).
(3) Ontology of cultural variables which covers personal values, standard practices, and types of human interaction (Savard et al., 2020).
(4) Emotional ontology that stores positive, negative, ambiguous, and neutral emotional data (Khaled et al., 2019).
(5) Feedback ontology which contains course content, educators, exams, and problem questions and answers (Belcadhi, 2016).

5.4.2. Inference engine

Along with an ontology component, recommender systems maintain a semantic reasoner component. A semantic reasoner, a rules engine, or simply a reasoner, is *an inference engine that performs reasoning tasks on the ontology to generate knowledge* (Matentzoglu et al., 2015; Parsia et al., 2017). Examples inference mechanisms are first-order predicate calculus, the tableau reasoning system, and chain-based rules (forward and backward) (Pollock, 2009). Two primary studies extracted in this review explicitly applied forward and backward chaining methods (Fonte et al., 2012; Khaled et al., 2019). Furthermore, using the W3C classification, the reviewed studies have RDFS reasoners (Khaled et al., 2019), OWL reasoners (Belcadhi, 2016; Gómez et al., 2016), and rule-based reasoners (Clemente et al., 2014; Fonte et al., 2012; Muñoz et al., 2015).

Among the generated knowledge are finding prerequisite materials (Fonte et al., 2012), determining the profile group based on activities (Muñoz et al., 2015), inferring probabilities for the predicted current bandwidth of a student's device (Benlamri & Zhang, 2014), and estimating the value of the relationship between message exchanges (Khaled et al., 2019). The knowledge was acquired using reasoner tools, such as Pellet (Gómez et al., 2016; Muñoz et al., 2015; Sánchez-Vera et al., 2012; Yago et al., 2018), HermiT (Mariño et al., 2018; Rani et al., 2015), Java Expert System Shell (Fonte et al., 2012), Fact++ (Mustafa et al., 2019), and the RDF[11] application programming interface for PHP[12] (Khaled et al., 2019).

5.5. RQ5 what are the ontology collaborators in the e-learning recommender systems?

Extraction results show diverse field supports recommender systems. The recommender system can be a standalone application or use environments such as context-aware systems and cloud computing. Also, theories and methods from educational/educational psychology support recommender system can be employed. For example, Bloom's taxonomy is used to recommend learning objects (Yago et al., 2018), feedback (Demaidi et al., 2018), and learning paths (Clemente et al., 2011). Moreover, there exist theories/methods (see Table 4).

Ontology in e-learning recommender systems is employed in collaboration with other disciplines. Moreover, eight studies incorporated three distinct fields, e.g., the eJRM prototype combines ontology, natural language processing, and storytelling (Capuano & Toti, 2019), and ON-SMMILE integrates ontology, Bloom's taxonomy, and educational modeling language (Yago et al., 2018).

[11] RDF stands for Resource Description Framework.

[12] PHP is an abbreviation for Hypertext PreProcessor.

Table 4
Ontology collaborators in ontology-based recommender systems for e-learning.

Discipline *(role)*	Theory/technology/approach
Computing technology *(system environment)*	Context-aware systems (Gómez et al., 2016; Yaghmaie & Bahreininejad, 2011) Cloud computing (Rani et al., 2015) Service-oriented architecture (Yaghmaie & Bahreininejad, 2011)
Education/educational psychology *(supporting theories/ methods)*	Learning activity (Bloom taxonomy (Clemente et al., 2011; Demaidi et al., 2018; Yago et al., 2018); Krathwohl taxonomy (Clemente et al., 2011); and Harrow taxonomy (Clemente et al., 2011)) Cognitive psychology (AlAgha, 2012; Caravantes & Galán, 2011; Mustafa et al., 2019) Instructional design (pedagogical scenario (Ullrich & Melis, 2010); problem-based learning (Jevremovic et al., 2017); teaching/learning method iCOPER D3.1 (Kurilovas et al., 2014)) Learning theory (constructivism (Kurilovas et al., 2014)) Storytelling (Capuano & Toti, 2019)
Other collaborators	Anthropology (Savard et al., 2020) Management (Iatrellis et al., 2019) Social network analysis (Khaled et al., 2019) Activity-centered design (Mariño et al., 2018) Bayesian probability theory (Grubišić et al., 2013) Educational Modeling Language (Yago et al., 2018) Graph theory (Nitchot et al., 2018)

5.6. RQ6 what are the evaluation techniques and the evaluation results of the e-learning recommender systems?

As software, the ontology-based recommender system also needs evaluation. This review study found that no evaluation methodology was used to systematically assess the quality of the developed ontology. However, several recommender systems use some evaluation techniques. The recommender models are evaluated in experiments with unreal students, while the prototypes can be evaluated by five methods: algorithmic performance tests, descriptive statistics, inferential statistics, questionnaires, and qualitative observations.

The recommender model might be evaluated in experiments with unreal students. For example (Clemente et al., 2011; Yago et al., 2018), conducted four experiments of their models in different scenarios. On the contrary, the prototypes of the recommenders were evaluated in terms of system usability (Capuano & Toti, 2019; Demaidi et al., 2018; Gómez et al., 2016; Porcel et al., 2018; Sánchez-Vera et al., 2012), student satisfaction (Sánchez-Vera et al., 2012; Tarus et al., 2017), processing efficiency (Capuano & Toti, 2019), and system clarity (Demaidi et al., 2018). Furthermore, the prototypes were tested in various academic environments, from the course level to the exam level (Sánchez-Vera et al., 2012). Most of the participants are students, and the most popular subjects are related to computer science in higher education (Demaidi et al., 2018; Jevremovic et al., 2017; Muñoz et al., 2015; Tarus et al., 2017), followed by courses in medicine and nursing (Gómez et al., 2016).

None of the primary studies explicitly described ontology evaluation methodologies. However, some articles use system comparison (Capuano & Toti, 2019), questionnaires (either customized or the System Usability Scale) (Demaidi et al., 2018; Gómez et al., 2016; Sánchez-Vera et al., 2012), and other methods (see Table 5). Moreover, the two studies use several evaluation methods to test a single system (Demaidi et al., 2018; Khaled et al., 2019).

To evaluate the results, various recommendation techniques were also compared. For example (Jevremovic et al., 2017), compared their results with those of previous research over three consecutive semesters. Similarly (Demaidi et al., 2018; Gómez et al., 2016), used a 40-student control group in the same subject. All primary studies produced positive test results, indicating that the recommendation technique improved students' performance, particularly those who initially did not understand the material (Demaidi et al., 2018). However, it is interesting to know that students with higher education tend to be more critical of the features of the systems (Capuano & Toti, 2019).

Table 5
Evaluation methods of personalization performance.

Evaluation Methods	Evaluation variables
Questionnaires	Perceived effectiveness (Capuano & Toti, 2019; Ullrich & Melis, 2010), usefulness (AlAgha, 2012; Ullrich & Melis, 2010), clarity (Demaidi et al., 2018), interestingness, approachability, adaptability, suitability for diver learners (Khaled et al., 2019)
Qualitative observation	Usability, effectiveness (Belcadhi, 2016)
Descriptive statistics	*Pre-test* and *post-test* score comparison (Demaidi et al., 2018), activity log (AlAgha, 2012)
Inferential statistics	Student behavior in the pre-test and post-test (Gómez et al., 2016; Jevremovic et al., 2017; Mustafa et al., 2019; Sánchez-Vera et al., 2012), activity log (Caravantes & Galán, 2011)
Algorithm performance test	*Similarity* (Khaled et al., 2019); Mean Absolute Error, Precision, and Recall (Tarus et al., 2017)

6. Discussion

6.1. Implications

6.1.1. Popular learning technology and ontology methodology

Most prototypes of the recommendation systems are standalone software, except for OntoSakai, which is integrated into the LMS (Muñoz et al., 2015). The recommender environment may be limited by the number of supported courses. We found that one study used six courses, but the majority of studies only used one. Furthermore, the resource difficulty of integrating a recommender system with existing technologies may prevent integration.

Learning technology can be a recommender system itself (e.g., ITS, courseware generator) or can contain a recommender system (e.g., LMS, VLE). Furthermore, the study revealed that LMS, ITS, CAI, and PLE are the most popular recommendation systems platforms. This finding is consistent with a previous study that reported LMS, e-assessment, VLE, ITS, and PLE as the most well-known learning technologies (Tibaná-herrera et al., 2018).

Only five studies documented ontology building methodologies (Labib et al., 2017; Mariño et al., 2018; Muñoz et al., 2015; Rani et al., 2015; Yago et al., 2018). Three others created domain ontologies using reused or reengineered non-ontological resources (Capuano & Toti, 2019; Demaidi et al., 2018; Jevremovic et al., 2017). Hence, we predict that the remainder of the major research would have created ontologies from scratch tailored to the specific courses. This is particularly true for domains ontologies. The methodologies were not adequately documented, possibly because the authors emphasized presenting recommendation techniques rather than ontology building.

Interoperability standards, on the other hand, are rarely employed. Interoperability standards were frequently overlooked because course numbers were limited and most systems were built from the ground up. However, this study shows that ontology language standards have been widely applied. Therefore, the reusability of recommender systems may be improved by using other standards, such as student profile standards and metadata standards for learning objects.

6.1.2. Recommendation items in learning environments

Most recommendation items (64% of primary studies) were learning objects, followed by personalized learning paths and feedback. The variety of recommendation items has grown as technology has become more user centric. Furthermore, a recent study found that the best learning path could lower students' cognitive surplus (Premlatha & Geetha, 2015) and that individualized feedback could boost affective engagement (Chen et al., 2021).

(AlAgha, 2012) benefited from an open learning environment in which new learning objects might be added to the browsing space. As open learning gains popularity, we may see more learning objects, learning paths, feedback, and device alternatives in the future. Therefore, recommended things will evolve and become more reciprocal.

The current study found that the recommender system generated recommendations independently of educators. Additionally, the system or students may initiate the recommendation process. Educators and students can assess students' achievement of learning gains at the end of a course or experiment (Demaidi et al., 2018; Gómez et al., 2016; Sánchez-Vera et al., 2012). However, because learning is such a two-way exchange between educators and students, educators are expected to be part in the recommendation process. Additionally, despite receiving recommendations, students may have difficulties while learning. Therefore, educators should support students to resolve motivational or competence issues.

6.1.3. *Inference engine and recommendation technique*

The semantic reasoner, used as an inference engine, is responsible for the inference tasks such as deciding student groups, selecting the learning objects' sequence, and determining the type of learning courses. These tasks could be expanded by integrating instructional designs, as proposed by (Vidal-Castro et al., 2012). For example, the reasoner could execute a new rule such as "*Group concepts and supporting content into 'learning episodes' that are not so large as to make review and synthesis difficult but not so small as to break the flow of the learning process*" (Vidal-Castro et al., 2012).

Our findings expand the use of ontologies in curriculum modeling, content search and retrieval (Al-Yahya et al., 2015), and peer recommendation in learning communities (Zheng et al., 2015). Furthermore, ontology-based recommender systems do not rely solely on ontology. Because educational technology has advanced so quickly, the supporting fields are diverse. As technology improves, so do the system environments. Table 4 shows how knowledge processing techniques have progressed from semantic reasoning to hybrid AI (see the resume in Fig. 4). Therefore, ontology-based recommender systems are more accessible to collaborators from various disciplines.

6.1.4. *Performance evaluation*

(Demaidi et al., 2018) found that students with higher educational backgrounds tend to be more critical of the recommender system. The condition is already known as the *expertise reversal effect* (Sweller et al., 2011). To minimize it (Sweller et al., 2011), proposed customization of the instructional methods during a learning session. For example, the recommender system could apply direct instruction to a novice learner, a mix of direct instruction and problem-solving practices to an

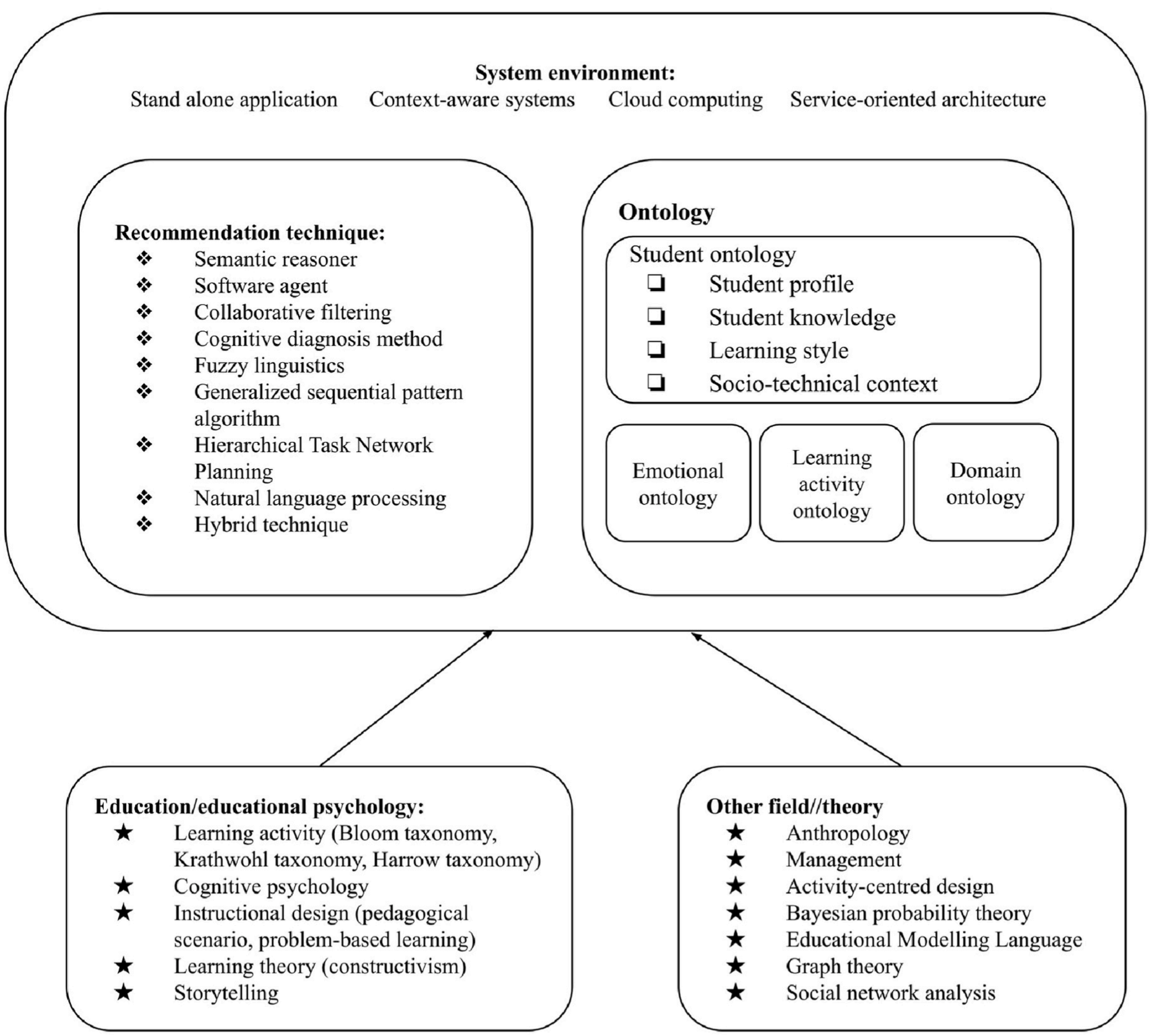

Fig. 4. The elements and environments of e-learning recommender system.

intermediate learner, and minimally guided problem-solving tasks to advanced learners.

6.2. Research agenda

6.2.1. Future development and adoption of methodologies

The findings of this review study indicate that ontology-based recommender systems are rarely integrated into existing learning technologies, particularly closed-source platforms. On the other hand, schools and colleges have incorporated a variety of educational technologies to assist students. Furthermore, the most researched and used learning technologies are LMS, e-assessment, and VLE. For example, Moodle LMS is known as the most popular LMS, used by more than 248 million users in 251 countries (Demaidi et al., 2018). Therefore, such recommender systems can be integrated into existing educational technology to provide students with a more personalized learning experience. Among the benefits are that educators can use the same recommendation techniques for related courses, and students will have quick access to tailored recommendations from a variety of courses.

Most of the primary studies have not explicitly mentioned the methodology for building ontology except for reuse and reengineering: (1) ontological resources and (2) nonontological resources. To facilitate future research collaborations, various scenarios could be used, and include the following as examples: reuse and merge ontological resources; reuse, merge, and reengineer ontological resources; reuse ontology design patterns; restructuring ontology resources; or localizing ontological resources (Suárez-Figueroa et al., 2012).

Furthermore, the adoption of standards and methodologies is a further concern. The interoperability standard will promote open education and future research collaborations by simplifying system testing and usage. Additionally, ontology methodologies have been established to aid diverse users in carrying out primary ontology engineering operations. The techniques are increasingly needed as more people go online and more ontologies exist. To drive adoption, it is necessary to investigate the researchers' or developers' difficulties in using standards for student profiles and learning objects. Further, identifying the problems with using ontology methodologies is important.

Recommender system needs to be evaluated using the proper software testing method. Moreover, the ontology component should be assessed using ontology evaluation methodology. This assessment is necessary to assure the technical quality of the ontology utilized in the recommender system. Thus, the evaluation methodology is designed to verify the correctness of the desired ontology model. Two types of evaluation are available: (1) ontology assessment based on individual characteristics (i.e., the "*glass box*" method) and (2) a performance test of the ontology used in the application system (i.e., the "*black box*" method) (McDaniel & Storey, 2019).

6.2.2. Prospective recommended items and learning environment

Recommender systems in the education domain provide direct and indirect benefits to students. The personalized learning object or learning path are examples of direct benefits. Meanwhile, indirect benefits address recommendation items for other stakeholders, which in turn provide personalized teaching services to students; examples are the authoring tool for educators (Labib et al., 2017) and the pedagogical scenarios advisor tool for instructional designers (Savard et al., 2020). We conclude from these findings that research opportunities for recommendation items are rising, owing to the fact that learning technology involves a large number of stakeholders (i.e., student, educator, instructional designer, administrator, support personnel). Moreover, such recommendation innovations could accommodate the stakeholders' needs and operate on various learning technology platforms.

Recommendations may also be used in open educational environments. These settings, which have grown in popularity over the last decade, present their own set of pedagogical issues and learning materials. As a result, the recommendation problem continues to grow in complexity. For instance, the recommender system can recommend learning paths, supported services, and individualized feedback based on students' self-determined learning approach.

6.2.3. Hybrid and multidisciplinary recommender system

Learning technology is rooted in psychology, computing technology, and educational disciplines. As indicated in the current study, ontology has been combined not only with artificial intelligence but also with other computing technologies to deploy hybrid techniques. Hence, optimal collaboration is required to develop a robust recommender system capable of producing meaningful recommendations. Additionally, the performance of hybrid techniques should be easily identifiable and compared to obtain the optimal combination. However, previous studies show difficulties in performance comparison due to the lack of a public data set (Tarus et al., 2017) and the difficulty in isolating the recommendation technique from the learning approach (Jevremovic et al., 2017). To establish a benchmark for the quality of hybrid techniques, future studies may analyze the outcomes of educational linked data (Nahhas et al., 2018) or the same learning approach used by one generation of students.

The current recommender system is also multidisciplinary, as the system collaborates recommendation techniques with education and educational psychology (e.g., learning activities, learning theory, instructional design), and others (e.g., anthropology and SNA). As part of educational research, future e-learning recommender systems will extend beyond computing, and ontology could someday interact with science, art, or other humanities (Akker et al., 2006). Therefore, various learning approaches present a new challenge to effectively utilizing recommender systems and learning methods. Furthermore, recommender systems can also be applied to primary and secondary education, social sciences, and humanities courses.

6.3. Limitation

The current study reviews the primary studies in relation to the technical aspects of ontology development. Therefore, we search into computer science/artificial intelligence subjects. however, there might be some relevant papers found in other subjects (e.g., engineering, multidisciplinary).

The development and implementation of the recommender system in real learning indeed involves other aspects, such as the technology readiness and educational theories (Hwang et al., 2020). The technological aspects include access to technology in the classroom (Callum et al., 2015), the educator's adoption (Cochrane et al., 2014), and the students' digital competence (Agonács et al., 2020). Furthermore, this study did not discuss the barriers to implement recommender systems. Therefore, future research is required to describe a more complete picture.

This review study is limited to articles in English, so additional papers in other languages would enrich the research results. However, these limitations do not weaken the value of this research; in fact, our findings form the basis for further ontology collaborations and more sophisticated e-learning recommender systems.

7. Conclusion

Ontologies are KBS that play an essential role in adaptive learning technology. The current review investigated the role of ontology in personalized learning, explored the development of an ontology-based recommender system, and surveyed the recommendation techniques for such systems. We conducted research using the PRISMA flow diagram, and the primary studies were found using a broad automated search method. The 28 articles extracted were high-quality articles in quartiles Q1 and Q2 of their respective journals from 2010 to 2020. The results are summarized below.

(1) ITS, LMS, CAI, and PLE are the most popular learning technology platform for ontology-based recommender systems. The diverse types of technology and multidisciplinary recommendations have extended personalized learning beyond technical computing into the overall architecture of the system.
(2) Some ontology-based recommender systems use the methodology of building ontologies, but other ontology methodologies are rarely used.
(3) The most popular recommendation item is the learning object, which can be personalized by referring to internal data (e.g., learning style, scores, and learning activities) or external data (e.g., location sensors). The learning path and feedback could be the next popular recommendation items for students in the upcoming years. Similarly, recommender systems also can provide recommendations for other e-learning stakeholders, such as educators and instructional designers.
(4) The recommendation process is reciprocal and can be initiated either by the system or by the students. The recommendation process is based on the following functions: first, the system checks the student model and then provides recommendations according to the student model. Furthermore, recommendation items could be expanded according to the students' needs and could also be applied in open learning environments.
(5) Most ontologies store student models and learning objects' data. The next most popular types of data are feedback, assessment, and context data (e.g., emotional, cognitive, and cultural data). Ontology language standards are widely used in primary studies, but student profile standards and metadata standards for learning objects are rarely adopted in ontology models.
(6) A multidisciplinary approach has become a new trend in the development of ontology-based recommender systems. Ontology is collaborating with concepts and methods from other techniques, utilizing artificial intelligence, computing technology, education, education psychology, and social sciences. Software agents and learning activities have emerged as the two most popular collaborators in the last ten years, but the use of the ontology collaborator is increasing. Performance among hybrid techniques could also be compared by considering learning approaches and educational linked data.
(7) Ontology-based recommender models and prototypes are evaluated in experiments with a specific population using nonreal students, algorithmic performance tests, descriptive statistics, inferential statistics, questionnaires, and qualitative observations. Therefore, future research needs to evaluate such systems in a broader context or with more participants, applying appropriate testing methods.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Learning technology	Description of uses
Academic advisor system	Help students plan and make decisions about the study (e.g., learning pathways, learning outcomes) (Iatrellis et al., 2019).
Cloud e-learning	Store e-learning data/resources in the cloud (Rani et al., 2015).
CAI	Support learning interactions in which computers (teaching machines) provide instructional materials to students (Huang et al., 2019)
CSCL	Facilitate interactions between students and enables the dissemination of knowledge/expertise within the community (Magnisalis et al., 2011).
Courseware generator	Contains learning material and is used by educators to find and create learning objects (Labib et al., 2017; Ullrich & Melis, 2010).
E-assessment	Online test tool to assess students' knowledge/skills (Sánchez-Vera et al., 2012) with the purpose of obtaining information/feedback (Belcadhi, 2016).
Instructional design advisor tool	Used by instructional designers to plan teaching/learning (e.g., learning activities, materials, and assessments) (Savard et al., 2020).
ITS	(also called computer tutor (Aleven et al., 2016)), which is able for *one-to-one tutoring* by adapting the content and appearance of the learning according to the student's abilities (Grubišić et al., 2013).
LMS	Software to support learning (either online, face-to-face, or blended), both in an academic environment and in the professional environment (Barreto et al., 2020) to manage, distribute and monitor users, resources, and interactive and collaborative learning activities (Fonte et al., 2012; Kpolovie & Lale, 2017).
PLE	An integrated approach/system that allows students to control and manage their own learning (Al-Abri et al., 2019; Guettat & Farhat, 2016). Additionally, 28 definitions of PLE were found from both the educational and technological perspectives (Guettat & Farhat, 2016).
Ubiquitous Learning	A learning system/approach to recommend physical learning components (e.g., tools, media) according to student behavior (especially the location of the student and device's location) (Dron & Anderson, 2021; Gómez et al., 2016).
Virtual Learning Environments (VLE)	An integrated online learning environment containing learning Objects and tools (Kurilovas et al., 2014). A VE platform could be a virtual world, a game machine, or a 3D visualization/interaction tool (Clemente et al., 2014).
IVET	Combines VLE and ITS (Clemente et al., 2014).

Appendix B

Publication year	Paper	Title	Type	Model/system name	Learning technology	Recommendation item	Course/topic/domain
2020	Savard et al. (2020)	Considering cultural variables in the instructional design process: A knowledge-based advisor system	Model	Executable Cultural Adaptation Method	Instructional design advisor tool	Pedagogical scenarios	N/A
2019	Mustafa et al. (2019)	Effectiveness of ontology-based learning content generation for preschool cognitive skills learning	Prototype	CogSkills2	ITS	Learning objects	Cognitive skills of preschool curriculum
2019	Khaled et al. (2019)	Recommendations-based on semantic analysis of social networks in learning environments	Prototype	ILEARN	SLN	Learning objects	4 courses of computer science
2019	Capuano and Toti (2019)	Experimentation of a smart learning system for law based on knowledge discovery and cognitive computing	Prototype	eJRM (electronic Justice Relationship Management)	CAI	Learning objects	Legal mediation
2019	Iatrellis et al. (2019)	A novel integrated approach to the execution of personalized and self-evolving learning pathways	Prototype	EDUC8	Academic advisor	Learning paths	N/A
2019	Nitchot et al. (2018)	Personalized learning system for visualizing knowledge structures and recommending study materials links	Prototype	MyTeLeMap	PLE	Learning paths	Web technology
2018	Demaidi et al. (2018)	OntoPeFeGe: Ontology-Based Personalized Feedback Generator	Prototype	OntoPeFeGe	LMS	Feedbacks	Data networking, Computer networks
2018	Porcel et al. (2018)	Sharing notes: An academic social network based on a personalized fuzzy linguistic recommender system	Prototype	SharingNotes	SLN	Learning objects	9 courses of computer science
2018	Mariño et al. (2018)	Accessibility and Activity-Centered Design for ICT Users: ACCESIBILITIC Ontology	Model	ACCESIBILITIC	N/A	Learning devices	Accessibility and e-inclusion
2018	Yago et al. (2018)	ON-SMMILE: Ontology Network-based Student Model for MultIple Learning Environments	Model	ON-SMMILE	IVET	Learning objects	Chemistry experiment (virtual laboratory)
2017	Tarus et al. (2017)	A hybrid knowledge-based recommender system for e-learning based on ontology and sequential pattern mining	Prototype	N/A	LMS	Learning objects	12 courses of computer science
2017	Jevremovic et al. (2017)	IP Addressing: Problem-Based Learning Approach on Computer Networks	Prototype	IPA-PBL (IP Addressing: Problem-Based Learning)	ITS	Learning objects	Computer network
2017	Labib et al. (2017)	On the way to learning style models integration: a Learner's Characteristics Ontology	Model	LOAT (Learning Object Authoring Tool)	Courseware generator	Learning objects	Introduction to Java Programming
2016	Belcadhi (2016)	Personalized feedback for self-assessment in lifelong learning environments based on semantic web	Prototype	N/A	E-assesment	Feedbacks	4 computer science courses
2016	Gómez et al. (2016)	A Contextualized System for Supporting Active Learning	Prototype	N/A	Ubiquitous learning	Learning objects	Physiology (Medicine), Clinical practice (Nursing) and Physics (Systems engineering)
2015	Muñoz et al. (2015)	OntoSakai: On the optimization of a Learning Management System using semantics and user profiling	Prototype	OntoSakai	LMS	Learning objects	Database Administration
2015	Rani et al. (2015)	An ontology-based adaptive personalized e-learning system, assisted by software agents on cloud storage	Prototype	N/A	Cloud e-learning	Learning objects	Algorithm
2014	Clemente et al. (2014)	Applying a student modeling with non-monotonic diagnosis to Intelligent Virtual Environment for Training/Instruction	Prototype	SMA(Student Modeling Agent)	IVET	Learning objects	Biotechnology
2014	Benlamri and Zhang (2014)	Context-aware recommender for mobile learners	Prototype	N/A	CAI	Learning objects	C++ programming language

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Publication year	Paper	Title	Type	Model/system name	Learning technology	Recommendation item	Course/topic/domain
2014	Kurilovas et al. (2014)	Web 3.0-based personalization of learning objects in virtual learning environments	Model	N/A	VLE	Learning objects	E-Learning Systems
2013	Grubišić et al. (2013)	Ontology based approach to Bayesian student model design	Model	AC-ware Tutor (Adaptive-Courseware Tutor)	ITS	Learning objects	Computer system
2012	AlAgha (2012)	KnowledgePuzzle: A Browsing Tool to Adapt the Web Navigation Process to the Learner's Mental Model	Prototype	KnowledgePuzzle	PLE	Learning paths	Computer viruses
2012	Sánchez-Vera et al. (2012)	Semantic Web technologies for generating feedback in online assessment environments	Prototype	OeLE (Ontology eLEarning)	E-assesment	Feedbacks	Design and Production of Educational Materials
2012	Fonte et al. (2012)	An intelligent tutoring module controlled by BDI agents for an e-learning platform	Model	INES (INtelligent Educational System)	LMS	Learning objects	N/A
2011	Yaghmaie and Bahreininejad (2011)	A context-aware adaptive learning system using agents	Model	N/A	LMS	Learning objects	N/A (simulation)
2011	Caravantes and Galán (2011)	Generic Educational Knowledge Representation for Adaptive and Cognitive Systems	Prototype	COES (Cognitive Ontology of Educational Systems)	ITS	Learning objects	Web design
2011	Clemente et al. (2011)	A proposal for student modeling based on ontologies and diagnosis rules	Model	N/A	ITS	Learning paths	Chemistry experiment (virtual laboratory)
2010	Ullrich and Melis (2010)	Complex Course Generation Adapted to Pedagogical Scenarios and its Evaluation	Prototype	Piagos	Courseware generator	Learning objects	Mathematics

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