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Article

A literature review on intelligent services applied to distance learning

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Abstract: Distance learning has assumed a relevant role in the Educational scenario. The use of Virtual Learning Environments contributes to obtain a substantial amount of educational data. In this sense, the analyzed data generate knowledge used by institutions to assist managers and professors in strategic planning and teaching. The discovery of students' behaviors enables a wide variety of intelligent services for assisting in the learning process. This article presents a literature review in order to identify the intelligent services applied in distance learning. The research covers the period from January 2010 to May 2021. The initial search found 1,316 articles, among which 51 were selected for further studies. Considering the selected articles, 33% (17/51) focus on learning systems, 35% (18/51) propose recommendation systems, 26% (13/51) approach predictive systems or models, and 6% (3/51) use assessment tools. This review allowed to observe that the principal services offered are recommendation systems and learning systems. In these services, the analysis of student profiles stands out to identify patterns of behavior, detect low performance and identify probabilities of dropouts from courses.

Keywords: distance learning; intelligent services; literature review; virtual learning environments.

1. Introduction

The emergence of the internet facilitated access to information and the dissemination of knowledge through the distribution of educational materials. This scenario boosted distance learning (DL), expanding its adoption in educational institutions around the world [1].

Distance learning allows for advancement in the educational system, overcoming the limitations of traditional fully face-to-face classes. It provides independence from the classroom, allowing students to freely choose the place and time of study, thus reaching a significant number of students with different socioeconomic profiles, which contributes to the democratization of learning.

The absence of a physical presence caused by remote access is one of the main problems faced by DL. This problem has been mitigated by virtual learning environments (VLEs). VLEs have tools that allow and encourage contact between students and teachers. The use of discussion forums, debates, virtual meetings, chats, among others, diversifies the teaching-learning routine and promotes interaction between them.

The growing search for information, high connectivity, and the use of virtual learning environments have generated a significant amount of data. These data can be analyzed,

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allowing the discovery of student behavior and enabling the creation of intelligent services for monitoring, prediction, and intervention in the teaching and learning process [2].

Becker *et al.* [3] argued that mediation of learning is a trend, with an increasing amount of methods and tools used by teachers to assess, measure, and document students' academic life, learning advancement, skill attainment, and other educational needs. Becker *et al.* [3] also mentioned that the increase in adaptive learning technologies expands the amount of data that can be collected and analyzed. Learning Analytics (LA) is an alternative for the treatment and discovery of knowledge in databases generated by educational platforms [4].

Acatech [5] stated that the storage, analysis, and interpretation of data allow the development of intelligent services, which can be customized according to the requirements of each user.

Koldewey *et al.* [6] claimed that intelligent services were first described by Allmendinger and Lombreglia [7]. The authors indicated that these services are data-based, connected to smart objects, and allow continuous and interactive feedback [8]. Furthermore, Beverungen *et al.* [9] stated that intelligent services are based on co-creation involving monitoring, optimization, control, and autonomous adaptation of results.

This article presents a study on intelligent services and how they are being applied to distance learning environments. The research covered the period from January 2010 to May 2021, considering five academic databases. The initial search returned the number of 1,316 articles. After applying the exclusion criteria, 51 articles remained to be analyzed.

The article is divided into five sections. The second addresses basic concepts that form the background of this study. The third section defines the research methodology. Next, the article contains a section dedicated to the results, mainly discussing the types of smart services applied to distance learning. Finally, the last section addresses final considerations and future work.

2. Background

This section presents principles related to Distance Learning, Virtual Learning Environments, Intelligent Services, and Learning Analytics.

2.1. Distance Learning

Cambruzzi *et al.* [10] affirmed that the definitions of Distance Learning are diverse, but they all take into account these characteristics: 1) non-presential education does not share the same physical spaces; 2) DL allows the students to study at different times and; 3) mediation is done through technologies. Due to the high level of mediation, the DL generates data that can be used in different kinds of analysis [10].

Traxler [11] pointed the DL requires the autonomy of the student and if associated with the use of information technology, it promotes knowledge quickly and widely, stimulating the student to search for new knowledge.

2.2. Virtual Learning Environments

When dealing with distance learning, it is worth highlighting the use of environments that support the educational processes. VLE allows the sharing of contexts during the development of activities. Furthermore, it allows synchronous and asynchronous communication between people involved in the teaching and learning process [4].

Waheed *et al.* [2] defined VLE as a computational software that aggregates different media and resources, allowing the propagation of information. It enables data storage, retrieval, and distribution, as well as synchronous and asynchronous bidirectional communication, contributing to the generation of digital data that can be used to assess students.

According to Clow [12], there is a large amount of data available about users, due to the increased use of online learning environments. In this sense, the growing use of VLE provides tools to develop learning patterns adaptable to the user's profile [13].

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2.3. Intelligent Services

According to Cummaudo *et al.* [14] and Hosseini *et al.* [15], the development of intelligent services differs from the usual web services, as they are developed with components based on artificial intelligence (AI).

The predictions performed by the intelligent services focus only on training data sets and the results obtained are presented as probabilities that the inference satisfies one or more labels in the training data [14].

According to Cummaudo *et al.* [14] due to the evolution of intelligent services, training datasets must be representative and frequently evaluated concerning the chosen service. This data allows the continuously update of prediction algorithms.

Marquardt [16] defined an intelligent service as part of an intelligent task performed by a computer system, with behavior equivalent to that of a human being when performing a similar task.

The Smart Urban Services project defined intelligent services as services adapted to specific use cases of customers with the help of data and intelligent processing [17] and according to Koldewey *et al.* [18], intelligent services allow a company to become competitive and innovative.

2.4. Learning Analitycs

Learning Analytics (LA) refers to the application of analytical techniques to analyze educational data, such as data on student and teacher activities, the identification of behavior patterns, and the provision of information that can be used to improve learning [10].

According to Andrade *et al.* [4], LA is a rapidly growing field of research, focused on the development and application of processes and tools to collect, explore and analyze large amounts of data. This analysis allows to better understand the learning behavior of students, helping teachers to provide better support and appropriate interventions, and ultimately improve the quality of learning and teaching, as well as educational outcomes.

According to Waheed *et al.* [2], through learning analytics platforms, LA supports pedagogical strategies by offering real-time opinions and recommendations through learning analytics panels and VLE visualization systems. LA uses educational data and translates it into useful information for decision-making, based on responses and records of students' academic life available on online learning platforms [2].

3. Methodology

This article carried out a study on intelligent services applied to distance learning from January 2010 to May 2021. The work used the following academic databases: ACM Digital Library (https://dl.acm.org/), IEEE Xplore Digital Library (https://ieeexplore.ieee.org/Xplore/home.jsp), ScienceDirect (https://www.sciencedirect.com/), Springer Library (https://www.springer.com/br) and Scopus (https://www.scopus.com/home.uri).

The search string considered the following words: Distance, Education, Learning, Educational, Environment, Analysis, Data Science, and Data Mining, including synonyms or related words to compose the terms. The defined terms were joined by the Boolean expressions OR and AND divided into three sets of interests, forming search string presented in Table 1.

Table 1: Search string terms

Major Terms	Search Terms
Distance learning	(Distance learning OR Distance education OR E-Learning OR online education OR Educational technology OR virtual learning environment OR learning management system)
	AND
Learning Analytics	(Learning Analytics OR learning analytic OR data analysis OR data Science OR educational data mining OR learning data mining OR academic data mining OR school data mining)
	AND
Intelligent services	(smart services OR smart service OR smart methods OR Intelligent service OR intelligent task OR intelligent systems OR Smart processes OR Intelligent processes)

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The following inclusion criteria (IC) allowed the selection of articles: publications with complete content; publications at conferences, journals, and workshops; publications that have data analysis methods applied to distance learning; publications that offer some type of intelligent service for the DL area and publications from January 2010 to May 2021. On the other hand, the Exclusion Criteria (EC) were: publications that precede 2010; publications with a language other than English; theses, dissertations, abstracts, books, and systematic reviews; publications unrelated to the topic and duplicate publications.

The first step consisted of searching in the five databases and removing impurities, resulting in a total of 1316 articles, 271 in the ACM Digital Library database, 315 in the IEEE Xplore Digital Library, 188 in Science Direct, 289 in the Springer Library and 253 in Scopus (Table 2). In the second step, the texts were filtered considering the title, abstract, and keywords. In this stage, 1036 articles were discarded, leaving 280 works that were revised through the introduction, results, and conclusions. The third step discharged 229 works, selecting 51 articles. The selected articles were fully read to ensure their suitability for this review study.

Table 2: Number of articles obtained by database and selected in the study

Database	Return articles	Percentage return articles	Selected articles	Percentage of selected articles
ACM Digital Library	271	21%	17	33%
IEEE Xplore Digital Library	315	24%	10	20%
Science Direct	188	14%	4	8%
Springer Library	289	22%	13	25%
Scopus	253	19%	7	14%
TOTAL	**1316**	**100%**	**51**	**100%**

4. Results and Discussions

This section presents the types of intelligent services that are being offered in distance learning, according to this literature research. Among the intelligent services, the study found learning systems in 33% (17/51) of the selected articles, recommendation systems in 35% (18/51), models or forecasting systems in 26% (13/51), and the assessment tools in 6% (3/51).

Table 3 presents the list of selected articles, containing authors, year of publication, the database of publication and a summary of the intelligent services. The following sections organize and discuss the articles as learning systems, recommendation systems, forecasting models or systems, and assessment tools.

4.1. Learning Systems

Lavoie and Proulx [19] developed a Learning Management System (LMS) with features oriented to flipped courses that allow students to watch videos and interact in Jupyter Notebooks. The LMS automatically creates progression graphs for students and sends automatic messages related to their progression. For instructors, the LMS automatically creates statistics on overall class and exercise progression. It allows teachers to target students in dificulty who can be helped individually, decreasing the failure rate.

Dahdouh *et al.* [20] developed an online learning system based on big data technologies and cloud computing. The authors suggested a methodology to use the huge amount of data produced by online learning platforms. In addition, the authors proposed to develop a course recommendation system that helps students to select the most appropriate courses and guides them throughout the learning process.

Wang *et al.* [21] proposed a system that uses natural language processing (NLP) technology as a development and design tool. The assistant was built for online learning platforms to provide timely feedback to students and increase their enthusiasm for learning.

Kozierkiewicz-Hetmańska and Zyundefinedk [22] proposed a method to determine an opening learning scenario based on the ant colonies optimization technique. The algorithm tries to choose the learning material best suited to the learning styles and current level of

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knowledge stored in the student profile. The method for determining an initial learning scenario required defining a student profile and a representation of knowledge. According to the authors, the customization of the learning scenario is an important task in the design of intelligent tutorial systems, because research indicates that students achieve better learning outcomes if the teaching material is appropriate to their learning styles.

Table 3: List of articles containing intelligent services in distance learning

ID	Authors	Source	Summary
1	Anaya *et al.* [23]	ACM	Recommendation system based on an ID in the context of collaborative learning in the e-learning environment.
2	Balderas *et al.* [24]	ACM	Domain-specific language to customize online learning assessments in Moodle.
3	Chanaa and Faddouli [25]	IEEE	Custom model with 3 main components, sentiment analysis, cognitive analysis and learning style.
4	Chen *et al.* [26]	IEEE	Enhanced recommendation method called Adaptive Recommendation based on Online Learning Style.
5	Dahdouh *et al.* [20]	Springer	Online learning systems based on big data technologies in cloud computing.
6	Dahdouh *et al.* [27]	Springer	Recommendation system of courses distributed to the e-learning platform.
7	Dimopoulos *et al.* [28]	ACM	Evaluation tool, called Enriched Learning Analytics Rubric, which was developed as a Moodle plug-in.
8	El Fouki *et al.* [29]	ACM	Decision-making system to help instructors.
9	El Moustamid *et al.* [30]	ACM	System capable of analyzing the profile of students and indexing videos on the Web in order to offer students a database with courses that correspond to their levels.
10	Florian *et al.* [31]	Springer	Prototype that implements indicators as examples of learning analytical applications.
11	Hamada [32]	ACM	Model of an e-learning system based on Java2D technology and containing an intensive set of learning materials to support all types of students.
12	Huang *et al.* [33]	ACM	Deep Reinforcement learning structure for Exercise Recommendation.
13	Iqbal *et al.* [34]	IEEE	Kernel Context Recommendation System algorithm, which is a flexible, fast and accurate.
14	Joy *et al.* [35]	ACM	Ontology model that encompasses the student profile and learning object attributes, which can be used for recommending content on an e-learning platform.
15	Kapembe and Quenum [36]	ACM	Hybrid recommendation, based on the student's profile, the relevance and quality of learning objects for the program in which the student is enrolled, and student feedback.
16	Kim and Kim [37]	IEEE	Individualized Tutor of Artificial Intelligence as a system that integrates three developmental learning networks.
17	Kolekar *et al.* [38]	ScienceDirect	User interface customized according to the students' learning styles, based on web log analysis.
18	Kozierkiewicz-Hetmańska and Zyundefinedk [22]	Springer	Algorithm to determine an opening learning scenario based on the ant colony optimization technique.
19	Lagman and Mansul [39]	ACM	System that captures each student's e-learning paths and determines difficult topics and subjects and provides academic intervention.
20	Lavoie and Proulx [19]	ACM	Learning management system (LMS) with unique features oriented to inverted courses.

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21	Manhães *et al.* [40]	ACM	WAVE architecture that provides useful information about student performance.
22	Sharma and Ahuja [41]	ACM	Semantic recommendation using ontology to recommend relevant and personalized learning content to students.
23	Thai-Nghe *et al.* [42]	ScienceDirect	Recommendation system techniques for mining educational data, especially to predict student performance.
24	Venugopalan *et al.* [43]	ACM	Content-based recommendation system.
25	Wang *et al.* [21]	IEEE	Intelligent teaching assistant system that replaces the way the user waits for manual response.
26	Zakrzewska [44]	ACM	Agent-based recommendation system, which, for each new student, suggests a group of students of similar profiles.
27	Zaoudi and Belhadaoui [45]	ACM	Learner Behavior Analytics model based on a system called Score and Behavior Analytics to analyze student outcomes and behavior.
28	Khosravi *et al.* [46]	ACM	Adaptive learning system with a focus on the student, scalable and independent of content that depends on crowdsourcing and partnership with students for the development.
29	Zhang *et al.* [47]	SCOPUS	Learning analysis using Moodle plugins to discover possibilities to improve the learning process and reduce the number of under performing students.
30	Angeline *et al.* [48]	SCOPUS	Discriminant analysis to measure student performance.
31	Hashim *et al.* [49]	SCOPUS	Student performance prediction model based on supervised machine learning algorithms (decision tree, Naïve Bayes, logistic regression, support vector machine, nearest neighbor K, minimal and neural sequential optimization Network).
32	Maâloul and Bahou [50]	SCOPUS	Recommendation system based on machine learning that is fundamentally based on a digital learning technique (ie, semi-supervised learning) and that determines the degree of similarity between students.
33	Freitas *et al.* [51]	SCOPUS	IoT system for predicting school dropout using machine learning techniques based on socioeconomic data.
34	Villegas-Ch *et al.* [52]	SCOPUS	Integration of technologies, with artificial intelligence (AI) and data analysis, with learning management systems to improve learning.
35	Villegas-Ch *et al.* [53]	SCOPUS	Architecture for Integration of Chatbot with Artificial Intelligence in Intelligent Campus for Improvement of Learning.
36	Han and Xu [54]	ScienceDirect	Intelligent education platform based on deep learning and image detection.
37	Shi *et al.* [55]	ScienceDirect	Learning path recommendation model based on a multidimensional knowledge graph structure.
38	Chang *et al.* [56]	IEEE	Ontology capable of mapping students interaction data with respect to a set of tutorial actions, allowing an artificial tutor to observe students and their interactions with the learning environment and provide an appropriate tutoring.
39	Rajkumar and Ganapathy [57]	IEEE	Recommendation system to increase classification accuracy.
40	Ruangvanich *et al.* [58]	IEEE	Architecture of a learning analysis system in a virtual intelligent learning environment as a tool to support student learning.
41	Barlybayev *et al.* [59]	IEEE	Intelligent system for assessing students' professional skills levels in e-learning.
42	Leithardt *et al.* [60]	IEEE	Control system for learning environments specialized in special education.
43	Lin *et al.* [61]	Springer	Complementary recommendation structure for freshmen under restrictions or requirements, based on objective-oriented standards.
44	Chen *et al.* [62]	Springer	Phased forecasting model to predict students at risk at different stages of a semester.
45	Niknam and Thulasiraman [63]	Springer	Intelligent learning path recommendation based on meaningful learning theory.
46	Turabieh *et al.* [64]	Springer	Harris Hawks algorithm optimization enhanced as a feature selection for predicting student performance.
47	Iatrellis *et al.* [65]	Springer	Two-stage machine learning approach to predict student outcomes.
48	Ullah *et al.* [66]	Springer	IoT model based on Software Defined Network for student interaction, which interconnects students and teacher in a smart city environment
49	Nuguri *et al.* [67]	Springer	Cloud-based virtual reality learning environment (VRLE) system that can be deployed on high-speed networks using the platform.
50	Azzi *et al.* [68]	Springer	Classifier capable of identifying the student's learning style in the E-Learning System.
51	Mendes *et al.* [69]	Springer	Educational tool based on motion detection using the Kinect sensor in a game that is projected on the classroom wall.

Lagman and Mansul [39] conducted a study with individualized and personalized learning, adapted to specific learning requirements and preferences. The research focuses on student assessments and learning as the main key component of e-learning processes. The system captures student's e-learning paths and determines difficult topics and subjects, and provides academic intervention to students. The system serves as a complementary educational tool to help students improve their academic performance.

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Chanaa and Faddouli [25] proposed a customized model with three main components: sentimental analysis, cognitive analysis, and learning style. The model uses trails of learners when using a learning management system to find convenient information about students. In addition, the model also improves course completion rate and provides appropriate content to meet individual student needs.

Kolekar *et al.* [38] aimed to understand the characteristics of students and generate the user interface customized according to their learning styles, based on web log analysis. The sample selected was the second-year engineering students, comprising seventy-six students grouped into two class units called experimental and control groups. The inference proves that the identification of learning styles and recommendation of course content and topics increase students' performance.

Khosravi *et al.* [46] developed an adaptable, scalable, content-independent learning system (RiPPLE) that depends on crowdsourcing and partnering with students to develop learning resources that are served by adaptive forms. RiPPLE is an adaptive learning system that recommends personalized learning activities to students, based on their state of knowledge. The system recommends from a grouping of crowdsourced learning activities that are generated and evaluated by educators and students themselves.

Villegas-Ch *et al.* [52] proposed the integration of technologies, such as artificial intelligence (AI) and data analysis, with learning management systems to improve learning. The proposal was based on an online education model from a university in Ecuador. As a tool, the model used an LMS, where students had sections with resources and activities that served for the training of the model.

Villegas-Ch *et al.* [52] presented an assistant for students and teachers, allowing the management of students' calendars, as well as the generation of events e reminders. The assistant sends notifications to the student informing them which activities must be performed. In addition, it performs continuous monitoring, allowing students to improve their performance.

Han and Xu [54] proposed an intelligent education system that was customized to provide the student with resources to suit their perceptions when starting the platform. The systems provide an environment with a full range of asynchronous and synchronous communication tools. The designed system requires a combination of sensors, devices, software, applications, and services in real-time.

Chang *et al.* [56] developed an ontology capable of mapping student interaction data to a set of tutoring actions. This mechanism allowed an artificial tutor to observe students in terms of their interactions with the learning environment. It also provides an appropriate tutoring action to improve the learning process. The learning environment discretizes the learning process in a sequence of activities, and the student's interaction data comes from the last activity, but also includes a set of data aggregating information from previous activities (learning history). Although normally an ontology is built by humans (knowledge engineers and experts in the field), in this work, the authors proposed an automatic process of building ontology.

Ruangvanich *et al.* [58] developed a learning analysis system as a tool to support student learning. The technologies have been proposed as a means of supporting reflective practice based on instructor data, these technologies are considered a priority in educational research and innovation. The system consists of ten elements, namely: Virtual Learning Environment, Learning Analysis, Alert, LMS, Learning Records, Stakeholders, Data, Student Information, Learn Direct, and Report Information.

Azzi *et al.* [68] proposed a classifier capable of identifying the student's learning style in the E-Learning System. The student's learning behavior was captured in different contexts, usually in different courses related to a specific subject. Web usage mining was used to capture students' behaviors and then learning styles were mapped to the Felder-Silverman Learning Style Model (FSLSM) categories. The authors used the Fuzzy C Means (FCM) algorithm to group the behavioral learning data.

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Ullah *et al.* [66] proposed the IoT model based on Software Defined Network (RDS) for student interaction, which interconnects students to a teacher in a smart city environment. Students and teachers are free to move anywhere, anytime, and with any hardware. An RDS-IMSI model interconnects students with the teacher through their heterogeneous IoT devices.

Nuguri *et al.* [67] presented vSocial, a cloud-based virtual reality learning environment (VRLE) system that can be deployed on high-speed networks using the high-fidelity "social VR" platform. For the development of vSocial, the authors relied on the use of an existing special education VLE, the iSocial that trains young people with Autism Spectrum Disorder through the implementation of the Social Competence Intervention (SCI) curriculum.

Leithardt *et al.* [60] developed a control system for learning environments specialized in special education. Among its many possible uses, the system focuses on managing the attendance to classes of special education students, teachers, and other classroom users through the use of widespread and ubiquitous technologies. The system aims to contribute to the extension of pervasive computing systems to educational environments.

Mendes *et al.* [69] proposed an educational tool based on motion detection using the Kinect sensor in a game that is projected on the classroom wall. Students use balls to hit the projected elements. These collisions are detected by the sensor and registered in the program, thus completing the task in question. According to the authors, the system and architecture were designed to make life easier for teachers in promoting physical activity in combination with classroom learning. The proposed system is based on the projection of educational activities and the possibility for students or users to interact with them through the exercises.

Table 4: Articles containing learning systems

Authors	Learning systems
Chanaa and Faddouli [25]	Custom model with 3 main components, sentiment analysis, cognitive analysis and learning style.
Dahdouh *et al.* [20]	Online learning systems based on big data technologies and cloud computing.
Kolekar *et al.* [38]	User interface customized according to learning styles of students.
Kozierkiewicz-Hetmańska and Zyundefinedk [22]	Algorithm to determine an opening learning scenario based on the ant colony optimization technique.
Lagman and Mansul [39]	A system that captures each student's e-learning pathways and can determine difficult topics and subjects, in which it is essential to provide academic intervention to students.
Lavoie and Proulx [19]	Learning management system with unique features oriented to inverted courses.
Wang *et al.* [21]	Intelligent teaching assistant system that replaces the way the user waits for manual response.
Khosravi *et al.* [46]	Adaptive learning system with a focus on the student, scalable and independent of content that depends on crowdsourcing and partnership with students for the development of learning resources.
Villegas-Ch *et al.* [52]	Integration of technologies, with AI and data analysis, with learning management systems to improve learning.
Han and Xu [54]	Intelligent education platform based on deep learning and image detection.
Chang *et al.* [56]	Ontology to mapping student interaction data with respect to a set of tutorial actions, allowing an artificial tutor to observe the student and his interactions with the learning environment.
Ruangvanich *et al.* [58]	Architecture of a learning analysis system in a virtual intelligent learning environment as a tool to support student learning.
Leithardt *et al.* [60]	Control system for learning environments specialized in special education.
Ullah *et al.* [66]	IoT model based on Software Defined Network for student interaction, which interconnects students to a teacher in a smart city environment.
Nuguri *et al.* [67]	Cloud-based virtual reality learning environment (VRLE) system that can be deployed on high-speed networks using the platform.
Azzi *et al.* [68]	Classifier capable of identifying the student's learning style in the E-Learning System.
Mendes *et al.* [69]	Educational tool based on motion detection using the Kinect sensor in a game that is projected on the classroom wall.

Table 4 presents the 17 works with learning systems from 51 articles analyzed. In addition, Figure 1 shows the distribution of the learning systems and technologies used by the researchers in the articles. Among the main technologies, Deep Learning Algorithms stood out with 3 articles.

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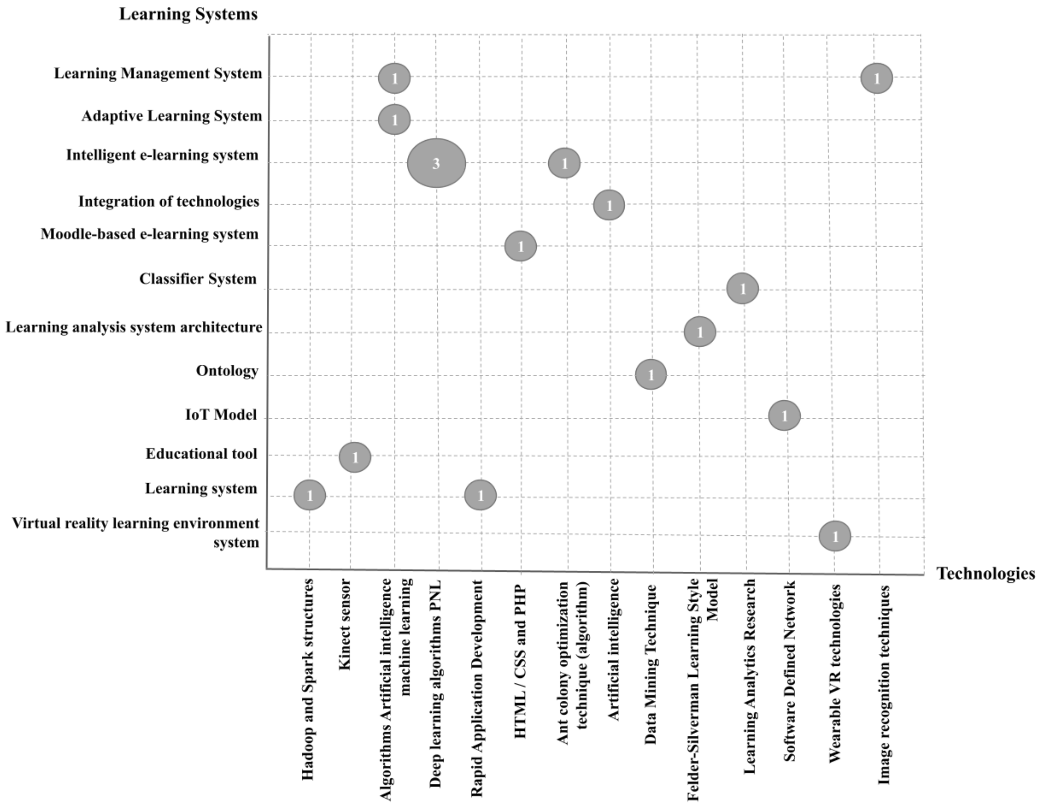

Figure 1. Learning System and Technology

4.2. Recommendation Systems

Huang *et al.* [33] proposed a new deep reinforcement learning framework for Exercise Recommendation (DRE). Two exercise Q networks (EQN) were proposed to select exercise recommendations following different mechanisms, namely, a direct EQNM with Markov property and a sophisticated EQNR with a recurrent way. Three domain-specific rewards were also leveraged to characterize the benefits of factors such as review and exploration, smoothness, and engagement to enable the DRE to find the optimal recommendation strategy. The work carried out experiments on two sets of real-world data. The results show that the proposed DRE can effectively learn from student interaction data to optimize multiple objectives in a single unified structure and adaptively recommend appropriate exercises to students.

Joy *et al.* [35] proposed an ontology to integrate the student's profile and the attributes of the learning objects. The ontology conceptualizes the characteristics of the student and the learning object and suggests an adaptive learning environment. The static and dynamic characteristics of a student are considered in the ontology. Static data is collected directly through forms and questionnaires, and dynamic data is collected by tracking student behavior while interacting through a learning management system.

Kapembe and Quenum [36] presented a hybrid recommendation model, based on the student's profile, the value and quality of learning objects for the program in which the student is enrolled, and student comments. The approach uses student learning behavior, performance, and interests to suggest learning objects based on the student's profile. The recommendation system consists of two components, the content-based learning object filtering module, and the collaborative filtering module.

Sharma and Ahuja [41] presented an integrated approach to semantic recommendation using ontology to recommend relevant and personalized learning content to students. According to the authors, during their early stages, recommendation systems often face the problem of cold booting. This is due to the scarcity of information available during these phases. The proposed system approaches this problem, maintaining an ontological

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approach to the user profile, and improving the accuracy of the recommendations during the experiment.

Florian *et al.* [31] presented a study based on Engeström's Activity Theory and the Actuator-Indicator model as pillars to implement an apprentice model based on Moodle's activities. The authors developed a prototype that implements indicators as examples of analytical learning applications. The prototyping process indicated that moodle activity tracking includes data on more complex social structures. The authors analyzed the reuse of Moodle tracking data for modeling students and groups. Moodle's activity log was used to build advanced models based on students' activities in social contexts and their implications for learning support.

Anaya *et al.* [23] proposed a recommendation system based on Influence Diagrams (ID) for collaborative learning in the e-learning environment. The ID solution provided a recommendation decision table, which alerts to problematic situations. An ID was proposed including the essential variables to assess the student's collaboration and the variable that represents whether there was a collaboration or not.

Hamada [32] developed an improved version of a learning style index, considering students' cultural differences. The model allows students to verify their learning preferences and teachers have a broader view of their students' learning preferences. The model was integrated into an e-learning system based on Java2D technology that contains a set of learning materials to support students.

Chen *et al.* [26] created an enhanced recommendation method called Adaptive Recommendation based on Online Learning Style (AROLS). This method is integrated into a comprehensive learning style model for online learners. The method makes recommendations considering the learning style as previous knowledge. First, it generates groups of students of different learning styles. Second, the behavioral patterns represented by the similarity matrix of learning resources and the membership rules of each cluster are extracted using the students' browsing history, creating a set of custom recommendations of variable size according to the data mining results of the previous steps.

Iqbal *et al.* [34] proposed a context-aware framework for both user and item-based versions by using the kernel mapping concept in collaborative filtering. The Kernel mapping recommender system algorithm is based on a novel structure learning technique. This framework has the flexibility to exploit various user and item-related contexts during the recommendation process using different kernels that influence the performance of the system by improving the predictive accuracy, scalability, and flexibility factors. The proposed algorithm was compared with pre and post-filtering approaches since they are the favorite approaches in the literature to solve the problem of context-aware recommendation.

A system for course recommendation distributed to the e-learning platform was also developed by Dahdouh *et al.* [27]. The system aims to discover the relationships between the student's activities using the association rules method to help choose the most appropriate learning materials. In addition, it was used to analyze historical data passed from enrollment in courses or registration data. The article especially discussed the concept of frequent itemsets for determining interesting rules in the database. The extracted rules are then used to find the most appropriate course according to the student's profile. The recommendation system uses big data technologies and techniques.

Venugopalan *et al.* [43] proposed a content-based recommendation system based on pedagogical content modeling. The system considers user queries and finds the best match. The experiment validated the system involving students seeking engineering education. The result showed that the system presents a high recovery of relevant and accurate results.

Zakrzewska [44] presented an agent-based recommendation system, which, for each new student, suggests a group of students with a similar profile and indicates corresponding learning resources. The method can be used when creating the course or when creating activities for groups. The system assumes that groups of students were created with similar characteristics, such as cognitive styles, usability preferences, or similar historical behaviors. Tests were done with real data and different groups of students. The performance of the

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technique was validated based on student data described by cognitive traits, such as the dimensions of the dominant learning style.

The work proposed by Rajkumar and Ganapathy [57] found a correlation between introverted and extroverted personality types and their corresponding learning styles. The modified VARK questionnaire was implemented as a chatbot to classify individuals. After chatbot evaluations, all students (introverts and extroverts) watched the visual and auditory content in a completely silent environment. While watching the content, the students' Beta brainwaves were recorded and a dataset was created at an interval of one second. This dataset was validated using machine learning classification algorithms such as Naïve Bayes, N48 tree, and clustering algorithms, improving the accuracy of students' classification.

Maâloul and Bahou [50] proposed a recommendation system that is fundamentally based on a digital learning technique (that is, semi-supervised learning) and that determines the degree of similarity between the students, to recommend the items corresponding to the interest of the student. The system aims to process student profiles from the e-learning platform. The proposal aims to predict and determine student preferences based on information shared on their different social media.

Shi *et al.* [55] proposed a learning path recommendation model based on a multidimensional knowledge graph structure. Initially, the authors designed a multidimensional knowledge graph structure that separately stores learning objects organized in several classes. Then they proposed six main semantic relationships between learning objects in the knowledge graph. Second, they designed a path recommendation model based on the multidimensional knowledge graph structure. The model generates and suggests personalized learning paths according to the student's target learning object. The results of the experience indicated that the proposed model can generate and recommend qualified and personalized learning paths to improve learning experiences.

Table 5: Articles that contain recommendation systems

Authors	**Recommendation systems**
Anaya *et al.* [23]	Recommendation system based on an ID in the context of collaborative learning in the e-learning environment.
Joy *et al.* [35]	Ontology model that encompasses the student profile and learning object attributes, which can be used for recommending content on an e-learning platform.
Chen *et al.* [26]	Enhanced recommendation method called Adaptive Recommendation based on Online Learning Style (AROLS).
Dahdouh *et al.* [27]	System of recommendation of courses distributed to the e-learning platform.
Florian *et al.* [31]	Prototype that implements indicators as examples of learning analytical applications.
Hamada [32]	Model of an e-learning system based on Java2D technology and containing an intensive set of learning materials to support all types of students.
Huang *et al.* [33]	Deep Reinforcement learning structure for Exercise Recommendation.
Iqbal *et al.* [34]	Kernel Context Recommendation System algorithm, which is a flexible, fast and accurate.
Kapembe and Quenum [36]	Hybrid recommendation, based on the student's profile, the relevance and quality of learning objects for the program in which the student is enrolled.
Sharma and Ahuja [41]	Semantic recommendation using ontology to recommend relevant and personalized learning content to students.
Venugopalan *et al.* [43]	Content-based recommendation system.
Zakrzewska [44]	Agent-based recommendation system, which, for each new student, suggests a group of students of similar profiles.
Maâloul and Bahou [50]	Recommendation system based on machine learning that is fundamentally based on a digital learning technique and that determines the degree of similarity between students.
Villegas-Ch *et al.* [53]	Architecture for Integration of Chatbot with Artificial Intelligence in Intelligent Campus for Improvement of Learning.
Shi *et al.* [55]	Learning path recommendation model based on a multidimensional knowledge graph structure.
Rajkumar and Ganapathy [57]	Recommendation system to increase classification accuracy.
Lin *et al.* [61]	Complementary recommendation structure for freshmen under restrictions or requirements, based on objective-oriented standards.
Niknam and Thulasiraman [63]	Intelligent learning path recommendation based on meaningful learning theory.

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Lin *et al.* [61] proposed a complementary recommendation framework for freshmen under constraints or requirements, based on goal-oriented standards. Students can get the results of recommendations according to different types of learning objectives. The structure developed by the authors presents the following contributions: (1) convex optimization framework through the integration of the characteristics of the University's courses and students; (2) data-based machine learning algorithm using resources extracted from formatted and unformatted data.

Niknam and Thulasiraman [63] designed and implemented a learning path recommendation (LPR) system. The system groups students and chooses a suitable learning path for students based on their prior knowledge. The clustering component used the Fuzzy C-Mean (FCM) algorithm, which can recommend more than one learning path for students located on the cluster boundaries. The effectiveness of the LPR system was assessed by developing and offering a database course for real students.

Villegas-Ch *et al.* [53] proposed an architecture for the integration of a chatbot with artificial intelligence in an intelligent campus for improving learning. The authors developed a model that integrates the identification and evaluation of variables through the analysis of data that students generate in the academic systems. The results of the data analysis are transferred to an AI tool for decision-making.

Among the 51 articles evaluated, Table 5 presents 18 works with different recommendation systems to use as strategies to improve students' learning.

Figure 2 shows the distribution of recommendation systems and technologies used by researchers in the articles. Among the main technologies, the most used were machine learning techniques with 3 articles.

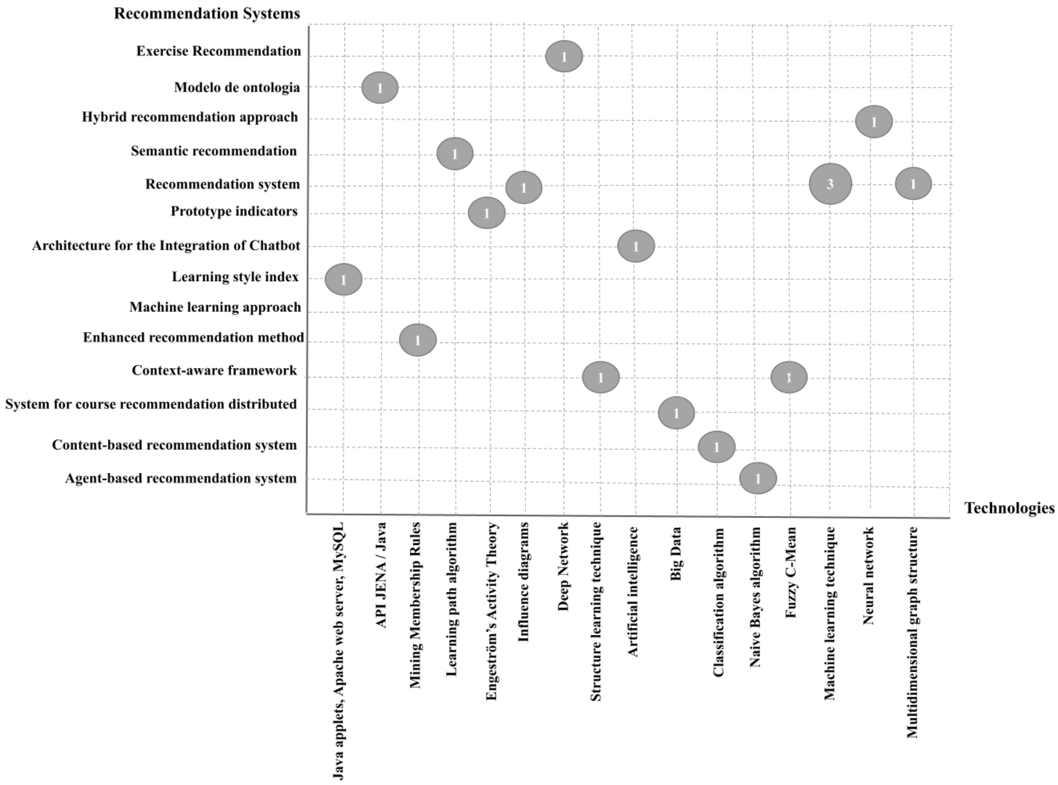

Figure 2. Recommendation systems and technologies used

4.3. Forecasting models or systems

Table 6 presents prediction models or systems observed in 13 articles among the 51 analyzed.

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Table 6: Articles that contain forecast models or systems

Authors	Forecast models or systems
El Fouki *et al.* [29]	Decision-making system to help instructors.
El Moustamid *et al.* [30]	System capable of analyzing the profile of students and indexing videos on the Web in order to offer students a database with courses that correspond to their levels.
Kim and Kim [37]	Individualized Tutor of Artificial Intelligence as a system that integrates three developmental learning networks (DLNS).
Manhães *et al.* [40]	WAVE architecture that provides useful information about student performance.
Thai-Nghe *et al.* [42]	Recommendation system techniques for mining educational data, especially to predict student performance.
Zaoudi and Belhadaoui [45]	Learner Behavior Analytics (LBA) model based on a system called Score and Behavior Analytics (SBAN) to analyze student outcomes and behavior.
Chen *et al.* [62]	Phased forecasting model to predict students at risk at different stages of a semester.
Turabieh *et al.* [64]	Harris Hawks algorithm optimization enhanced as a feature selection for predicting student performance.
Iatrellis *et al.* [65]	Two-stage machine learning approach to predict student outcomes.
Angeline *et al.* [48]	Discriminant analysis to measure student performance.
Zhang *et al.* [47]	Learning analysis using Moodle plugins to discover possibilities to improve the learning process and reduce the number of underperforming students using plugins from the virtual Moodle environment.
Hashim *et al.* [49]	Student performance prediction model based on supervised machine learning algorithms (decision tree, Naïve Bayes, logistic regression, support vector machine, nearest neighbor K, minimal and neural sequential optimization Network).
Freitas *et al.* [51]	IoT system for predicting school dropout using machine learning techniques based on socioeconomic data.

El Fouki *et al.* [29] proposed a decision-making system that helps instructors respond to problems using intelligent general techniques applied to data collected on e-learning platforms. The adapted system explores parameters such as learning styles and teaching styles, based on deep neural network algorithms and reinforcement learning, and takes into account the use of the teacher to improve the accuracy of the recommendation system. Principal component analysis and reinforcement learning improve classification models and increase the prediction performance of a deep neural network algorithm, reducing the dimensionality of dataset variables, with accuracy and reliability.

Manhães *et al.* [40] proposed the WAVE architecture that supports useful information on the performance of undergraduate students and predicts those who are at risk of dropping out of the educational system. The authors used several classifier algorithms. The Naïve Bayes algorithm showed the highest true positive rate in the three undergraduate courses analyzed.

El Moustamid *et al.* [30] developed a multimedia recommendation system capable of analyzing student profiles and indexing videos on the web to offer a database with courses according to the student's level, aiming at their improvement. The first block represents a standard learning management system. In this block, the students must authenticate themselves. The second block represents a system that retrieves the results, processes and converts them into exploitable data, and then sends to the third block in the form of an order. The third block retrieves the data from the second block and looks for videos that are located on the web or in a data source provided by the user, and keeps the videos that match the student's profile.

Thai-Nghe *et al.* [42] proposed a new approach that uses recommendation system techniques for educational data mining to predict student behavior. Recommendation systems techniques were compared with traditional regression methods, using data from intelligent tutoring systems. The work presented the following contributions: (1) application of recommendation systems techniques, such as matrix factoring in the educational context, to predict student performance; (2) educational data mapping research and; (3) comparison of recommendation systems with traditional techniques such as linear regression or logistic regression. Experimental results showed that the proposed approach can improve prediction results.

Kim and Kim [37] developed an individualized AI tutor as a system that integrates three Developmental Learning Networks (DLNs) to help a student achieve a high level of academic success. The AI Tutor suggests learning content that matches the educational

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standard of the academic grade. The AI tutor considers the student's current status and preferences to deliver education programs on an individual basis.

Zaoudi and Belhadaoui [45] proposed a Learner Behavior Analytics (LBA) model based on a system called Score and Behavior Analytics (SBAN) to analyze student outcomes and behavior. Responsible for continuously monitoring and evaluating the student's actual level throughout their training trajectory. The authors intend to further detail these models, proposing an architecture and prototypes that will allow better modeling for the LBA system, making it possible to present content more adaptable to the profiles of evolving students.

Chen *et al.* [62] proposed a phased forecasting model to predict at-risk students in different semesters. Students' characteristics and online learning behaviors were analyzed.The proposed model has three main contributions: 1) restriction strategies to obtain valuable resources; 2) a dynamic prediction model and; 3) it can predict at-risk students at different stages of the semester.

Iatrellis *et al.* [65] proposed a two-stage machine learning approach that uses supervised and unsupervised learning techniques to predict outcomes for students in higher education. The objective of the research was to predict the results of students in undergraduate courses in computer science offered by higher education institutions in Greece. Students involved in the case study were grouped based on similarity of education-related factors and metrics. The K-Means algorithm was used in the clustering experiments, and the result produced evidence that the proposed approach can contribute to the accuracy of predicting student outcomes.

Turabieh *et al.* [64] simulated the proposed modification of the Harris Hawks Optimization algorithm as a resource selection algorithm for the students' performance prediction problem. The proposed approach improves the original Harris Hawks Optimization algorithm and supports the claim that the control of population diversity improves the process of exploring the algorithm.

Zhang *et al.* [47] performed learning analytics to discover possibilities to improve the learning process and reduce the number of underperforming students using plug-ins from the Moodle virtual environment. The analysis considered records of 124 participants, to verify the relationship between the amount of records in the e-course and the students' final grades. The authors also performed a correlation analysis to determine the impact of students' educational activity on the Moodle system in the final assessment.

Angeline *et al.* [48] used discriminant analysis to measure student performance. The data mining technique identified students' cognitive skills and their associated behaviors in a virtual instructor-led classroom. The data sets collected in the research study refer to different subjects addressed by students of engineering graduates from Dr. G. U. Pope College of Engineering (Hyderabad, India). The students' performances in the respective discipline prerequisites were collected from the departmental records of summaries of results related to the computer science course and the engineering discipline. According to the authors, the discriminant analysis works well with the data set covering all data groups and provides a better forecast.

Hashim *et al.* [49] compared the performance of various supervised machine learning algorithms to predict students' academic success and their performance in higher education. The authors used a set of data provided by the courses in the Bachelor's Degree Programs of the Faculty of Informatics and Information Technology at the University of Basra, in the 2017-2018 and 2018-2019 academic years, to predict student performance on final exams. The experiments showed that the Logistic Regression classifier algorithm showed the best performance.

Freitas *et al.* [51] proposed an approach to detect and classify students at risk of dropping out based on their socioeconomic data. The IoT platform was designed to allow this task to be performed using any device connected to the Internet. Machine learning methods were used to identify the possibility of evasion.

Figure 3 shows the distribution of forecast models or systems and technologies used by

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researchers in the articles. The 13 works contain proposals that identify the characteristics and profiles of students with learning problems and probable dropout before the end of the course, enabling actions to improve the learning process.

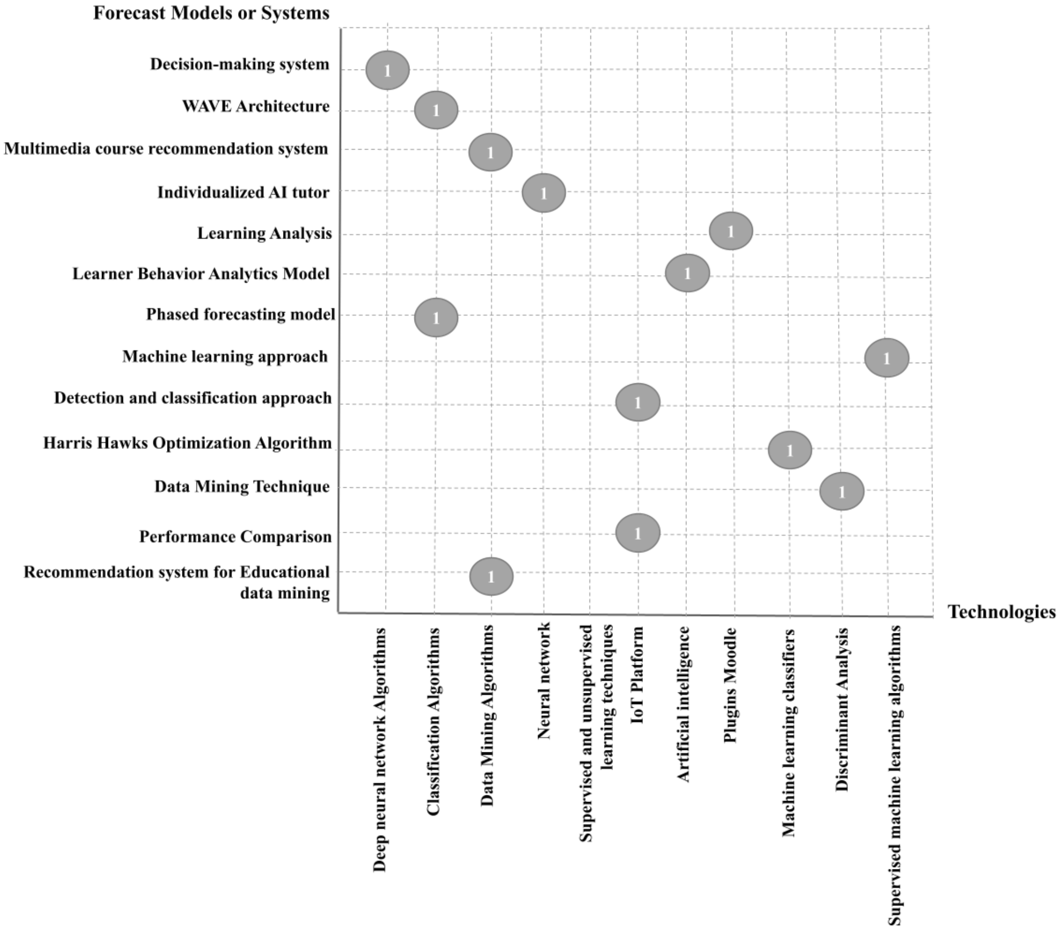

Figure 3. Prediction models or systems and technologies used

4.4. Assessment Tool

Among the 51 articles analyzed, only 3 presented assessment tools (Table 7): Domain-specific language to customize online learning assessments in Moodle [24], an evaluation tool called Enriched Learning Analytics Rubric (LAe-R) [28], and an intelligent system for assessing students' professional skills levels in e-learning [59].

Table 7: Articles that contain assessment tool

Authors	**Summary / Assessment tool**
Balderas *et al.* [24]	Domain-specific language to customize online learning assessments in Moodle.
Dimopoulos *et al.* [28]	Evaluation tool, called Enriched Learning Analytics Rubric (LAe-R), which was developed as a Moodle plug-in.
Barlybayev *et al.* [59]	Intelligent system for assessing students' professional skills levels in e-learning.

Balderas *et al.* [24] developed a domain-specific language to customize online learning assessments in Moodle. The authors implemented EvalCourse, a computer system that performs queries written in this language, providing in the output the requested information. In this way, teachers can retrieve indicators of information stored in Moodle activity logs without any technical knowledge in databases or computer programming. The study was carried out at the University of Cádiz, Spain, in a mandatory course of Language Processors II from its degree in Computer Science, with 36 students from the first semester and the fifth year enrolled in the academic year 2012/13.

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Dimopoulos *et al.* [28] presented an evaluation tool called Enriched Learning Analytics Rubric (LAe-R), which was developed as a Moodle plug-in. LAe-R allows teachers to create enriched rubrics containing related criteria and classification levels. For this, data extracted from the analysis of student interaction and learning behavior in a course in the moodle environment are used, such as the number of messages posted, access times, material, and task notes. LAe-R was considered a stable and promising assessment tool that can fill the gap in evaluating student performance in e-learning environments using student interaction data.

Barlybayev *et al.* [59] proposed the creation of an intelligent system for assessing students' professional skills levels in e-learning. Mathematical models and methods were used to evaluate the formation of students' professional skills at the level of subjects, modules, and the entire educational program. Competency (knowledge) assessments were carried out at three levels of the educational program. To assess knowledge, fuzzy binary relationships were used with standard responses from the knowledge base and the responses of students. The authors used fuzzy calculations on data obtained by the comparison algorithm. The construction of fuzzy calculations used the Mamdani method implemented in Matlab.

5. Conclusion and Future Research

Distance Learning aims to offer a complete, dynamic, and efficient teaching and learning process mediated by technological resources. It has been growing exponentially and taking an important role in the educational environment. The use of this modality contributes to the generation of data from interaction and learning behavior of students in the Virtual Learning Environments (VLEs).

The data extracted from the VLEs are analyzed using data analysis techniques that identify student behavior patterns. The discovery of standards helps managers and teachers in strategic planning, allows monitoring the student's academic progress, and offers solutions through intelligent services for monitoring, intervention, motivation, and improvement in the students' learning process.

A research methodology based on a literature review allowed the identification of 51 publications on intelligent services applied to distance learning. Among the intelligent services, 33% (17 articles) presented learning systems, 35% (18 articles) contained recommendation systems, 26% (13 articles) presented models or forecasting systems, and only 6% (3 articles) contain assessment tools.

The study indicated that recommendation systems and learning systems are research trends. These systems analyze student profiles, identify patterns of behavior, detect low performance and identify probabilities of dropouts from courses.

Most research papers analyze the learning profile to indicate personalized content and courses or extracurricular activities that contribute to student learning. In addition, the works allow teachers and educational managers to take preventive actions to minimize possible problems in the learning paths.

Future work will expand this literature review through a specific focus on mobile learning (m-learning) [70–72] and ubiquitous learning (u-learning) [60,73–77]. Both technologies allow expanding the limits of distance learning environments mainly collaborating to the infrastructure of intelligent systems. In this sense, the use of temporal series of contexts to organize and analyze data is an emergent research theme. This organization of data is called Context Histories [78–80] or Trails [81,82]. Context histories allow advanced strategies for data analysis, such as profile management [83], pattern analysis [84], context prediction [85], and similarity analysis [86]. The continuity of this review will consider research works that applied Context Histories to implement intelligent services in distance learning.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
DL	Distance Learning
DLNS	Developmental Learning Networks
EC	Exclusion Criteria
FCM	Fuzzy C-Mean
IC	Inclusion Criteria
ID	Influence Diagrams
LA	Learning Analytics
LBA	Learner Behavior Analytics
LMS	Learning Management System
LPR	Learning Path Recommendation
NLP	Natural Language Processing
SBAN	Score and Behavior Analytics
SCI	Social Competence Intervention
VRLE	Virtual Reality Learning Environment
VLEs	Virtual learning environments

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