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LEARNING OBJECT FROM EMERGENCE TO NOWADAYS: SYSTEMATICS LITERATURE REVIEW

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ABSTRACT

The e-learning domain is one of the richest fields of scientific research. It has witnessed a rapid development and has become a popular topic since the 1990s. In this article, we present a systematic literature review of the evolution and development of the learning object concept. Firstly, we present the different proposed definitions, characteristics, and types of learning objects. Secondly, we introduce learning object metadata standards, and learning object models. Finally, the different types of recommender systems are presented, as well as the different recommender systems and models developed to recommend learning objects to learners. Analyzing and summarizing studies on learning objects published in the 21st century is the objective of this study. Through the use of appropriate keywords and the application of inclusion and exclusion criteria, a total of 205 papers were identified during the search process.

Keywords: *Learning Object, E-learning, Recommender system, Learning style, LOM*

1. INTRODUCTION

In the 21st century, the e-learning area has been developed rapidly, and has become a major subject and alternative approach in the learning and teaching processes [1]. In 1998, Jay Cross wrote coined the term “e-learning” and he defined it as “learning on Internet Time, the convergence of learning and networks. E-Learning is a vision of what corporate training can become. E-Learning is to traditional training as e-business is to business as usual” [2]. However, the initial usage of the term "e-learning" being employed in a professional setting occurred in October 1999 at a seminar on Computer-Based Training (CBT) Systems. It is described as: “a way to learn based on the use of new technologies allowing access to online, interactive and sometimes personalized training through the Internet or other electronic media (intranet, extranet, interactive TV, CD-ROM, and so on), to develop competencies while the process of learning is independent of time and place” [3]. According to [4], concerning e-learning, three essential components are identified: Learning Objects (LO) are the educational materials, Learning Objects Repository (LOR) is where they are stored, and Learning Environment (LE) is where these materials are used. Similarly [5], [6] considered LO as one of the most important component of e-learning. Ritzhaupt [7] provided a thorough analysis on the history, definition, application, and evolution of LO systems. Similarly, the authors [8] described the design, the sequencing, the composition, the presentation, and the evaluation of LO. Recently, LO become one of the most important research topics in the e-learning community [9], especially in the context of COVID-19 pandemic, where the usage of LO has increased rapidly [10]. LOs are developed under e-learning specifications and standards, the majority of those standards are presented in [11]. On the other hand With the fast growth of LOs in various media formats, finding the correct learning objects (LOs) that meet their needs and preferences can be a challenging task for students [12]. While, recommender systems in e-learning attempt to find and provide appropriate LO to learners based on learner's interest [13], [14]. LOs are recommended through implementing a variety of recommendation algorithms focusing primarily on content based filtering and collaborative filtering approaches, each employed individually or together [15]. This article presents a systematic literature review on the development and evolution of the learning object and its use in recommender systems. 205 studies published in the 21st century are analyzed and summarized in order to answer the following research questions:

- RQ1: What is a learning object, and what are its characteristics?
- RQ2: What is the most common metadata standard used in learning object?
- RQ3: How is learning object modeled?
- RQ4: How are learning objects recommended?

This paper is organized into four sections this introduction being the first. Section 2 outlines the research methodology, while section 3 covers the results and discussion. The conclusion is provided in section 4.

2. METHODOLOGY

This study presented a systematic review, which consists of clearly identifying, selecting, and assessing the pertinent studies that enable us to respond to our research questions clearly and explicitly. This survey article is done in four phases [16],[17],18]:

- Identification: Identify the systematic review objectives, research questions, and keywords.
- Search: Conducting a database search through the selected keywords.
- Filtering: Application of inclusion and exclusion criteria.
- Report: Summarization and thorough analysis of the selected study.

2.1 Data Collection

The research carried out mainly in the following databases: the libraries of the Institute of Electrical and Electronics Engineers (IEEE)[1], Science direct[2], Springer Link[3], and Multidisciplinary Digital Publishing Institute (MDPI[4])., the Association for Computing Machinery (ACM)[5]. For the other databases, Google Scholar[6] was used as a search engine. The keywords used in search are "Learning object", "Classifications", "Characteristics", "Model", "Ontology", and "Recommender systems". These keywords are combined with the Boolean operators (AND, OR).

[1] https://ieeexplore.ieee.org
[2] https://www.sciencedirect.com
[3] https://link.springer.com/
[4] https://www.mdpi.com/
[5] https://dl.acm.org/
[6] https://scholar.%google.com/

2.2 Inclusion and Exclusion Criteria

The most relevant studies were selected after retrieving the publications and reading the abstract, keywords, and the conclusion. In the next stage of filtering, the following inclusion criteria were applied:

- Presented the LO history, definitions, and classifications.
- Proposed LO model.
- Presented or compare LO metadata standard.
- Proposed prototype, or model to recommend the LO.
- Presented systematic literature review on recommender systems in e-learning flied.

The final stage of filtering was the application of the below exclusion criteria to the previously chosen papers.

- The full text of the article is inaccessible.
- The language of the article is not English.
- The model presentation is vague.
- The recommended item is not LO.

In the final phase of data collection, the selected publications were read, analyzed, and summarized.

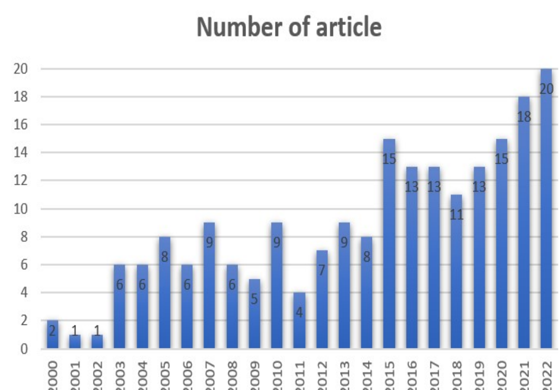

Figure 1: Distribution of publications by year.

3. RESULTS AND DUSCUSSION

3.1 Learning Object

In 1994, Wayne Hodgins used, for the first time, the term "learning object" to name his group at Computer Education Managers Association (CedMa):" Learning Architectures, APIs, and Learning Objects" [19],[20],[21],[22].

3.1.1 Definitions Learning Object

Research have attempted to define the learning object since its inception in order to fill gaps in its definition; therefore, there are several proposals. For example, the authors [22],[23],[24], classified

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and critiqued the previous definitions, and they suggested these definitions, respectively: "A LO is an independent and self-standing unit of learning content that is predisposed to reuse in multiple instructional contexts." [22], "A LO is a digital file (image, movie, etc.) intended to be used for pedagogical purposes, which includes, either internally or via association, suggestions on the appropriate context within which to utilize the object."[23], and "Any reusable digital resource that is encapsulated in a lesson or assemblage of lessons grouped in units, modules, courses, and even programmes."[24]. While, Churchill [25] presented twelve definitions from 1998 to 2005 and defined LO as "a representation designed to afford uses in different educational contexts.". Whereas, the authors [26] presented and analyzed 24 proposed definitions from 2000 to 2015, and they conclude that "The vast majority of definitions identify a LO with an entity, atom, piece of Lego, building blocks, learning units or resources. An underlying concept of an independent and minimal element that can form part of bigger ones is underlying".
The following definitions in Table 1 are not mentioned in the previous study:

Table 1: Learning object's definitions.

Citation	Year	LO definition
[27]	2003	"A digital learning resource that facilitates a single learning objective and which may be reused in a different context."
[28]	2003	"A LO is a collection of digital materials — pictures, documents, simulations — coupled with a clear and measurable learning objective or designed to support a learning process."
[29]	2004	"Any digital resource that can be used and reused to achieve a specific learning outcome or outcomes".
[30]	2005	"A significant instruction entity (maybe a text, a talk, a test, or other kinds of representations), which belongs to a fact, concept, principle, or mental model.".
[31]	2005	"A digital object that is used in order to achieve the desired learning outcomes or educational objectives.".
[21]	2007	"A digital resource that can be reused to mediate learning".
[32]	2008	"Interactive web-based tools that support the learning of specific concepts by enhancing, amplifying, and guiding the cognitive processes of learners".
[33]	2014	"Any digital resource that can be reused to provide a competency gain."
[34]	2015	"A LO is an example of a resource used to facilitate accessibility, interoperability, and reusability of learning materials."
[35].	2015	"An independent digital didactic unit formed by a specific learning goal, contents, activities, and self-assessment that can be reused in various educational and technology contexts (repositories teaching and learning virtual environments)."
[36]	2018	"A modular resource, usually digital and web-based, that can be used and re-used to support learning activities"
[37]	2020	"Any entity, digital or non-digital, that is used for learning, education, or training".
[10]	2022	*"Digital,* independent and autonomous units, which might be used and reused in different teaching/learning contexts.".
[38]	2022	"Verified information resources (data, facts, pictures, and videos) related to the learning objectives/goals".

3.1.2 Characteristics Learning Object

According to [20],[22],[29],[39], LO should meet certain characteristics or properties to be considered as such. Friesen [40] presented the characteristics agreed upon by the scientific community for LO which are: accessibility, reusability, and interoperability. Some authors, such as [41],[42],[43],[44] add durability.

- Accessibility: This characteristic is defined by [20],[43] as "the ability to locate and access instructional components in a remote location and distribute them to other locations".
- Interoperability: is defined as "the ability to take an instructional component from one location, developed with a particular set of tools, and use it in another location and with a different set of tools or platforms" [20],[43].

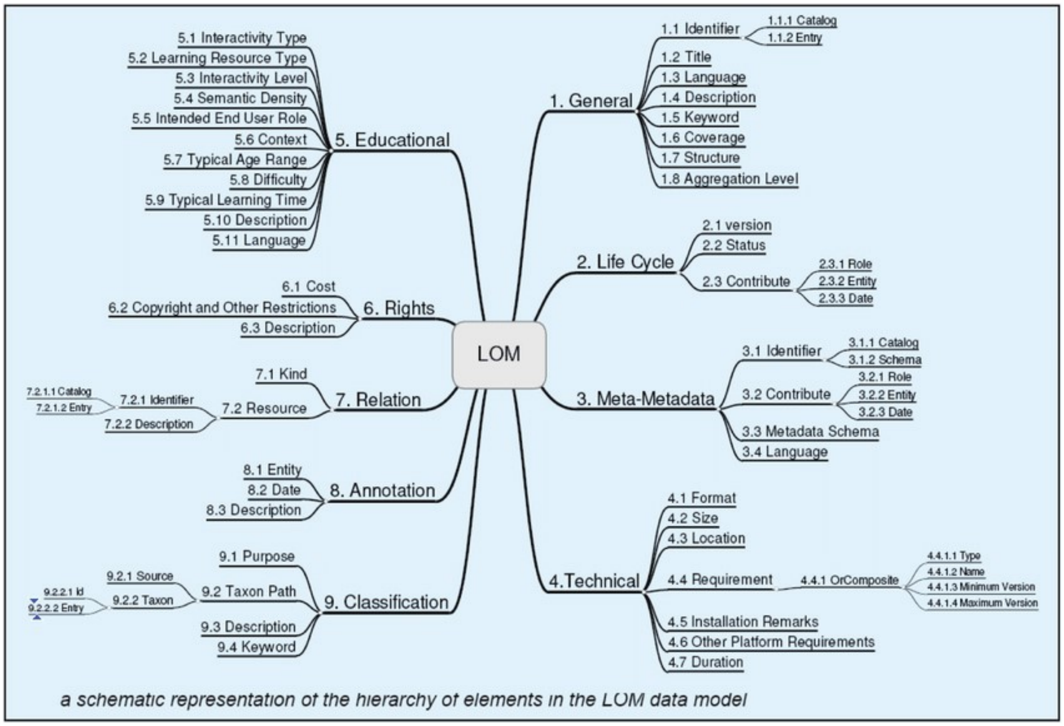

Figure 2 : Complete IEEE LOM hierarchy [62].

- Reusability: defined as "the possibility and adequacy for the object to be usable in prospective educational settings" [44], while for [43], reusability is the "ability to incorporate educational components in multiple applications and contexts".
- Durability: can be defined as "the ability to withstand technology evolution and change without undergoing costly redesign, reconfiguration or recoding" [43]. While McGreal considered it the ability for "instructional components to be used when base technology changes without the need to be redesigned or re-coded" [20].

It is not possible to leave this section without addressing a topic as controversial for LO as it is sensitive for reuse, i.e., granularity that represents the size of a LO. "The most difficult problem for LO designers is 'granularity'- how big should a LO be?" [45],[46]. There is a general agreement that lower granularity favors reusability. That is, the smaller the number of topics a LO addresses (low granularity) the greater the chances of reusing the LO. "The size of a LO is crucial for successful reuse" [40],[47].

3.2 Learning Object Metadata Standards

Learning Object Metadata Standards specify a collection of data fields for describing LOs, along with the terms, characteristics, and formats that may be utilized [49]. The authors [50],[51] presented and compared many standards, while, according to [8],[11],[49],[52–57], the most common metadata standard used in the representation of learning objects is IEEE LOM.

In this section, we detail the most common learning object metadata standards used to model LO [56,58–61].

3.2.1 Learning Object Metadata

The model specifies how LO should be described. It has nine categories: General, Life cycle, Meta-Metadata, Technical, Educational, Rights, Relationship, Annotation, and Classification [37].

The standard's objective is to make easier for learners, teachers, and automated software processes to find, assess, acquire, share, trade, and use LOs [37]. The complete IEEE LOM hierarchy can be seen in Figure 2.

The IEEE Std 1484.12.1™-2020 (Revision of IEEE Std 1484.12.1-2002) standard on metadata for LOs describes each category as follows in Table 2 [37].

Table 2: Description of IEEE LOM Standard.

Category	Description
General	Groups the overall information that characterizes the LO.
Life Cycle	Provides an overview of

	the history and current state of the LO, as well as the entities that have influenced its development over time.
Meta-Metadata	Focuses on the metadata record itself instead the LO it describes.
Technical	Explains the technical prerequisites and benefits of the LO.
Educational	Outlines the fundamental educational or pedagogical features of the LO.
Rights	Explains how the LO can be used and its intellectual property right
Relationship	Specifies the relationship between the LO and other LOs,
Annotation	Offers insights on the educational application of the LO, including details about the timing and authorship of the provided comments
Classification	Specifies the placement of the LO within a specific classification system

3.2.2 Sharable Content Object Reference Model

The Advanced Distributed Learning (ADL) Initiative developed the Sharable Content Object Reference Model (SCORM®), in 2000 to overcome e-learning interoperability, reusability, and durability issues. The most recent release (2009) is SCORM 2004 4th Edition [63].

This specification integrates components from the IEEE LTSC and IMS specifications, forming the basis of the SCORM standard, which encompasses four key elements [64,65]:

- Part 1, an overview is presented, encompassing high-level conceptual details, the historical background, current status, and future directions of ADL and SCORM.
- Part 2, focusing on the SCORM Content Aggregation Model (CAM), delves into the components of learning objects, their packaging for system-to-system exchange, description for search and discovery, and the definition of sequencing rules for these components.
- Part 3 elucidates the sequencing and navigation of learning objects, outlining how SCORM-compliant content can be sequenced through a series of events initiated by the learner or the system.
- Part 4 addresses the SCORM run-time environment, aiming to facilitate interoperability between learning content and Learning Management Systems (LMSs). This section outlines LMS requirements for managing the run-time environment, including the content launch process, standardized communication between content and LMSs, and the use of standardized data model elements for conveying information relevant to the learner's experience with the content.

3.3 Learning Object Model

The literature has shown that there are numerous LO models, the majority of which use the Unified Modeling Language (UML) and ontology, more recently, the LOs are modeling by standards [66], and the LO model has become a required component of e-learning recommender systems.

The authors proposed [64],[67],[68], reviewed [64],[67–71], and compared [64],[71],[72],[73] LO models. The most common LO models used are:

- National Education Training Group (NETg) Learning Object Model [64],[67–70],[72],[73]
- Learnativity content model [64],[67],[68],[70–73]
- SCORM content model [64],[67–73]
- Navy content model [64]
- Cisco Reusable Learning Object (RLO) / Reusable Information Object (RIO) Model [64],[67–73]
- Dynamic Learning Content Management System Component Model (dLCMSC) [64]
- New Economy Didactical Model [64]
- Semantic Learning Model (SLM) [64]
- Passauer Knowledge Management System (PaKMaS) [64]
- Aggregation model of the IEEE LOM [68],[69],[70],[71]
- Object Oriented Generic Learning Object Model (OOGLOM) [68]
- Reusable Multipurpose Learning Object Model (RMLOM) [67]
- General Learning Object Content Model [67]
- VMC-Graz Learning Content Model [67]

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- Abstract Learning Object COntent Model (ALOCOM) [64]
- Knowledge Puzzle Content Model [74]
- Learning content management system (LCMS) [71],[75]
- Distributed National Electronic Resource & Learning Objects (DNER&LO) [63,68]

3.4 Learning Object Repository

Learning Object Repositories (LORs) are basically electronic databases or digital libraries, where LOs and/or related metadata are structured, classified, and stored. Those LOs can be shared, used, and, reused by different teachers to provide online learning opportunities for their learners [48],[77].

Four different types of LORs can be identified based on their infrastructure [78]: centralized LO and metadata, centralized LO and distributed metadata, distributed LO and centralized metadata, and distributed LO and metadata.

The authors [50] presented, and compared many LOR. According to [48],[79], the most popular LOR includes:

- MERLOT (Multimedia Educational Resource for Learning and Online Teaching) is a free LOR operated by the California State University system. It offers to higher education learners and instructors interactive e-learning objects.
- DOOR (Digital Open Object Repository) is a centralized LOR created by the University of Italian Switzerland to aid in the creation, distribution, and reuse of LOs, improve the effectiveness and efficiency of developing and delivering online learning.
- ARIADNE was developed by the Rhaptos project. It is a tool for managing and storing digital LOs. These LOs can be generated by both teachers and students and utilized for a range of activities, such as teach, learn, research, and professional development.

More recently, researchers introduced their own LORs such as Dihya [80], Photodentro [81], FLORE (French Learning Object Repository for Education) [82], and Mobile Learning Object Repository (MLOR) [83].

3.5 Learning Management System

Learning Management System (LMS) is "a technology tool that provides functionalities beyond the instructional contest such as management tracking, personalized instruction, and facilitative learning" [84].

Six LMS are presented in [85] which are: Moodle, Sakai, ATutor, Blackboard, SuccessFactors and SumTotal. The authors compared them, and they recommended Moodle. Similarly, [86],[87] compared Moodle with others LMS, and they recommended Moodle.

The modern version of LMS is Learning Content Management System (LCMS). It is "an environment where developers can create, store, reuse, manage and deliver learning content from a central object repository, usually a database. LCMSs generally work with content that is based on a learning object model" [88]. It can be incorporated with an LMS to facilitate the structure and presentation of LOs [89]. A comparative study between LMS and LCMS is given in [90].

3.6 Learning Object Recommendations

3.6.1 Recommender systems

In the mid-1990s, recommender systems have become an independent research field [91] , and a popular subject of research [92]. In the field of e-learning, recommendation systems are improving with the development of machine learning algorithms and big data techniques[93].

Recommender systems are "tools and techniques that suggest items that are most likely of interest to a particular user" [94],[95]. They are considered also as "software tools and techniques that provide suggestions for items to be of use to a user" [38],[96]. The principal aim of e-learning recommender systems is to forecast a target learner's preference or rating of a LO in order to provide recommendations.[97]

There are several classifications of recommender system types in the literature. The most popular classification proposes three types of recommender systems: Content-Based, Collaborative filtering, and Hybrid-Based [91],[93],[95],[98–122]. While, other types are included by some authors: Knowledge-Based [38],[123–128], Demographic-Based [38],[124],[127],[129], and Community-Based [125],[130]. Similarly, [131] presented nine recommendation techniques which are: Content-based, Collaborative filtering, Ontology-based systems, Context-aware, Trust-aware, Fuzzy-based, Social network-based, Group-based, and Hybrid. while [132] add two recommendation technique: Demographic-based, and Utility-based. However, for [133], the recommender systems in e-learning are divided into three types. The first one is recommender systems that use neither the concept of ontology nor hybridization for example Matrix factorization-based recommender systems, Machine learning-based recommender systems, User-based

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recommender systems, Tag-based recommender systems, and Group-based recommender system. The second type is Ontology-based recommender systems, and the third is Hybrid recommender systems.
Recommender system evolution [93],[98],[123],[130],[134], classifications [13],[99],[127],[131],[135],[136],[137],[138], objectives, challenges [13],[94],[101],[102],[131],[143–146], and solutions [139],[143],[145],[146] are reviewed, likewise, types of recommender system including: collaborative filtering [103],[147–153], content-based [55],[125],[153], ontology-based [34],[38],[97],[133],154], and hybrid-based [97,153,155,156] are discussed and compared [13],[104],[105],[114],[118],[153],[157],[158],[159].

Table 3: Summary of systematic literature review in e-learning

Citation	Database source	Number of articles	Timespan
[188]	ACM Digital Library, IEEE Xplore Digital Library, Science Direct, Scopus, and Google Scholar	39	2002-2020
[14]	Not Available	154	2016-2021
[38]	IEEE Xplore, JSTOR, Proquest, SAGE Journals, Science Direct, SpringerLink, and Taylor & Francis Online	72	2010-2020
[139]	ACM Digital Library, Springer Link, Web of Science, ScienceDirect	Over 100	2015-2020
[131]	Web of science and Scopus	210	2015-2020
[55]	Scopus, IEEE Xplore, ACM digital library, Google scholar, Web of science	52	2015-2020
[93]	IEEE, Springer, Elsevier, ScienceDirect, Google Scholar	36	2000-2020
[160]	Not Available	66	2009-2020
[133]	Springer, Elsevier, IEEE, ACM Digital Library, and Google Scholar	108	2010-2018
[130]	Not Available	142	1992-2019
[189]	ABI-Inform Academic Search Complete EBSCO	99	2010-2018
[132]	Web of Science, Engineering Index, Science Direct, EBSCO Academic Search Premier, Springer, IEEE Xplore and ACM Digital Library.	80	2005-2014
[136]	Not Available	222	1992-2017
[156]	SpringerLink, Scopus, ACM Digital Library, Science Direct, IEEE Explore	240	2005-2015
[34]	ACM Digital Library, IEEE Xplore, Science Direct, Web of Science	33	2000–2012
[26].	Not Available	34	2000-2015
[141].	Science Direct, ACM Digital Library, IEEE Xplore, SpringerLink.	177	1994-2014
[135].	ABI/INFORM Database, ACM Portal; EBSCO Academic Search Premier; EBSCO Business Source Premier; IEEE/IEE Library; Science Direct.	210	2001-2010

3.6.2 Learning Object Recommendation Techniques

The authors [14],[38],[55],[110],[128],[131],[141],[155],[160] reviewed various recommender systems, and models have been developed to provide to the students a LO, or learning path which is a sequence of LO [55],[128],[160],[161],[162]. While, the authors [12],[87],[97],[112],[122],[162–175] presented their own recommender systems and compared it with others solutions.
LOs are recommended based on learning style using the Felder and Silverman Learning Styles Model (FSLSM) and IEEE LOM [66], and FSLSM and SCORM [176].
In [177], a model for providing personalized and most appropriate learning objects, modeled with IEEE LOM, to learners based on their preferences and learning styles, was proposed, and this model was later implemented as a recommender system called LORecommdNet [178]. While based on the learners' needs, knowledge and preferences LOs are recommended in the iLearn framework [179].
To provide LO recommendations based on a teachers' context model, [180] proposed a hybrid method where the teachers' context is defined in an ontology that serves as the foundation for the LOs

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metadata and the teachers' profile. Additionally, a collaborative filtering method based on the ontology is provided.

In [119],[181], the authors proposed an adaptive recommendation model for retrieving and recommending suitable LOs modeled using SCORM to a learner. [119] recommended LOs based on preference and ontological approaches, whereas [181] recommended LOs based on semantic-aware discovery and the learner's preference pattern.

By using an ontology-based approach, [182] suggested a new framework for learning object recommendations that is responsive to the cognitive activities of the learner.

For providing learning resources to learners, a hybrid knowledge-based recommender system based on ontology and sequential pattern mining (SPM) is proposed [97].

In [54], the authors presented an automatic and dynamic approach for personalized recommendation of learning objects. The IEEE LOM is used to provide personalized suggestions of LO in accordance with particular learner's learning style.

In [183], the authors presented a framework called the Enhanced e-Learning Hybrid Recommender System (ELHRS), which recommended the best e-learning materials based on the learner's specific needs.

In [184], the authors proposed a hybrid recommender system named MoodleRec developed as a part of the Moodle learning management system, MoodleRec recommended a list of LOs classified following a straightforward keyword-based query.

In [185], the authors presented a learning path recommendation model based on a knowledge graph to satisfy a variety of learners' needs and increase learners' performance. However, [162] proposed an adaptive learning path recommendation based on graph theory, and the Improved Immune Algorithm (IIA) to enhance students' learning outcomes while taking into account their learning preferences, objectives, and prior knowledge, similarly. [186] proposed a learning path recommendation based on the Compatible Genetic algorithm (CGA) taking into consideration the user's learning preferences, level of knowledge, and degree of interaction.

In order to categorize, arrange, and deliver the best LOs in accordance with professors' preferences, a Multi-Agent Recommendation System for Recommending Accessible Learning Objects named SIMROAA was created based on the qualitative analysis of the questionnaires used and responded by the area professors [187].

Table 4: survey of systems and models proposed for recommending a learning object or learning path.

Citation	Type	Model/system name	Learning technology	Type of RS	attributes
[190]	Prototype	DRFLO (Dynamic Recommendation of Filtered LOs)	LMS	Hybrid (Machine Learning and Collaborative filtering)	learning preferences
[164]	Prototype	N/A	N/A	Semantic Fuzzy Humming Birds Optimization and RoBERTa algorithm	Learners' interests, learners' needs, and learning capability.
[183] .	Prototype	ELHRS (Enhanced e-Learning Hybrid Recommender System)	VLE (Virtual learning environment)	Hybrid	learner's specific needs
[112] .	Prototype	N/A	Personalized e-learning environment (PLE)	Ontology-based.	Learning style, knowledge level, and background knowledge. IEEE LOM
[122].	Prototype	N/A	LMS	Hybrid (Ontology-based,	LO similarity and

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				Content-based, and Collaborative filtering)	Learner similarity. IEEE LOM
[184].	Prototype	MoodleREC	LMS	Hybrid (Content-based and Collaborative filtering)	Simple keyword-based query.
[191]	Prototype	PerLCol	LMS	Hybrid	Learning style
[192]	Prototype	EduRecomSys	N/A	Collaborative filtering	Preferences/interests of learners
[193]	Prototype	IHCBR	Case-Based Reasoning (CBR)	Hybrid	Learning style
[185].	Model	N/A	N/A	Knowledge graph-based	learners' needs
[167]	Prototype	Personalised bee recommender for e-learning (PBReL)	LMS	Hybrid (Collaborative filtering, and artificial bee colony (ABC))	Learner behavior
[171]	Prototype	RAUI	LMS	Rule-based	Learning style
[179].	Prototype	ILEARN	SLN (Social Networks Learning)	Ontology	Learners' needs, knowledge and preferences
[162].	Prototype	Not Available	Adaptive Learning Environment (ALE)	Graph Theory and an Improved Immune Algorithm	Learning goals, the knowledge base, and the learning styles
[187].	Prototype	SIMROAA	LOR	Content-based	Professors' preferences
[194]	Prototype	MyTeLeMap	PLE	Knowledge-based	Learners' preferences
[195]	Prototype	TBHR	Cloud e-learning	Hybrid (Trust-based and collaborative filtering)	Learning style, and learner behavior
[196].	Prototype	eJRM (electronic Justice Relationship Management)	SLM (Smart Learning Environment)	Ontology	Users' learning needs,
[158].	Prototype	ULEARN	SLM (Smart Learning Environment)	Hybrid (Collaborative filtering and content-based)	Learning style
[165]	Prototype	Not Available	LMS	Hybrid (context awareness, sequential pattern mining (SPM) and collaborative filtering)	Knowledge level and learning goals

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[197]	Prototype	AULA (Adaptive and Ubiquitous Learning Architecture)	Ubiquitous Learning	Rule-based	Learning style
[170]	Model	Leaner Learning Object Recommendation (LLOR)	LMS	Collaborative filtering	Learners' preferences
[97] .	Prototype	Not Available	LMS	Hybrid (Ontology, Collaborative filtering, and Sequential Pattern Mining)	Learning style, and level knowledge
[198].	Model	LOAT (Learning Object Authoring Tool)	Personalized e-learning environment (PLE)	Ontology	Learning styles.
[166] .	Prototype	PLORS (personalized learning object recommender system)	LMS	Content-based (Attribute-based)	Learning styles, expertise level, prior knowledge, and Performance
[199]	Prototype	Not Available	Ubiquitous Learning	Context-based ontology	Learning styles, interruption frequency
[200] .	Prototype	OntoSakai	LMS	Hybrid (Ontology, and content-based)	Learner preferences
[201]	Prototype	Not Available	Cloud e-learning	Ontology	Learning style
[168].	Prototype	Not Available	Technology enhanced Learning (TeL)	Collaborative filtering	LO similarity
[178]	Prototype	LORecommendNet	LMS	Ontology	Learners' preferences and learning style. IEEE LOM
[202].	Model	N/A	Web-based learning	Hybrid (collaborative filtering sequential pattern mining (SPM) algorithm)	Learner preferences
[169].	Prototype	N/A	LMS	Utility-Based	Learning style and learners' preferences
[163] .	Prototype	DELPHOS	LOR	Hybrid (Collaborative filtering, content-based, and demographic)	Profile similarity and content similarity
[177]	Model	N/A	LMS	Ontology-based	Learners' preferences, and learning style

					IEEE LOM
[203]	Prototype	INES (Intelligent Educational System)	LMS	Ontology	Learning style
[204] .	Prototype	Not Available	LMS	Ontology	Learning style SCORM
[182].	Prototype	Not Available	LOR	Ontology	Learner's prior knowledge and cognitive activities
[205].	Prototype	PSDLO (personalized search and delivery of learning objects)	LOR	Ontology	Learner's preferences. IEEE LOM
[175]	Prototype	Not Available	PLE	Ontology-based	Learners' goals
[174]	Prototype	CourseAgent	Not Available	community-based	Learning objective, and learners' interest
[173]	Prototype	Not Available	PLE	Collaborative filtering	Learner interest and background knowledge
[172]	Prototype	personalized learning recommender systems (PLRS).	PLE	Content-based (Attribute-based)	Learning styles and learning needs.

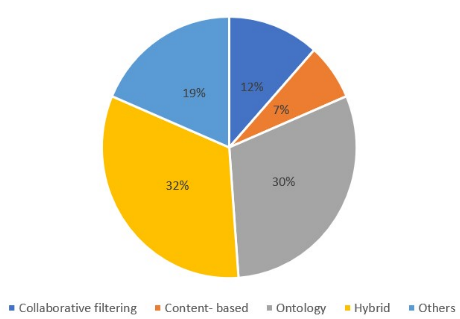

Figure 3: Distribution of recommender system types in this study

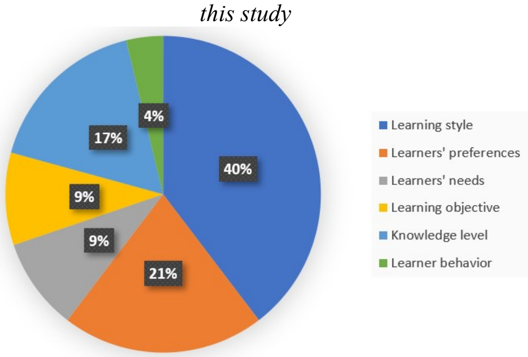

Figure 4: Distribution of attributes in this study

4. CONCLUSION

In this paper, we present a systematic literature review of 205 papers on the LO published between 2000, and 2022. This study introduces the different proposed definitions, features, kinds of LO, as well presents the various models and metadata standards used to model LO. In addition, the serval models and recommender systems created to suggest LO or learning path are summarized. The combination of two or more techniques such as content-based, collaborative filtering, and ontology as know hybrid technique is the most common used as shown in figure 3 similarly, as shown in figure 4 learning style is the most common attribute used in LO recommendation. The next article will be a survey on the student model in order to propose and develop a recommendation system for learning objects using deep learning and big data.

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