A Survey of Ontologies and Their Applications in e-Learning Environments

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Abstract

Ontology technology has been investigated in a wide range of areas and is currently being utilized in many fields. In the e-learning context, many studies have used ontology to address problems such as the interoperability in learning objects, modeling and enriching learning resources, and personalizing educational content recommendations. We systematically reviewed research on ontology for e-learning from 2008 to 2020. The review was guided by 3 research questions: "How is ontology used for knowledge modeling in the context of e-learning?", "What are the design principles, building methods, scale, level of semantic richness, and evaluation of current educational ontologies?", and "What are the various ontology-based applications for e-learning?" We classified current educational ontologies into 6 types and analyzed them by 5 measures: design methodology, building routine, scale of ontology, level of semantic richness, and ontology evaluation. Furthermore, we reviewed 4 types of ontology-based e-learning applications and systems. The observations obtained from this survey can benefit researchers in this area and help to guide future research.

Keywords: Ontology, semantic web, e-learning, adaptive learning.

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1 Introduction

Ontology has been applied to a wide range of domains such as biomedicine [1, 2], agriculture,[1] and education [3, 4]. An ontology is a set of axioms stated in an ontology language [5]. Ontologies defined in W3C standards, including RDF, RDFS, and OWL, largely facilitate data resource sharing and re-use, and are key components of the Semantic Web. In the last 10 years, ontology technology has made substantial advancements in many fields. For example, based on the linked data principle, the Linked Data Cloud[2] contained 1,269 datasets with 16,201 links as of May 2020. Google uses the Knowledge Graph,[3] which collects information from various sources to enhance its search results. In the area of education, the application of ontology in e-learning has been a research focus since 2000 [6, 7], and it has become more significant in recent years.

Technologies such as machine learning and intelligent computing have been applied to education to solve various problems in e-learning environments (e.g., the interoperability in learning objects (LOs), modeling and enriching learning resources, and personalizing educational content recommendations [4, 8]). Among those technologies, ontology has accounted for a large portion of approaches from 2000 to 2012 [6]. The characteristics of ontology, including resource sharing and re-use, knowledge modeling, and inference [7], make it ideal for solving e-learning problems. For example, ontology is used to model course resources [9, 10], instructional design theories [11], and learning styles [12]. By transforming these types of knowledge into ontologies, various applications for e-learning (such as learning resource recommendations [13] and learning path personalization [14]) can be developed. More importantly, existing educational ontologies can be re-used for different e-learning systems.

This survey aims to provide a systematic overview of the latest educational ontologies and ontology-based applications for e-learning. To perform a comprehensive and systematic review of recent research, we formulated the following 3 research questions:

> RQ1: How is ontology used for knowledge modeling in the context of e-learning?

[1]AGROVOC: http://aims.fao.org/vest-registry/vocabularies/agrovoc-multilingual-agricultural-thesaurus.

[2]The Linked Open Data Cloud: https://lod-cloud.net/.

[3]The Knowledge Graph: https://en.wikipedia.org/wiki/Knowledge_Graph.

RQ2: What are the design principles, building methods, scale, level of semantic richness, and evaluation of current educational ontologies?
RQ3: What are the various ontology-based applications for e-learning?

To identify the papers for this survey, we carried out the following steps.

Step 1: A set of keywords was identified: ("ontology" OR "semantic technology") AND ("e-learning" OR "education"). These keywords were used to search for papers from 2008 to 2020 in 5 databases: ACM Digital Library, IEEE Xplore Digital Library, Springer, ScienceDirect, and Web of Science. We used both "ontology" and "semantic technology" to avoid missing relevant studies.

Step 2: To select the papers from the initial search results, we defined the following exclusion criteria: (1) papers not in English, (2) studies not in the field of e-learning or learning technology, and (3) studies not related to ontologies based on the Semantic Web standards. Criteria (2) and (3) were based on the scope of this survey, which is ontology defined using the Semantic Web standards for e-learning. For example, papers focusing on concept maps (without being related to the Semantic Web) or learning analytics were excluded. We applied the above criteria by reading abstracts and looking further into the retrieved papers to filter out irrelevant studies. By performing Step 2, we selected 112 papers. Among them, 14 papers were surveys.

The remainder of this paper is organized as follows: Section 2 reviews the survey papers related to ontology-based e-learning. Section 3 presents the selected measures for analyzing ontologies and then discusses the 6 types of educational ontologies using the 5 measures. Section 4 reviews the major applications of ontology to education. Section 5 discusses the three research questions and Section 6 concludes the paper.

2 Related Work

In this section, we discuss the related survey papers from the 3 aspects: the use of ontologies in e-learning, ontology engineering in e-learning and ontology-based approaches in e-learning.

2.1 The Use of Ontologies in e-learning

Yalcinalp and Gulbahar [15] (2000–2009), Al-Yahya et al. [16] (2000–2012) and Stancin et al. [17] (2015–2019) reviewed the use of ontologies in the context of e-learning from 2000 to 2019. In [15], the authors reviewed the use of ontologies to support personalization in web-based environments. They suggested that the development of educational ontologies requires collaboration between educational and technological experts. In [17], ontologies were classified into four types: curriculum modeling and management, describing learning domains, learning data, and e-learning services. Both studies of [15] and [17] did not provide comparison of the existing educational ontologies, techniques, approaches, and applications related to e-learning systems. In [16], a classification framework consisting of ontology types and categories of e-learning tasks was proposed to classify and analyze the related studies. Ontologies were classified into application, domain-task, task, and domain ontologies, while e-learning tasks were categorized into curriculum modeling and management, describing learning domains, describing learner data, and describing e-learning services. From the survey, those authors found that most ontologies belonged to the task type, describing the vocabulary relevant to a generic task or activity. In addition, most ontologies were used to support learning personalization.

Although our survey and the studies [15–17] have a common focus (analyzing the usage of ontology for e-learning), our survey presents more information about the educational ontologies and ontology-based e-learning systems. Not only do we identify the classifications of educational ontologies and the ontology-based learning systems, but we also analyze the different types of educational ontologies using 5 measures: design methodology, building routine, scale of ontology, level of semantic richness, and ontology evaluation. In addition, we discuss the applications of ontology-based methods and summarize a list of e-learning systems. Such information is useful for researchers to understand the current trends in and status of educational ontologies.

2.2 Ontology Engineering in e-learning

Mizoguchi and Bourdeau [18] summarized the ontology engineering in AIED (artificial intelligence in education) from 2000 to 2015. Research works contributing to the development of OMNIBUS, an ontology of learning/instructional theories, and SMARTIES, a theory-aware authoring system, were reviewed. Several projects related to OMNIBUS and SMARTIES, such as group formation in CSCL (Computer Supported Collaborative Learning), intelligent authoring, ontology-based learning design, and culturally-aware instructional design, were also discussed. Although educational ontologies and ontology-based e-learning systems were reviewed, these authors only focused on OMNIBUS- and SMARTIES-related contributions. Kurilovas and Juskeviciene [19] studied several ontology development tools, such as Protégé, WebODE, Ontolingua, OntoSaurus, and WebOnto, using a set of criteria (interface clarity, consistency checking, and import facilities). The authors concluded that Protégé was the best tool for creating educational ontologies. The focus of the study was on ontology editors, but not the ontologies themselves.

Unlike the above studies, our paper analysed the various types of educational ontologies (not only limited to OMNIBUS) from 5 measures (not only limited to engineering aspect): design methodology, building routine, scale of ontology, level of semantic richness, and ontology evaluation. By reviewing the various aspects for educational ontologies, we also elucidated the state of the art in current educational ontologies.

2.3 Ontology-based Approaches in e-learning

A number of papers reviewed ontology-based approaches by focusing on specific aspects of e-learning systems (e.g., recommendation and personalization). Tarus et al. [20] studied ontology-based recommendation systems for e-learning from 2005 to 2014. Recommendation systems were classified by the types of recommendation techniques and knowledge representation types. The article summarized the ontologies used in 36 recommenders by 3 criteria: ontology type (domain ontology, generic ontology, and reference ontology), language (RDF/XML, OWL, SWRL rules), and recommended learning resources. The study noted that ontology improved the quality of recommendations, and that the use of hybrid recommendation methods can enhance recommendation performance. Since the focus was on recommendation systems, other types of e-learning applications were not addressed. Pereira et al. [21] reviewed the application of linked open data (LOD) technology in educational environments. They summarized 3 main applications of LOD: educational data as LOD, interoperability of different sources based on LOD, and consumption of LOD. They also highlighted a number of challenges, such as re-using existing educational resources, high consumption costs, and managing constantly changing repertories. Since that survey focused on educational resources as LOD, other aspects of educational ontologies and applications were not addressed. A few surveys studied knowledge- and intelligent-computing-based methods in the context of e-learning. In [6], 190 papers published between 2000 and 2012 on adaptive e-learning systems (AESs) were analyzed. That study showed that the dominant technique used in AESs was machine learning, accounting for 52% of the papers, whereas 18% used ontology-based approaches. Klašnja-Milićević et al. [22] surveyed recommendation techniques for e-learning but did not limit them to ontology-based approaches. That study advocated extensions of tag-based recommender systems for personalization in e-learning environments. The application of knowledge-based methods (such as rule-based reasoning) and intelligent computing methods (such as multiagent systems for e-learning) was discussed in another study [23]. Those authors suggested using integrated knowledge based/intelligent computing methods to solve e-learning problems, including learning path generation and Learning Object (LO) recommendation.

Although these surveys covered ontology-based methods for e-learning, educational ontologies were not their focus. Therefore, a detailed analysis of educational ontologies was not provided by these surveys. Unlike these surveys, we looked into both the 6 types of usages of educational ontology first and then the 4 types of ontology-based e-learning applications (not limited to recommendation and LOD-based applications). Our findings can be beneficial for many researchers, including ontology developers and e-learning researchers.

3 Educational Ontologies and Their Use in e-Learning

3.1 Measures for Analyzing Educational Ontologies

In order to analyze and compare the educational ontologies developed in the selected papers, we used the following 5 measures: design methodology (DM), building routine (BR), scale of ontology (SO), level of semantic richness (LSR), and ontology validation (OV). These 5 measures cover the aspects of ontology design, creation, scale, semantic richness, and evaluation. Table 1 summarizes the 5 measures, which are introduced in Sections 3.1.1 to 3.1.5.

3.1.1 Design methodology (DM)

To understand the ontology design methods used in e-learning environments, we used the NeOn methodology [7] for comparing the ontology design methods used in the related papers. As shown in Figure 1, the NeOn methodology categorizes ontology design into 9 scenarios covering commonly occurring situations. In this survey, we classified and summarized

Table 1 Measures for analyzing educational ontologies

DM	Methodology A: from specification to implementation without Competency Questions (CQs)
	Methodology B: from specification to implementation with CQs
	Methodology C: re-using non-ontological resources
	Methodology D: re-using ontological resources
	Methodology E: re-using ontological design patterns
	Methodology F: re-structuring ontological resources
	Methodology G: localizing ontological resources
BR	Manual
	Semi-automatic
	Automatic
SO	No. of domain classes
	No. of domain properties
LSR	Catalog
	Glossary
	Thesaurus
	Formal taxonomy
	Proper ontology
OV	Vocabulary level
	Structural level
	Application level

the NeOn methodology into 7 types, from Methodologies A to G. Figure 1 displays the correspondences between the NeOn methodology scenarios and the methodology used in this survey.

Specifically, Scenario 1 is split into Methodology A and B, which describe the situations where an ontology is developed from scratch without (A) or with (B) competency questions (CQs). The intention was to differentiate whether an ontology was designed based on CQs. Methodologies D summarizes Scenarios 3–6, which cover the cases of re-using, re-engineering, and re-structuring ontological resources. The 4 scenarios were merged into a single method because, in many cases, differentiating the 4 scenarios from the papers is difficult due to a lack of information. In fact, the NeOn methodology is normally used by ontology developers in ontology engineering, so they need a detailed classification of how to use existing ontological resources.

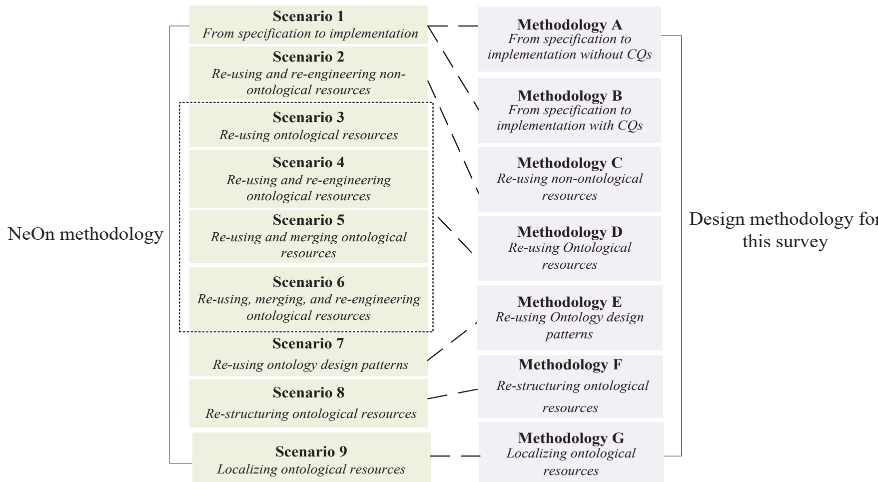

Figure 1 Design methodology.

Methodologies C, E, F, and G correspond to Scenarios 2, 7, 8, and 9, respectively.

3.1.2 Building routine (BR)

An ontology can be created in manual, semi-automatic, and automatic ways. Automatically creating high-quality ontologies is a challenging task. Simple ontologies, such as catalogs or glossaries, can be constructed automatically by defining the generation or transformation algorithms [24]. Manual approaches are normally used to ensure the quality of complex ontologies with OWL axioms. However, when the scale of the ontologies becomes large, manual development requires a great deal of time and effort. As a compromise, a semi-automatic approach can solve the low efficiency of the manual approaches and the poor quality of fully automatic methods. From this measure, we are able to understand the ways of building ontologies in e-learning environments.

3.1.3 Scale of ontology (SO)

This measure provides the metrics about the scale of an ontology. The scale of an ontology can be described by the numbers of RDF triples, classes, instances, and properties. However, these metrics were often not provided explicitly in the literature of e-learning. Therefore, in this survey, we selected No. of domain classes and No. of domain properties to describe the scale of

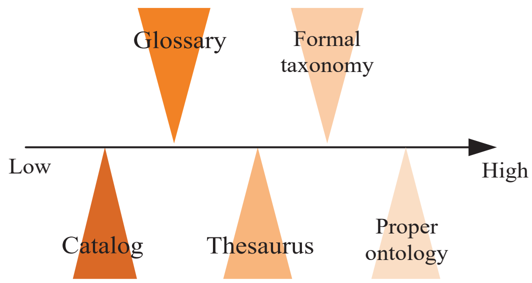

Figure 2 Level of semantic richness.

a given ontology. Even these 2 metrics were not provided directly by many studies. In this paper, most of the numbers were obtained by counting the entities exhibited in the ontology graphs.

3.1.4 Level of semantic richness (LSR)

The concept of ontology spectrum was proposed to classify ontologies by semantic richness [5]. Ontologies can range from simple and inexpressive to highly complex and precise: catalogs, glossaries, thesauri, formal taxonomies, and proper ontologies (Figure 2). The more expressive an ontology is, the more intelligent and complicated the applications it can support. A catalog-type ontology refers to a list of the entities IDs. A glossary-type ontology refers to a set of definitions of terms. A thesaurus-type ontology includes a set of terms with a number of pre-defined relations between them. A formal-taxonomy-type ontology refers to a set of concepts with subsumption relationships. Finally, a proper ontology is an ontology with all possible axioms, such as OWL restrictions and SPIN rules. We applied the ontology spectrum to classify the educational ontologies.

3.1.5 Ontology validation (OV)

Ontology validation is an essential part in ontology engineering. The task of ontology evaluation is to assess the correctness of an ontology. We identified 3 levels of ontology evaluation: vocabulary level, structural level, and application level [5]. Vocabulary level evaluation refers to assessing the names (URIs or literals) used in an ontology. Structural level evaluation refers to assessing the structure of an ontology. For example, when treating an ontology as an RDF graph, the metrics for the graphs can be applied to the ontologies. Application level evaluation refers to evaluating an ontology in the context of an application.

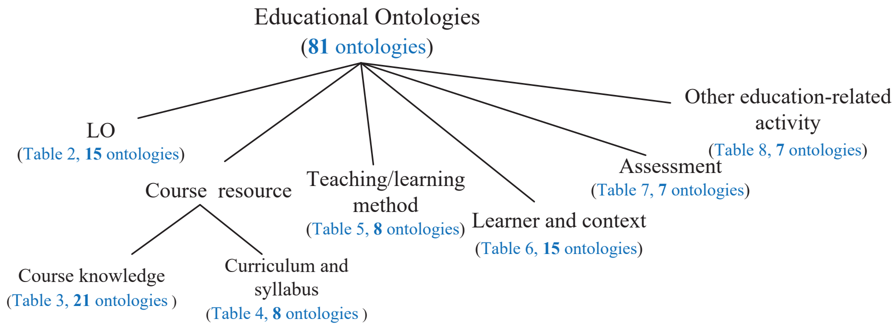

Figure 3 Classification of the ontology based on usage.

Note: The number of ontologies in each category is annotated. In addition, the corresponding table that lists the results of the 5 measures for each category is also annotated.

3.2 Ontology Use in e-Learning

In the following sub-sections, we discuss the educational ontologies proposed in the selected papers and evaluate these ontologies using the 5 measures (DM, BR, SO, LSR, and OV). As shown in Figure 3, we classified the educational ontologies into 6 categories: LO, course resource, teaching/learning method, learner and context, assessment, and other education-related activity. This classification of research works was based on the different uses of the educational ontologies. The course resource category is further classified into course knowledge and curriculum and syllabus. The LO category includes ontologies that are related to LO enriching and modeling. The course resource category includes ontologies that model course knowledge and the curriculum/syllabus. The teaching/learning method category refers to ontologies that model teaching and learning theory and activities. The learner and context category includes ontologies that model learner profiles and contextual information. The assessment category refers to ontologies created for assessment and examination. The other education-related activity category consists of ontologies for other learning aspects, such as teaching cooperation.

3.2.1 LO modeling

LOs are learning resources accessible on the internet and can be specified by the IEEE standard "learning object metadata (LOM)". Figure 4 shows some of the example attributes (title, description, and coverage) of LOM. Even though LOM provides a standardized specification format using XML, the interoperability problems remain for LO re-use and searching. The ontology

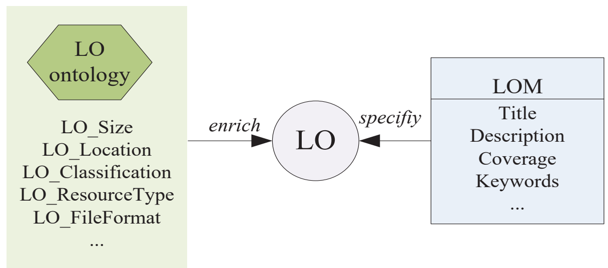

Figure 4 LOM and LO ontology.

used in the LO-related studies focused on enriching LOs to enhance LO interoperability and facilitate LO search, retrieval, and display.

In general, properties (such as the size and resource types of an LO) were defined to provide more information for applications as required. For example, the property LO_ResourceType may specify that the LO is a video or an image [25]. Solomou et al. [26] defined an ontology for LO discovery in distance learning. The proposed LO ontology was based on the elements of the IEEE LOM schema. Some attributes were kept and some new elements, such as the expected learning outcomes of a course, were defined. Koutsomitropoulos and Solomou [27] transformed the LOM schema into an ontology using the Dublin Core terms. Similarly, Lama et al. [28] defined LO ontology directly based on the LOM. Then, mappings between the ontological LOs could be linked to DBpedia resources.

In Hsu's study [29], the author presented a multilayered semantic LOM framework consisting of URLs (LOs), XML (LOM), ontology, and rule layers to facilitate LO interoperability and re-use. In the ontology layer, a set of properties (e.g., overlap, format, and template) were defined to specify the relationships between LOs. Lee et al. [30] proposed an ontological approach for LO retrieval. The query expansion algorithm could automatically aggregate a user's original short query and remove ambiguity in the query.

Instead of defining new properties, existing resources such as the Dublin Core that provide "core" information properties (e.g., "Title", "Creator", and "Date"), can be used to annotate LOs [31]. Paramartha et al. [25] focused on LO searching. They defined an LO ontology using the FOAF vocabulary and the IEEE LOM standard; the search engine used SPARQL to perform LO searches. Brut et al. [32] extended the LOM standard with ontological annotations to improve the LO searching efficiency.

3.2.2 Course resource modeling

Much attention has been paid to modeling course resources as ontologies for the purposes of learning resource re-use, adaptive and personal content selection, and adaptive learning pathways. We further identified the following 2 types of ontology uses in course resource modeling: course knowledge modeling and curriculum and syllabus modeling.

Course Knowledge Modeling

Constructing high-quality course knowledge repositories is an important research problem in the e-learning field. Figure 5 depicts the 2 types of course knowledge modeling approach based on ontologies, i.e., the manual approach and natural language processing (NLP)-based approach.

For the manual approach, course concepts and their relationships were normally identified by domain experts. Then, the taxonomy of the domain concepts was outlined. Finally, the taxonomy and relationships were defined as ontologies. For example, Lubliner and Widmeyer [9] focused on designing and realizing a knowledge repository, with the objective to assist students in learning by exploring interconnected concepts. They incorporated a ranking/voting mechanism that enables learners and instructors to add new concepts to the knowledge base.

In the NLP-based approach, NLP algorithms were used to automatically extract domain concepts and relations from textual learning materials. Then, domain ontologies can be constructed based on the concepts and relations. In [10, 40], the authors used Text-2-Onto to semi-automatically extract concepts and relations from textual learning materials. Pedroni et al. [10] organized the extracted knowledge using 3 concepts (truc, notion, and cluster) and 2 relations (is-a and requires). This concept map was then transformed into OWL ontologies. Similarly, concept maps were extracted from texts

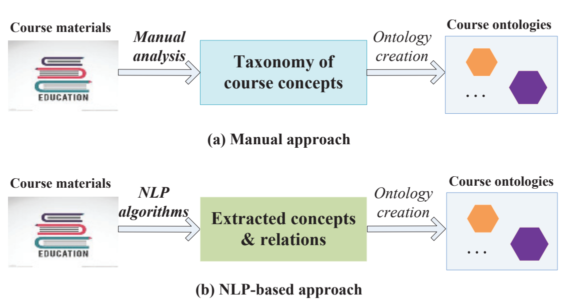

Figure 5 Two types of course knowledge modeling approaches.

by TEXCOMON and converted into domain ontologies specified in OWL by identifying classes, properties, and instances [41]. Gueffaz et al. [42] used ontology to index and rank educational resources. A basic ontology was defined and subsequently populated by extraction from annotated documents. The ontologies were also enriched by external data resources such as DBpedia.

In addition to the above 2 types of ontology uses, light-weighted ontologies were defined to annotate educational resources [43, 44]. Fernandez et al. [43] annotated video lectures in the educational domain. The authors created RDF descriptions of video lectures extracted from YouTube and Videolectures.net. Various properties of video metadata were specified using standard existing semantic vocabularies, such as Dublin Core, FOAF, and W3C.

Curriculum and Syllabus Modeling

A curriculum specifies how learning content is organized and sequenced to create a structured program of learning and teaching, while a syllabus is an outline of the topics to be taught in a course. Machine-readable curricula and syllabi are the basis for adaptive learning management in e-learning environments. Ontologies were proposed for modeling curricula and syllabi by specifying teaching contents and their relationships (e.g., prerequisite relation).

In [59], ontology was used to model the knowledge of competency management in pharmacy. The main tasks of competency management include evaluating a learners' knowledge level and generating learning pathways. The proposed ontology of pharmacy competency was developed to solve interoperability and cooperation problems in pharmacy competency management. The ontology could be used by pharmacists for curriculum building or by educational institutions for educational material management. Fernández-Breis et al. [60] defined a curriculum ontology for secondary school. The ontology covers relevant aspects including teachers, departments, objectives, subjects, tasks, and policies in the curriculum management. Petiwala and Moudgalya [61] proposed an open syllabus based on ontology, which can be used to assist with automated textbook generation.

3.2.3 Teaching/learning method modeling

In order to design and guide learning/teaching activities in e-learning environments, ontologies were studied to model various teaching/learning methods. Paneva-Marinova et al. [67] formalized Bloom's Taxonomy (Knowledge, Comprehension, Application, Synthesis, and Evaluation) using an ontology. Then, various learning scenarios were designed based on that ontology. Ouf et al. [14] proposed a teaching method ontology in which methods such as online discussion, peer-to-peer teaching, and reflection were defined as OWL classes. Dobreski and Huang [68] presented LILO, an ontological model that defines developers' learning strategies, learning resources, and learning objectives. The model could be used to aid the design of learning systems.

Instructional design theories provide guidelines for designing learning activities and arranging associated resources. Ontologies can be used to model these theories, which are normally expressed in natural language. Mizoguchi and Bourdeau [11] introduced the use of ontology engineering in AIED problems. The authors discussed the development of a system involving OMNIBUS, an ontology of learning/instructional theories, and SMARTIES, a theory-aware authoring system. OMNIBUS contains 1,259 concepts and 4,452 relations that cover different learning/instructional theories and paradigms.

3.2.4 Learner and context modeling

A learner model normally includes information such as learning styles, personal information, background knowledge and performance, learning goals, and preferences. Based on these aspects, a user can be classified into different categories. In addition, contextual information, such as network conditions and mobile devices, is also considered in some learner models [8, 73]. A rich and accurate definition of the learner profile is fundamental to achieve personalized and adaptive learning [4, 74]. Ontology is an effective means for modeling learner profiles and contextual information. Figure 6 shows the general aspects considered in a learner model in the context of e-learning.

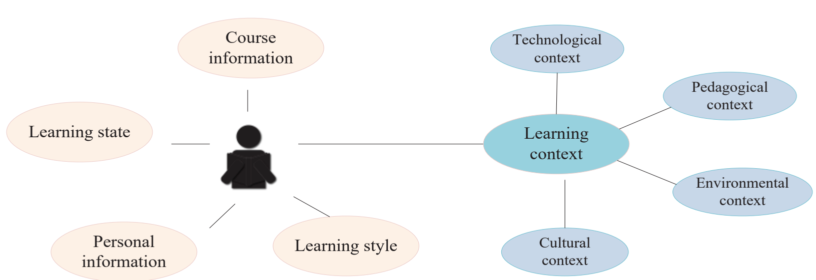

Figure 6 Learner profile and context.

The common method to model a learner is by defining classes and properties that capture the related aspects of a learner profile. For example, in [75], researchers proposed a student model consisting of 2 types of knowledge: student academic information and personal information. The Felder-Silverman theory for student learning style was transferred to ontology classes. The aim of this model was to provide a domain-independent vocabulary that could be used in the intelligent tutoring system (ITS). The student model defined in another study also modeled learning styles in its Learner's Characteristics Ontology [12]. The ontological student model proposed in [76] described dynamic learning styles by monitoring students' actions during the learning process. Yago et al. [74] proposed a student model called ON-SMMILE, defined as an ontology network containing information such as student knowledge and assessment.

Contextual information was also modeled as ontology. As shown in Figure 6, context can be classified into the cultural, environmental, pedagogical, and technological context. Some learning systems rely on the context data to realize learning content adaptation. For example, in one study, researchers modeled the student context by learning domain, profile, and environment using the network of ontologies [77]. The network of ontologies consists of learning, student, situation, and technological ontologies. In another study, a context-based ontology was defined that contained information such as the student, device, and location [78]. The aim of that ontology was to realize a context-aware e-learning environment. Pattanasri and Tanaka [79] proposed context ontologies to improve the efficiency of selecting proper learning resources.

3.2.5 Assessment modeling

An assessment is composed of activities that evaluate a particular domain topic. A number of studies focused on the use of ontologies for assessment modeling. In these works, assessment types (such as self-assessment and co-assessment) and questions (such as multiple-choice questions and open questions) were modeled as ontology classes and properties.

Romero et al. [88] developed an assessment ontology to define the concepts and relations of assessment in the e-learning context. The ontology modeled all related concepts of an assessment, such as the type, author, student, moment, and evaluator of an assessment. Mouromtsev et al. [89] proposed an educational ontology consisting of student activity and knowledge rate. The ontology was used to evaluate students' knowledge understanding in the e-learning system ECOLE. Jia et al. [90] proposed a performance-oriented approach to enhance e-learning in the workplace. Ontology was used for formal conceptualization of the learning assessment, such as the objectives and levels of a test.

3.2.6 Other education-related activity modeling

In addition to the above-mentioned educational ontologies, ontology has been applied to modeling other education-related activities (e.g., teaching through Twitter [95]) and other aspects (e.g., student disability assistance [96]). Muñoz et al. [97] proposed an ontology-based virtual education framework consisting of 4 layers (e.g., knowledge management and education process). The ontology layer is a transversal layer that defines the concepts, instances, and properties for the other 3 layers. Zemmouchi-Ghomari and Ghomari [98] described the process of building a heavyweight reference ontology for higher education that can be used to create specific ontologies and thus avoid having to build a domain ontology from scratch. In the specification phase, 81 CQs were identified. In the conceptualization phase, the authors identified concepts and their relationships using the data–dictionary–concepts hierarchy, attributes classification tree, and object properties table. An ontology, called AcademIS, for modeling teaching and research activities was defined in [99] to achieve better cooperation among the academic staff and to monitor cooperation status. AcademIS reused the VIVO ontology, which modeled the research aspects of an institution (e.g., the personnel, the courses and events offered within an academic institution). AcademIS also extended VIVO by defining classes: TeachingCollaborations, Internships, Scholarships and Thesis, so as to model the teaching activities and connections of academics. In [100], a set of online document editors, including Google Drive and Microsoft's OneDrive, were analyzed in an educational setting. The authors proposed an ontology consisting of a generic vocabulary for the interoperability of the online document editors used in e-learning environments. Iatrellis et al. [101] presented the EDUC8 ontology which covers the holistic aspects of e-learning processes including learner, learning pathway, organization, and quality.

4 Ontology-Based Educational Applications

In this section, we focused on ontology-based applications in e-learning environments, aiming to answer RQ3: "What are the various ontology-based applications for e-learning?" Studies dealing only with the development of

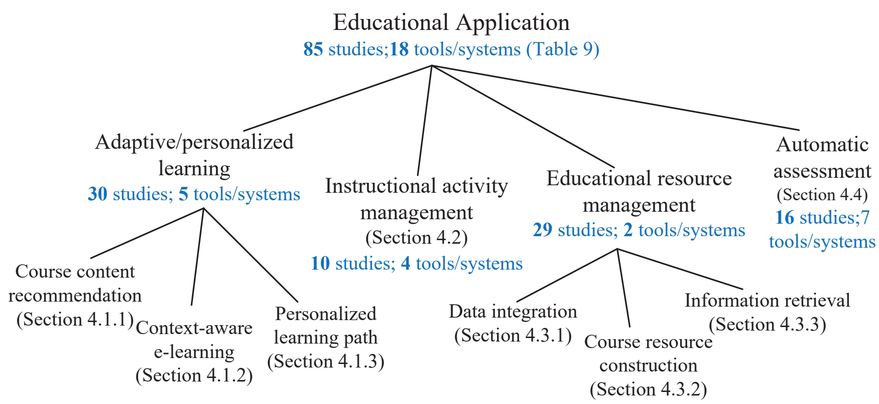

Figure 7 Classification of the research based on educational applications.

Note: The number of studies in each category is annotated. In addition, the number of tools or systems for each category is also annotated.

educational ontologies were omitted here. As shown in Figure 7, we classified the 85 studies related to ontology-based e-learning into 4 categories: adaptive/personalized learning, instructional activity management, educational resource management, and automatic assessment. In the following sub-sections, we review each type of application.

4.1 Adaptive/Personalized Learning Applications

The goal of adaptive/personalized learning is to improve educational outcomes by adjusting learning content and methods according to the learner's background knowledge and preferences. Much effort has been made to apply ontologies to adaptive or personalized learning. The main idea in such research is to use ontologies to model and transform learning content, student background knowledge, and contextual information into computer-understandable data resources, thereby achieving adaptable learning content and learning paths for different contexts.

4.1.1 Course content recommendation

Course content recommendation is an important functionality in adaptive e-learning systems. The task of the course content recommendation is to suggest suitable learning content for individual students according to their needs [4]. The fundamental part of such a learning system is course knowledge ontologies. A number of studies have realized the adaption of learning content based on course knowledge ontologies. Zeng et al. [13] proposed personalized course content recommendations based on course ontology according to users' knowledge requirements. An algorithm was presented for determining the learner's knowledge status by reading behavior logs. The approach presented in another study [102] adjusted content presentation, navigation, or content selection according to the user's situations, such as task and preference. Rani et al. [103] and Perišić et al. [76] presented ontology-based mechanisms to realize learning personalization according to various learning styles. Kontopoulos et al. [38] developed a system called PASER to automatically construct course plans based on AI planning and ontologies. LOs were stored and composed by PASER with metadata defined as the SKOS ontology. The key module in PASER is the planning engine, which could provide the learner with personalized curricula from educational resources.

4.1.2 Context-aware e-learning

As addressed in Section 3.2.4, context and learner information have been modeled by ontologies. Rich contextual information leads to a better understanding of users' behavior in order to adapt learning content. For example, Gómez et al. [78] developed a context-aware system that could deliver adaptable learning content according to time, location, and date. Gamalel-Din [104] proposed a smart e-learning knowledge base (SELK) for adaptive and personalized learning that contained ontologies related to student background knowledge and course material. Abech et al. [37] proposed a model called EduApdapt, which adapted LOs according to students' contexts, including their learning styles and devices. The core part of the model is a set of ontologies, including LO ontology and user context ontology. Gutiérrez-Carreón et al. [105] proposed using semantic web services to integrate a cloud service API with an educational system. Google Apps Cloud and Chamilo were integrated into a learning management application that took into consideration students' cognitive loads.

4.1.3 Personalized learning path

The learning path, in the context of e-learning, refers to a sequence of LOs or learning content [4]. If a learning system supports a personalized learning path for an individual student, it adapts the learning sequence to suit the background of the student. The system proposed in [101] can adjust learning pathways based on the EDUC8 ontology and SWRL rules. Puustjärvi [59] realized individual learning paths based on a competency ontology in the field of pharmacy. In another study [14], learning activities could be adjusted to different learners' characteristics. The core components were a set of educational ontologies, including the learning activities ontology and teaching method ontology.

4.2 Instructional Activity Management

Instructional activities refer to teaching-related activities, such as instructional design and curriculum management. As addressed in Sections 3.2.2 and 3.2.3, ontologies have been used to formalize curricula and syllabi as well as teaching methods. Based on these ontologies, instructional activity management in the e-learning context can be realized. Fernández-Breis et al. [60] introduced a software tool, Gescur, which is an educational curriculum management system. Teachers can use Gescur to create, access, and analyze educational curricula. Gescur supports detecting nonconformity in the execution of curricula and can assist teachers in defining corrective tasks and procedures. Isotani et al. [106] developed an authoring tool called CHOCOLATO that can assist teachers in designing collaborative learning scenarios. SMARTIES [11] also supports instructional designers for developing learning scenarios. The learning-support-related theory ontology OMNIBUS was built as a conceptual base. In [107], an educational ontology framework was presented to cover the lifecycle of a university course; the ontologies were categorized into 3 types: teaching activity, learning activity, and examination activity. Mandic [108] developed a software platform based on ontology matching for curriculum harmonization. A curriculum in the form of an ontology could be aligned with the reference model.

4.3 Educational Resource Management

The ontology technique is an ideal means for educational resource management. Ontology-based methods were proposed to deal with data integration, course resource construction, and course content retrieval.

4.3.1 Data integration

Ontology is an ideal technique for integrating various learning resources. A number of researchers used LOD to integrate learning resources. In [43], video lectures extracted from YouTube and Videolecutures.net were integrated by the vocabularies defined in Dublin Core and FOAF. Al Fayez and Joy [2] dealt with educational resource integration in the context of medical education. A system was presented for interlinking different types of

Educational Medical Objects (EMOs) into a linked data set named the Linked Educational Medical Objects (LEMO) data set. Bansal and Kagemann [109] proposed an extract–transform–load semantic framework to integrate various data sources and publish data as LOD. Other researchers [110] integrated heterogeneous e-learning resources by a mediate ontology. Contextual information, such as locality, was defined as a sub-ontology, which was used to realize resource re-use. Zemmouchi-Ghomari et al. [98] built a reference ontology for higher education based on the NeOn methodology. Reference ontologies can be used to create specific ontologies, helping developers to avoid building domain ontologies from scratch.

4.3.2 Course resource construction

Course resources can be built manually or automatically as ontologies. Lubliner and Widmeyer [9] developed a disciplinary knowledge repository for concept learning by using a voting mechanism involving teachers and students. Lama et al. [28] dealt with the construction and maintenance of large-sized LO repositories by classifying LOs using the categories of DBpedia. The linking from the LOs to the DBpedia resource was through the property dcterms:subject.

Some studies used NLP algorithms to (semi)-automatically extract course knowledge from textual materials. Zouaq and Nkambou [41] semi-automatically transformed textual LOs into concept maps first and then into domain ontologies. Larrañaga et al. [111] developed an ontology-based system called DOM-Sortze to support the semi-automatic construction of domain modules from textbooks. Gaeta et al. [57] also extracted concepts and relationships from text documents and created domain ontologies. A profile for LOM was proposed in the literature [26] to characterize the educational resources used in distance-learning courses.

4.3.3 Information retrieval

Researchers have also focused on learning content retrieval and LO searching for e-learning based on ontology. Ahmed-Ouamer [112] indexed educational documents based on domain ontologies. Semantic links between documents were created to allow the inference of the relevant documents. Pattanasri and Tanaka [79] enhanced lecture material retrieval, especially video lectures, based on an entailment ontology. The entailment ontology captured 2 types of context, primary and secondary, which were used to identifying the context of the learning materials. Hsu [29] defined LOFinder, an intelligent LOM shell, to enhance the semantics and knowledge representation of LOM. LO discovery could be enhanced by using LOFinder. In another study [30], course ontologies were used to re-write and improve users' queries in LO searches. The main idea was to extend users' short queries with an expansion algorithm.

4.4 Automatic Assessment

Automatically generating high-quality exercises or test questions is a challenging problem in e-learning. As addressed in Section 3.2.5, ontologies have been used to model the various aspects of assessments in order to support e-assessment applications. Sánchez-Vera et al. [113] generated feedback for online assessments automatically based on ontologies, semantic annotation, and NLP algorithms. The automatic feedback algorithm took questions and answers as inputs and generated feedback by calculating the similarities between annotations. Vinu and Kumar [114] developed a prototype called Automatic Test Generation, E-ATG, that could generate multiple-choice questions based on domain ontologies. In the system, a set of heuristics was employed to select only those questions that were most appropriate for conducting a domain-related test. Leo et al. [115] also focused on automatic multiple-choice questions creation. The authors developed a system called EMCQG based on the Elsevier Merged Medical Taxonomy (EMMeT) knowledge base, which could generate medical case-based questions requiring require more than recall of information to be solved. In one study [116], RDFS ontologies were applied to a semi-automatic assessment system for evaluating learners' credentials and competencies. Mouromtsev et al. [89] proposed an approach to estimate students' knowledge status based on the ontology of the knowledge rate. The knowledge rates were estimated by the metrics related to students' test results and learning experience.

5 Discussions

In this section, we discuss how Sections 3 and 4 addressed the three research questions RQ1–RQ3.

5.1 RQ1: How is Ontology Used for Knowledge Modeling in the Context of e-learning?

Section 3.2 addressed RQ1: How is ontology used for knowledge modeling in the context of e-learning? Figure 8 summarizes the current research trends

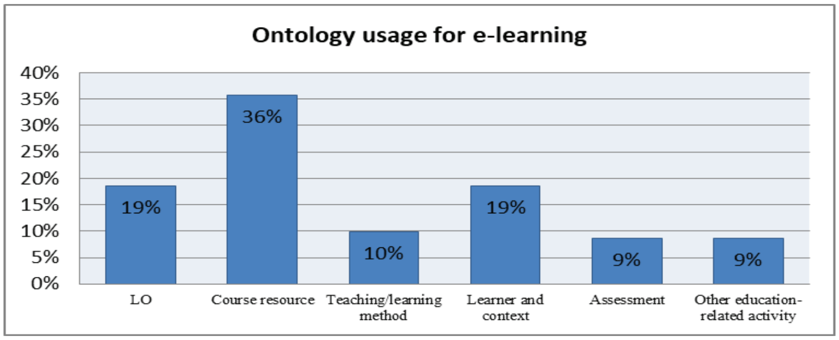

Figure 8 Ontology use in e-learning environments.

in ontology usage as indicated by Tables 2–8 of the 81 ontologies.[4] Among the 6 types of ontology usage, course resource modeling is the major one, accounting for 36% of the research efforts. Nineteen percent each of the ontologies model LOs and learner/contextual information. Ten percent of the ontologies model teaching and learning methods. In addition, 9% each of the ontologies were about assessment and other education-related activities. We observed that ontology is an ideal technique for solving the problems of modeling the various types of knowledge in e-learning systems. Ontology-based models improved the interoperability of learning resources, enriched learner models, and provided the basis for personalizing educational content.

5.2 RQ2: What are the Design Principles, Building Methods, Scale, Level of Semantic Richness, and Evaluation of Current Educational Ontologies?

Section 3.2 also addressed RQ2: What are the design principles, building methods, scale, level of semantic richness, and evaluation of current educational ontologies? Figure 9 summarizes the overall results from Tables 2–8 of the educational ontologies by the 5 measures (DM, BR, SO, LSR, and OV). Based these results, we are able to answer RQ2.

DM: As shown in Figure 9(a), 55% of the educational ontologies were created from scratch without CQs, and 6% used CQs in the design phase.

[4]Using the 112 selected papers, we analyzed the papers with enough details about ontologies in this section. Some of the papers were only studied in Section 5 for their ontology-based applications.

Twenty-nine percent of the ontologies were developed by re-using ontological resources, 8% re-using non-ontological resources, and 1% re-using ontology design patterns. Ontology development requires considerable effort. Thus, ontology re-use is a solution for improving the efficiency of ontology engineering. The W3C standards, such as RDF, RDFS, and OWL, advocate web resource sharing and re-use. As such, ontologies defined in these languages are easy to re-use and integrate. The results of DM indicate that most of the studies proposed defining their own ontologies from scratch, while not taking advantage of the ontology technology to re-use existing resources. Researchers should therefore pay more attention to platforms and approaches for facilitating ontology re-use in the educational field.

BR: As shown in Figure 9(b), among the 81 educational ontologies, 89% were constructed manually, and only 2% were automatically created; 7% were created semi-automatically, while 1% of the papers did not specify the building routine. Manually developing large-scale ontologies is both time consuming and prone to error. The cost and effort of manually developing and maintaining educational ontologies were not mentioned in the reviewed literature. In the field of ontology engineering, researchers have worked on ways to automatically create high-quality ontologies. The results of BR suggest that the educational domain needs to take advantage of the techniques obtained in the ontology engineering field to improve the efficiency of ontology development.

SO: Figure 9(c) presents the average and median values of the domain classes and properties, respectively. The average value of the domain classes is 71, while the median is 22. The average value of the domain properties is 132, and the median is 13. These values indicate that educational ontologies have small-scale ontology schema. Furthermore, most of the studies did not provide any data about the instances and scale. To benefit from the ontology technology for e-learning, large-scale and high-quality course knowledge bases and other types of educational ontologies need to be constructed as gold standards for future research.

LSR: Since educational systems are knowledge-intensive systems that require rich, high-quality knowledge bases to realize various e-learning applications, the richer the ontology, the more complex applications a system can support. For this reason, the semantic richness of educational ontologies is important. Figure 9(d) shows the levels of semantic richness for current educational ontologies. Among the 81 educational ontologies, 53% of the

Figure 9 Statistics for the 5 measures: (a) DM, (b) BR, (c) SO, (d) LSR, and (e) OV.

ontologies are proper ontologies, indicating a high level of semantic richness. Twenty-three percent belong to thesaurus and formal taxonomy each.

OV: Ontology evaluation is an essential part of ontology development. Figure 9(e) shows that 59% of the ontologies were evaluated at the application level, 10% at the vocabulary level, and 4% at the structural level. There were 27% of the ontologies that did not specify the evaluation details. For ontology-based learning systems, the ultimate goal of building educational ontologies is to support e-learning management, and thus application-level evaluation proves the effectiveness of ontologies. Evaluations at the vocabulary and structural levels are also important for creating high-quality, large-scale, and complex ontologies. When re-using ontologies, vocabulary and structure information about an ontology is important for understanding and optimizing the ontology for better re-use.

5.3 RQ3: What are the Various Ontology-based Applications for e-learning?

Section 4 addressed RQ3 by reviewing ontology-based e-learning systems according to 4 categories: adaptive/personalized learning, instructional activity management, educational resource management, and automatic assessment.

Figure 10 shows that among the 85 research papers, most focused on adaptive/personalized learning (35%) and educational resource management

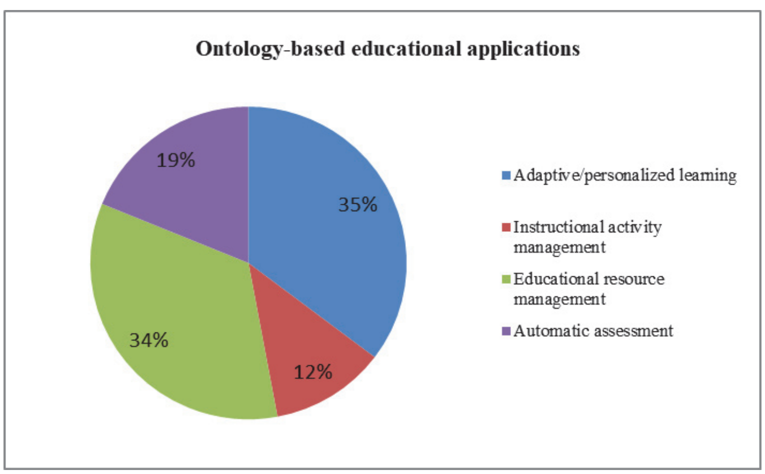

Figure 10 Ontology-based educational applications.

(34%). Meanwhile, 12% and 19% of the papers concerned instructional activity management and automatic assessment, respectively. The results indicate that the major applications of ontologies were adaptive/personalized learning and educational resource management. Few studies have investigated instructional activity management and automatic assessment. We suggest that more attention should be paid to these 2 applications since they are important for e-learning systems.

In addition to the classification of applications, Table 9 summarizes the educational systems and tools reported in the literature. Studies only involving approaches or algorithms, but with no implementations, were omitted from the table. Comparing the number of studies (85) with the systems and tools (18) listed in Table 9, we notice that the implementation of the proposed approaches and algorithms in recent research is inadequate. Most of the studies focused on methodologies, frameworks, and algorithms without implementing prototype tools and systems. Therefore, we suggest that more attention should be paid to developing and improving ontology-based e-learning systems and tools.

6 Conclusion

This study reviewed 112 papers from the last 12 years related to ontology for e-learning contexts. First, we classified the educational ontologies into 6 types and selected 5 measures related to ontology design, creation, scale, semantic richness, and evaluation. Then, we reviewed the educational ontologies in terms of the 5 measures. Finally, we summarized ontology-based educational applications and sorted out the systems and tools developed in these studies. In addition to those findings, we identified 4 issues in existing studies that should be addressed. First, the rate of re-using ontological resources (29%) suggests that learning resource sharing should be encouraged. Second, (semi)-automatic ontology engineering approaches remain immature; specifically, 89% of the ontologies were manually constructed, while only 2% were built automatically. In addition, the quality of educational ontologies needs to be guaranteed by paying more attention to structural evaluation, which was not considered in most of the studies. Finally, we suggest that researchers should value the development of ontology-based e-learning systems and tools, which could help to improve the comparison of the systems and tools.

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Appendix

Table 2 Comparison of LO ontologies using the 5 measures

Reference	DM	BR	SO		LSR	OV
			Domain Classes	Domain Properties		
[25]	Methodology D	Manual	15	8	Proper ontology	Application level
[26]	Methodology C	Manual	12	27	Proper ontology	Application level
[27]	Methodology D	Manual	26	42	Thesaurus	Application level
[28]	Methodology D	Manual	4	2	Thesaurus	Application level
[29]	Methodology A	Manual	4	7	Proper ontology	Application level
[30]	Methodology D	Manual	30	7	Thesaurus	Application level
[31]	Methodology D	Manual	Unclear	12	Proper ontology	Unclear
[32]	Methodology A	Manual	6	3	Thesaurus	Application level
[33]	Methodology A	Manual	12	10	Proper ontology	Unclear
[34]	Methodology B	Manual	18	21	Formal taxonomy	Unclear
[35]	Methodology A	Manual	23	21	Proper ontology	Unclear
[36]	Methodology A	Manual	6	15	Proper ontology	Unclear

(*Continued*)

Table 2 Continued

Reference	DM	BR	SO Domain Classes	SO Domain Properties	LSR	OV
[37]	Methodology B	Manual	30	47	Proper ontology	Application level
[38]	Methodology A	Manual	22	1	Formal taxonomy	Application level
[39]	Methodology C	Unclear	43	Unclear	Formal taxonomy	Unclear

Table 3 Comparison of course ontologies using the 5 measures

Reference	DM	BR	SO Domain Classes	SO Domain Properties	LSR	OV
[9]	Methodology A	Manual	Unclear	Unclear	Proper ontology	Application level
[10]	Methodology A	Semi-automatic (Text-2-Onto)	Unclear	2	Thesaurus	Vocabulary level
[40]	Methodology A	Semi-automatic (Text-2-Onto)	94	2	Formal taxonomy	Vocabulary level
[41]	Methodology A	Semi-automatic (TEX-COMON)	1,139	1,973	Proper ontology	Structural level
[42]	Methodology C	Semi-automatic (DBpedia Spotlight)	Unclear	Unclear	Formal taxonomy	Vocabulary level
[43]	Methodology D	Automatic	Unclear	12	Formal taxonomy	Application level

(*Continued*)

Table 3 Continued

Reference	DM	BR	SO: Domain Classes	SO: Domain Properties	LSR	OV
[44]	Methodology D	Manual	Unclear	7	Proper ontology	Application level
[45]	Methodology A	Manual	49	13	Proper ontology	Unclear
[46]	Methodology A	Manual	15	Unclear	Formal taxonomy	Application level
[47]	Methodology A	Manual	10	2	Thesaurus	Application level
[48]	Methodology D	Manual	23	14	Proper ontology	Application level
[49]	Methodology A	Manual	22	13	Proper ontology	Application level
[50]	Methodology A	Manual	35	24	Formal taxonomy	Application level
[51]	Methodology A	Manual	7	Unclear	Formal taxonomy	Application level
[52]	Methodology A	Manual	8	15	Proper ontology	Application level
[53]	Methodology A	Manual	3	Unclear	Thesaurus	Application level
[54]	Methodology A	Semi-automatic (NER)	8	2	Formal taxonomy	Vocabulary level
[55]	Methodology D	Manual	23	4	Formal taxonomy	Vocabulary level
[56]	Methodology C	Manual	19	9	Proper ontology	Application level
[57]	Methodology A	Automatic (NLP algorithms)	Unclear	4	Thesaurus	Vocabulary level
[58]	Methodology D	Semi-automatic	121	282	Proper ontology	Vocabulary level

Table 4 Comparison of the curriculum and syllabus ontologies using the 5 measures

Reference	DM	BR	SO		LSR	OV
			Domain Classes	Domain Properties		
[59]	Methodology A	Manual	8	20	Proper ontology	Unclear
[61]	Methodology C	Manual	23	7	Proper ontology	Unclear
[60]	Methodology A	Manual	91	242	Proper ontology	Application level
[62]	Methodology A	Manual	8	Unclear	Proper ontology	Unclear
[63]	Methodology C	Manual	33	4	Proper ontology	Unclear
[64]	Methodology D	Manual	34	Unclear	Proper ontology	Application level
[65]	Methodology E	Manual	23	3	Proper ontology	Unclear
[66]	Methodology D	Manual	55	69	Proper ontology	Structural level

Table 5 Comparison of the ontologies related to the teaching/learning method using the 5 measures

Reference	DM	BR	SO		LSR	OV
			Domain Classes	Domain Properties		
[11]	Methodology A	Manual	1259	4452	Proper ontology	Application level
[14]	Methodology A	Manual	33	35	Formal taxonomy	Unclear
[67]	Methodology A	Manual	47	Unclear	Formal taxonomy	Unclear
[68]	Methodology D	Manual	6	14	Thesaurus	Application level
[69]	Methodology A	Manual	933	64	Formal taxonomy	Vocabulary level
[70]	Methodology D	Manual	4	15	Proper ontology	Application level
[71]	Methodology A	Manual	7	6	Thesaurus	Unclear
[72]	Methodology D	Manual	Unclear	Unclear	Proper ontology	Application level

Table 6 Comparison of the ontologies related to the learner and context using the 5 measures

			SO			
Reference	DM	BR	Domain Classes	Domain Properties	LSR	OV
[12]	Methodology A	Manual	21	Unclear	Formal taxonomy	Application level
[74]	Methodology D	Manual	23	24	Proper ontology	Application level
[75]	Methodology C	Manual	18	9	Proper ontology	Unclear
[76]	Methodology A	Manual	36	Unclear	Formal taxonomy	Application level
[77]	Methodology D	Manual	31	20	Proper ontology	Unclear
[78]	Methodology D	Manual	10	5	Proper ontology	Application level
[79]	Methodology A	Manual	Unclear	2	Thesaurus	Application level
[80]	Methodology A	Manual	20	17	Thesaurus	Application level
[81]	Methodology A	Manual	22	16	Proper ontology	Application level
[82]	Methodology A	Manual	35	Unclear	Formal taxonomy	Unclear
[83]	Methodology A	Manual	14	Unclear	Thesaurus	Unclear
[84]	Methodology A	Manual	8	11	Thesaurus	Application level
[85]	Methodology A	Manual	10	Unclear	Thesaurus	Unclear
[86]	Methodology A	Manual	32	Unclear	Proper ontology	Structural level
[87]	Methodology A	Manual	5	26	Formal taxonomy	Unclear

Table 7 Comparison of the ontologies related to assessments using the 5 measures

Reference	DM	BR	SO Domain Classes	SO Domain Properties	LSR	OV
[88]	Methodology B&D	Manual	62	21	Proper ontology	Application level
[89]	Methodology D	Manual	26	41	Proper ontology	Application level
[90]	Methodology A	Manual	40	7	Proper ontology	Application level
[91]	Methodology A	Manual	14	13	Thesaurus	Application level
[92]	Methodology A	Manual	55	Unclear	Thesaurus	Application level
[93]	Methodology A	Manual	22	6	Proper ontology	Application level
[94]	Methodology A	Manual	34	Unclear	Proper ontology	Application level

Table 8 Comparison of the ontologies related to other educational activity using the 5 measures

Reference	DM	BR	SO Domain Classes	SO Domain Properties	LSR	OV
[95]	Methodology D	Manual	7	Unclear	Thesaurus	Application level
[96]	Methodology D	Manual	19	Unclear	Formal taxonomy	Application level
[97]	Methodology A	Manual	54	3	Formal taxonomy	Unclear
[98]	Methodology B&D	Manual	14	51	Proper ontology	Application level
[99]	Methodology D	Manual	78	Unclear	Proper ontology	Application level
[100]	Methodology A	Manual	7	10	Thesaurus	Application level
[101]	Methodology B	Manual	38	Unclear	Proper ontology	Application level

Table 9 E-Learning systems and applications

Category of Application	System/Tool	Function/Feature
Adaptive/ personalized learning	Adaptive e-learning system [103]	Felder-Silverman learning style model; cloud-based ontology storage
	PASER [38]	Ontology-based planning system for adaptive course plans
	Decision-support tool [68]	Ontology of users, teachers, courses, and specializations; recommendation system based on semantic knowledge base
	EDUC8 [101]	Learning process execution engine supported by a semantic framework; personalized learning pathways
	PROTUS [50]	Web-based programming tutoring system; recommends personalized links and actions for students
Instructional activity management	Gescur [60]	Curriculum management system based on ontologies; monitors the execution of a curriculum
	CHOCOLATO [106]	Intelligent authoring tool based on semantic technologies; selection of interaction patterns and learning strategies.
	PRINTEPS [117]	Knowledge-based reasoning; quiz editing module based on ontology and rules
	SMARTIES [11]	An intelligent authoring system based on OMNIBUS
Educational resource management	DOM-Sortze [111]	Semi-automatic construction of domain modules from textual documents
	LOFinder [29]	Retrieves LOs based on multilayered semantic LOM framework
Automatic assessment	GAMES [37]	Automatically generates math exercises based on ontology
	E-ATG system [114]	Generates multiple-choice questions based on ontology and heuristics
	ECOLE [89]	Assesses students' knowledge rates based on ontologies

(*Continued*)

Table 9 Continued

Category of Application	System/Tool	Function/Feature
	OeLE [113]	Automatic feedback generation of online assessment
	OFGA [88]	Assessment generation and validity checking according to the pedagogical rules
	Workplace e-learning system prototype [90]	A performance-oriented e-learning systems in the workplace
	EMCQG [115]	Automatic generation of multiple-choice questions targeting the medical domain.

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