

Research Article

Cite this article: Nuci, K. P. (2025). Cloud eLearning - A New Paradigm of eLearning System Using Artificial Intelligence Techniques for Generating Personalized Learning Paths. *Educational Process: International Journal*, 16, e2025226.

<https://doi.org/10.22521/edupij.2025.16.226>

Received March 1, 2025

Accepted April 22, 2025

Published Online May 15, 2025

Keywords: Artificial Intelligence, eLearning, Cloud eLearning, Recommender Systems, Automated Planner, Personalisation.

Author for correspondence:

Krenare Pireva Nuci

✉ krenare.nuci@uni-pr.edu

✉ Faculty of Education, STEM Department, University of Prishtina, Prishtina, Kosovo.

Cloud eLearning - A New Paradigm of eLearning System Using Artificial Intelligence Techniques for Generating Personalized Learning Paths

Krenare Pireva Nuci 

Abstract

Background/purpose. With advancements in technology, particularly in Artificial Intelligence (AI), personalized and adaptive systems are increasingly being integrated into conventional educational environments. These technologies create opportunities to place learners at the center of the educational experience through personalized learning. However, the lack of standardization among online educational learning resources limits their adaptability and re-use across different systems and contexts. To address this challenge, this study introduces a novel idea for an adaptable artificial intelligence system, namely the Cloud eLearning system (CeL), which includes Cloud eLearning Learning Objects (CeLLO) —standardized learning objects tagged with semantic metadata for flexible re-use.

Materials/methods. The system architecture features a Cloud eLearning Recommender System, which ranks educational learning resources using a vector space model and hierarchical clustering, and a Cloud eLearning Automated Planner, which generates personalized learning paths based on the recommender output. The study employed a two-phase evaluation methodology. First, the functionality of the AI-based Cloud eLearning prototype was assessed. Second, a user evaluation was conducted through a questionnaire administered to 17 undergraduate and postgraduate students selected from five Computer Science courses. The questionnaire collected both quantitative and qualitative data, including learner satisfaction and perceptions of personalization services.

Results. Quantitative data were analyzed through correlation analysis, revealing significant correlations: 99% between system performance and personalization services, 99% between system performance and learner satisfaction, 90% between system performance and learners' initial background, 95% between learners' background and personalization services, and 99% between learner satisfaction and personalization services.

Conclusion. These findings highlight the effectiveness of CeL in delivering personalized learning experiences and suggest that future work should focus on further validating the system across broader educational contexts and refining the algorithms output.



OPEN ACCESS

© The Author(s), 2025. This is an Open Access article, distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>), which permits unrestricted re-use, distribution, and reproduction, provided the original article is properly cited.

1. Introduction

Artificial intelligence approaches have influenced the design of many eLearning platforms available today. Specifically, these platforms in some cases use automated planning to construct personalized learning paths that take into consideration the learners needs, background, and their characteristics. eLearning is considered as the use of technology to enable access to the learners for various number of learning materials at any time and from any location. Moore, Dickson-Deane, and Galyen (2011) also highlights the need to make every learner, regardless of geographic distance, have access to education learning resources. To appeal to the broadest audience, eLearning courses have typically taken a "one-size-fits-all" approach, disregarding the unique differences among learners. This has frequently resulted in low learner engagement, which in turn reduces their capacity to learn and are demotivated to keep using the eLearning systems. This approach has decreased learner engagement and motivation, underscoring the need for more personalized solutions.

Many of the 20th century's usage barriers have been lessened by the expansion of the internet and advancements in personal computing, even though concerns about a "digital divide" persist. In response, there has been a great deal of advancement in the 21st century in terms of eLearning accessibility and platform variety, which also implies the kind and frequency of synchronous or asynchronous contact between teachers and learners. The idea of content re-use, compatible throughout various eLearning platforms, has evolved as a best practice in higher education amid the rising understanding that learning activities and content generation are labour- and time-intensive. The idea behind Digital Learning Objects, or shortly, Learning Objects, has impacted how learning content and related activities are created and presented. It is a practical method for producing, distributing, and re-purposing digital content. According to Wiley (2008), a digital learning resource that is used and repurposed to facilitate learning is called a learning object (LO), which has the lowest granularity in eLearning systems. The LO serve as building blocks or puzzle pieces for the learning content and exercises, emulating the approach of Lego building blocks that Hodgins (2006) first proposed. Moreover, Hodgins (2006) described LO as an assemblage of information objects that are assembled using meta-data to match the individual learner's personality and needs. The concept of reusable learning objects first surfaced in 1994 and has since been further developed by Duval, Wason, and Hodgins (2002) and Hodgins (2006) due to the absence of a uniform standard for re-using learning objects across multiple sources and situations. As a result, a number of organizations launched standardization initiatives that have an impact on the creation, representation, and organization of learning objects. These initiatives reflect standards and protocols that affect their ability to be shared, including the SCORM specification, the Dublin Core (2004) metadata standard, and the IEEE Learning Object Metadata (LOM) metadata standard, see Barker (2005). Learning objects are typically linked to files called meta-data that, by tagging with description, tend to characterize the learning object in a standard way. Re-using, sharing, and retrieving learning items for individualized usage became more likely when the tagging approach was employed.

Following the last two decades, there was a convergence in the development of Open Education Resources (OERs), web 2.0, and personal learning environment technologies. These developments aided in the creation and representation of learning content by Tuševljak, Majcen, Mervar, Stepankina, and Cater (2016), as well as its sharing and customization to meet the needs of individual learners. Within this particular context, personalized eLearning refers to the provision of eLearning services that are tailored to the individual characteristics of learners. Within this context, personalized eLearning is increasingly recognized as critical, offering tailored educational services that align with each learner's specific characteristics and learning needs, as claimed by Fan and Poole (2006). These days, institutions, professionals—including practitioners—and people produce LO. Depending on whether the platform and the content promote open access, different strategies are

used. A growing number of LOs are made available to the higher education community and beyond through open-access educational resource (OER) repositories that adhere to international standards.

A combination of new and established pedagogies as in Miranda et al. (2021); Oye, Salleh, and Iahad (2012) are being used by educational institutions that offer eLearning to create courses and programs. Four key components that compose a typical eLearning course are: (i) pedagogy, (ii) content, (iii) technology infrastructure, and (iv) course administration. These components can be found in both closed and open formats of learning materials, such as Massive Open Online Courses and Small Private Open or Online Courses. The pedagogy specifies the learning paths and pace as well as how the delivery and assessment strategies will meet the learning objectives. The content includes a range of text and media included in the content that are judged suitable to provide opportunities to meet the learning outcomes. With technological infrastructure is understood, the collection of learning technologies—such as wikis, teleconferencing tools, virtual learning environments (VLEs), file sharing, social interaction, support, and e-feedback—that teachers and learners use to help transfer knowledge and acquire new skills. Last but not least, course administration refers to the rules, procedures, and oversight that govern how learners register, attend, advance, etc. Regardless of how the aforementioned are combined, eLearning shares several restrictions with traditional in-person instruction, with the exception of MOOCs, which are typically credit-free. These kinds of learning approaches are limited in the following ways: (a) teachers use predetermined pedagogies; (b) teachers choose most of the material and/or recommend it; (c) teachers or institutions specify the technological infrastructure's tools; and (d) rules and procedures are specific to the provider or institution.

The main paradox in this scenario is that the learner, the one receiving the instruction, has no or minimal input into the decisions made by the course providers and must follow their decisions.

Even so, learning providers are frequently criticized for failing to employ a learner-centred strategy, which considers each learner's needs and characteristics, including learning styles, knowledge level and background - to name a few. This challenge underscores a major gap in current eLearning practices: the lack of personalized, learner-driven educational learning paths. This research addresses this critical gap by proposing an AI-driven Cloud eLearning (CeL) system designed to place the learner at the centre of the educational experience. The study builds on advances in Artificial Intelligence, such as automated planning, knowledge representation, and recommender systems, to offer flexible, personalized learning paths that accommodate each learner's background, needs, and preferences. It investigates learning environments and related learning processes that can automatically offer personalized learning paths tailored to each learner's progress, learner characteristics, and needs. Specifically, this study explores two key research questions: first, how is the generation of personalized learning paths affected when compared to Cloud eLearning system performance, and second, whether the AI-driven automated personalization of learning paths impacts learners' satisfaction. The findings of this study are expected to have significant implications for the design of future educational technologies, providing practical recommendations for institutions aiming to shift toward more learner-centred, AI-enhanced eLearning systems.

The rest of the paper is organized as follows. Section 2 provides some background information on eLearning and related work followed by Section 3 that describes the architecture of Cloud eLearning, followed by Material and Methods in Section 4. Section 5 presents the results. Lastly, the conclusion is drawn in Section 7.

2. eLearning and Related Work

2.1. Overview of eLearning

The term "eLearning" first appeared in the 1980s. Before then, though, a lot of researchers utilized other definitions and terminology to refer to the ideas of online learning, virtual learning environments, eLearning, network learning, and distance learning, see Brika, Chergui, Algamdi, Musa, and Zouaghi (2022); Martinez-Garcia, Horrach-Rosselló, and Mulet-Forteza (2023); Noesgaard and Ørngreen (2015); Sharma, Gautam, and Agarwal (2023). The review by Moore et al. (2011) provides the best explanation for these terminology discrepancies where the authors surveyed a significant amount of researchers and identified the variation in meaning attributed to concepts of eLearning, distance learning, and online learning and their characteristics. In general, electronic learning makes use of technology to give users access to learning materials anywhere, at any time. Electronic learning, which encompasses all education network activities conducted by individuals or a group of people working online or offline through electronic devices, is represented by the letter "e" in the name "eLearning" by Naidu (2006).

eLearning, as defined by Ruttenbur, Spickler, and Lurie (2000), is the application of technology that has revolutionized the field of education. Clark and Mayer (2023) defined eLearning as a computer-based learning possibility. Triacca, Bolchini,

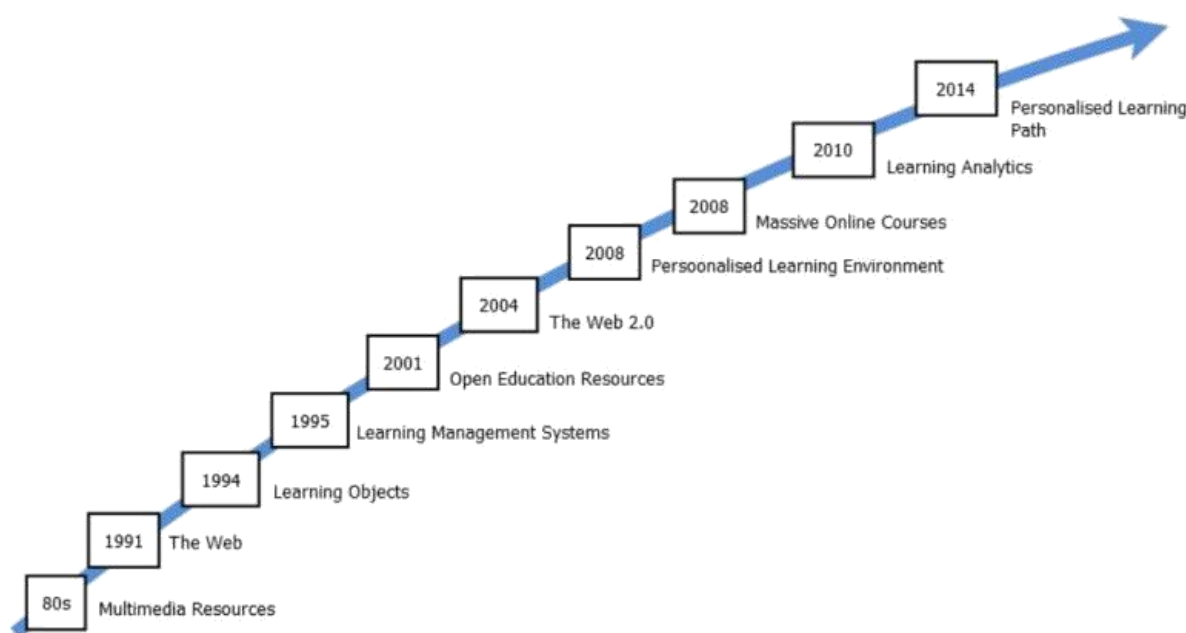


Figure 1. The Trend of Development in eLearning

Botturi and Inversini (2004) emphasized online learning as a type of online activities. Moore et al. (2011) stress the effort of giving access to learning for all learners who are geographically at a distance. Stamatis, Kefalas, and Kargidis (1999) described eLearning as a successful and affordable approach type of remote learning. Even further, King, Young, Drivere-Richmond, and Schrader (2001) distinguish between remote learning and distance education, characterizing the former as an ability and the latter as an activity falling under it. According to Pireva and Kefalas (2013), electronic learning is provided through information and communication technology infrastructure. It can be provided through web-based platforms, programs, disks, television, or even an online or offline approach. Either way, it helps learners by offering opportunities for learning to all types of learners. Recently, however, the focus of study has switched to the personalized eLearning environments and courses, taking into account a variety of individualized characteristics that may have an impact on the learning process as a whole. Figure 1 illustrates the evolution of eLearning through a roadmap, influenced by

Conole and Oliver (2006). The authors extended further this history with the "Personalised Learning Path" node, which has emerged with note-worthy outcomes following the development of computing processing power and the generation of massive amounts of data. By offering learners individualized learning paths that are tailored to their goals and characteristics, personalization generally has the potential to significantly alter the eLearning paradigm.

2.1.1. eLearning Platforms

These days, as shown in Zhang (2015), various terms for eLearning systems are used interchangeably, including Knowledge Management Systems (KMS), Collaborative Learning Environments (CLE), Virtual Learning Environments (VLE), Learning Management Systems (LMS), name a few. The CMS was described as a collaborative learning environment with tools for creating and delivering online courses by Gagné, Wager, Golas, and Keller in 2005 in Moore et al. (2011). On the other hand, Wilen-Daugenti (2009) stated in 2009 that the terms CMS, LMS, and VLE ought to be used synonymously. Further, Trafford and Shirota (2011) define a virtual learning environment as "a collection of software tools supporting academic administration, teaching, and research". Additionally, in Gupta (2016), the term "system for delivering learning materials to learners via the web" refers to the virtual learning environment, which is used interchangeably with learning management systems and content management system principles. Several definitions of the terminology used in this research paper are provided to highlight its diverse approaches, taking into account the diversity of language used in different works. In keeping with this notion, a virtual learning environment, or VLE, is described as a platform that provides an integrated environment approach of diverse resources that facilitates interaction between learners and teachers as well as between learners and the subject. In the VLE, learners are not only involved but also actors, as they either directly or indirectly contribute to the creation of content linked to a particular topic as part of social interaction. This covers the following:

(i) one-to-one, one-to-many, or even many-to-many communication; (ii) synchronous and/or asynchronous communication; and (iii) text, audio, or video communication as three-dimensional communication.

2.2. The Use of AI Technologies for Personalised Learning

There are several ways in which eLearning systems are transitioning from eLearning to personalized eLearning. In general, two criteria are used to categorize personalization: (i) customized processes and/or (ii) adaptive personalization processes. The customized personalization process gives the learner control over the environment by enabling explicit choice selection, while the second option, the adaptive personalization process, emphasizes the crucial role of the learner's progress with respect to the use of the system. Using intelligent tutoring techniques, adaptive personalization is an implicit process that tracks learners' learning activities and recommends learning materials that might be relevant to them based on learners profile characteristics. Personalized eLearning pertains to the possibility of tailoring the content and/or environment of online courses to the learner's characteristics. Per Klačnja-Milićević, Vesin, Ivanović, Budimac, and Jain (2016), technically, there are two main ways to accomplish personalization: (i) personalized content based on learners' profiles' characteristics and (ii) rule-based personalization, which creates personalized content based on predefined rules judgments in the absence of learners profiles. Artificial intelligence approaches can be used to tailor user settings, learning paths, assessment methods, learning activities, learning material recommendations, communication channels, and collaborative tools. This change makes it possible for the system to transition from a "one size fits all" strategy to a "learners-centric" strategy that tends to accommodate the preferences of the learners in terms of learning theories, learning stages, learning styles, motivation, and needs. A few examples of artificial learning approaches that aid in personalization are fuzzy matching rules in sWu, Lu, and Zhang (2015), ontologies in Villegas-

Ch and Garcí'a-Ortiz (2023), artificial neural networks in Gligorea et al. (2023); Hooshyar, Azevedo, and Yang (2024); Munir, Vogel, and Jacobsson (2022), automated planning in Pesovski, Santos, Henriques, and Trajkovik (2024); Pireva, Kefalas, and Cowling (2017) and recommender systems in Jena et al. (2022); Pireva and Kefalas (2018).

The theoretical framework underpinning this study is based on constructivist learning theory Koohang, Riley, Smith, and Schreurs (2009) combined with personalized learning. Constructivism holds that learners build new knowledge upon their previous experiences, emphasizing the active role of the learner in the learning process. Personalized learning supports adapting the environment, content, and learning pace to individual learner needs, maximizing engagement and promoting deeper understanding. This framework informs the development of the Cloud eLearning system, where AI techniques dynamically support personalized learning paths tailored to constructivist principles.

3. The Cloud eLearning

The term "cloud eLearning," which was originally used in Pireva, Kefalas, Dranidis, Hatziapostolou, and Cowling (2014), refers to the concept that anything available on the cloud, including both structured and unstructured resources, has the potential to be a learning resources that can be utilized to support personalized learning. Hence, the learning cloud be described and shown as an assortment of readily available learning resources that are found and shared via the cloud and are provided by different providers in a range of formats as (i) text, (ii) video, (iii) audio, (iv) photos, (v) exams - to name a few. Its mission is to provide personalized services that will increase interaction among learners, teachers and institutions by sharing a pool of experiences and knowledge available in cloud-open courses and recommending personalized learning paths that match learners' preferences. Cloud eLearning main actors are: (a) Learners, (b) Teachers, and (c) Institutions.

3.1. The Cloud eLearning Technical Architecture

An increasing number of prestigious universities have opened their courses on the cloud. Universities that have reduced their expenses by utilizing cloud technology or even building a cloud architecture for their educational offerings are mentioned in Sultan (2010). An excellent illustration of how to use the cloud economically is provided by the University of California's software as a service concept, which is powered by Amazon Web Services as claimed in Armbrust et al. (2009). This project is carrying on the University of Washington delivery paradigm, which, among other things, makes use of Google and Microsoft technology to provide cloud-based education to its users.

Since Cloud eLearning comprises various sources of learning materials and every-thing stored in it can potentially be used for eLearning purposes, the authors wondered whether the services should be part of any of the service models that are described in Figure 2 or whether it would be more appropriate to propose a new service model. From one side, the IBM Business Processes as a Service, developed based on their client experiences, is an excellent example to mention when considering to propose or build a new service model based on the demands of learners, see Gandhi (2011) approach. Figure 3 depicts a complete new abstract architecture proposal for providing the Cloud eLearning, the Learning as a Service (LaaS) model or the Education as a Service (PaaS) model. In this regard, it is necessary to analyze if the infrastructure and eLearning services—such as servers, storage, networking, framework, middleware, and visualization—as well as components like assessments, roles, databases, and data are provided as stand-alone services.

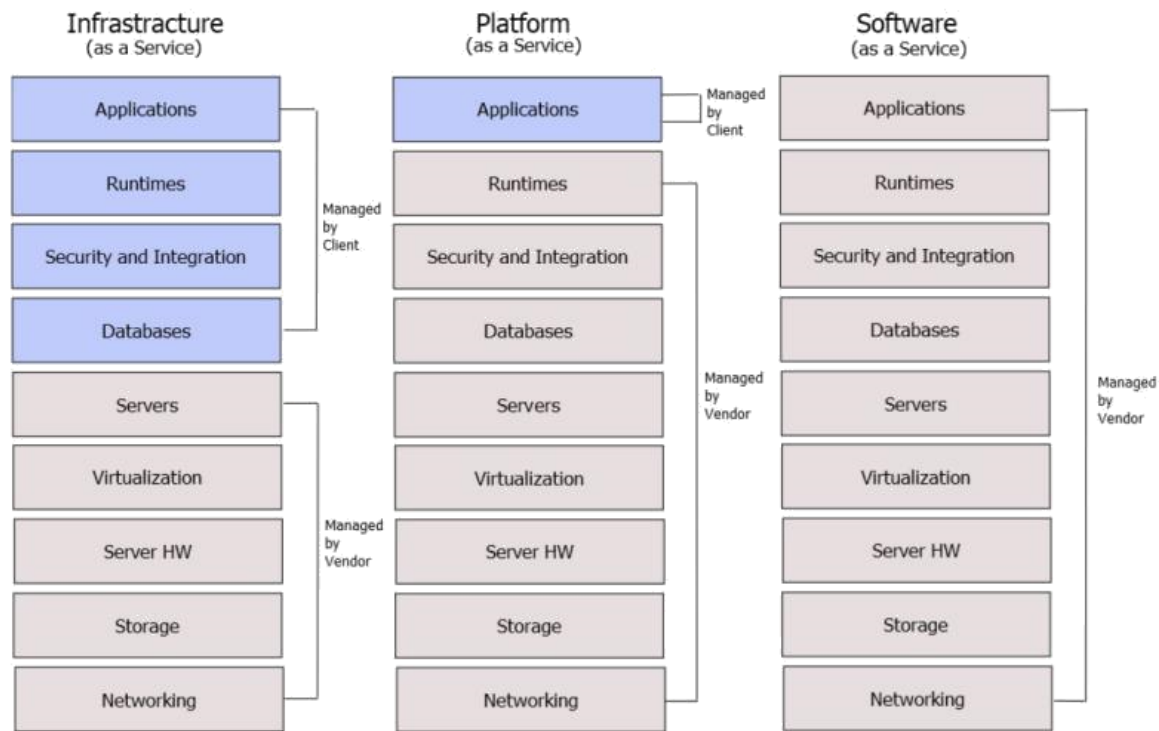


Figure 2. Cloud Computing Service Models (Teixeira et al., 2010)

Subsequently, research is required to determine which components the distributors should manage and which of the client. Using this proposal, the two bottom elements may be administered by the vendors, the middle three elements by University Institutions, and the remaining aspects by teachers and/or administrators, depending on the services offered by the model shown in Figure 3. In this level, the institution has to reach a decision based on its available resources.



Figure 3. CeL as Learning as a Service Model

Now, diving into the Cloud eLearning system, Figure 4 demonstrates the “big picture” of the architectural system consisting of three layers that integrate several technologies. The Learning Cloud is generated by knowledge representation in the top layer, which filters appropriate learning resources for each learner using recommender technology in the intermediate layer, as in Pireva and Kefalas (2018). The Artificial Intelligence automated planning at the bottom layer ultimately serves as an automated processor that designs flexible, uniquely customized learning paths for each learners characteristics.

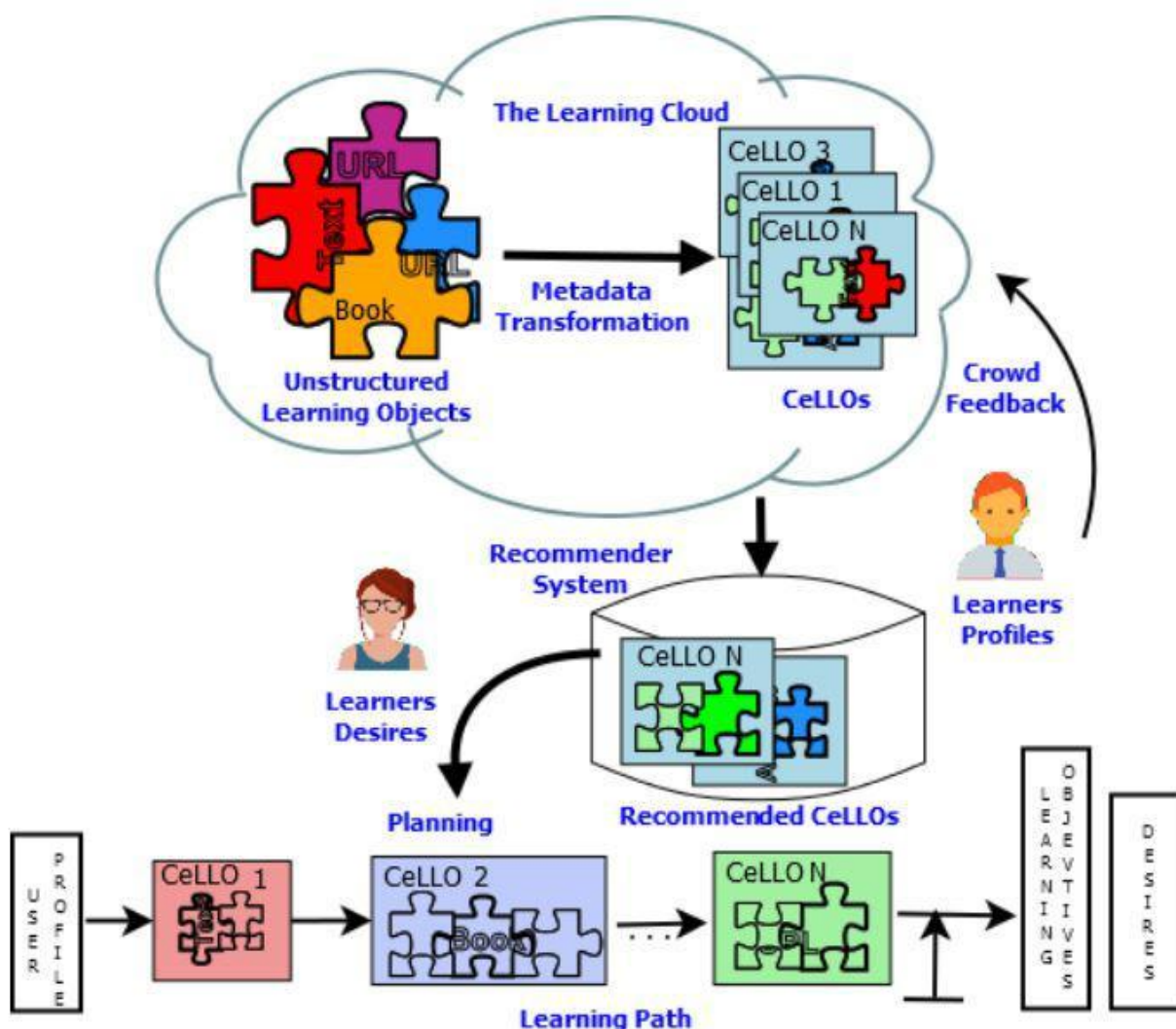


Figure 4. Big Picture of Cloud eLearning (CeL)

The Cloud eLearning Learning Objects (CeLLOs) created from the open learning resources in the top layer are subsequently fed into the recommender system placed in the intermediate layer, see in Pireva, Kefalas, and Stamatopoulou (2017). The Cloud eLearning Recommender System has a twofold role. Prior to ranking the Cloud eLearning Learning Objects (CeLLOs) from most to least relevant, it first filters the CeLLOs that are pertinent to a learner’s background, learning needs, and learning styles. Artificial intelligence planning has been reported to encounter a known issue; without filtering and ordering, planning would have to cope with an extraordinarily huge search space among all departing CeLLOs. The Cloud eLearning Planner uses the filtered CeLLOs as additional input learning materials to create an automatic plan that serves as a personalized learning path.

3.2. Personalization in Respect to Adaptive Learning Paths in CeL

In this section are presented several scenarios that demonstrate how users can use Cloud eLearning. These include choosing a single preferred topic, personalizing resources for a personalized learning environment, and choosing topics from different teachers as long as they align with the specific learning outcomes of the course.

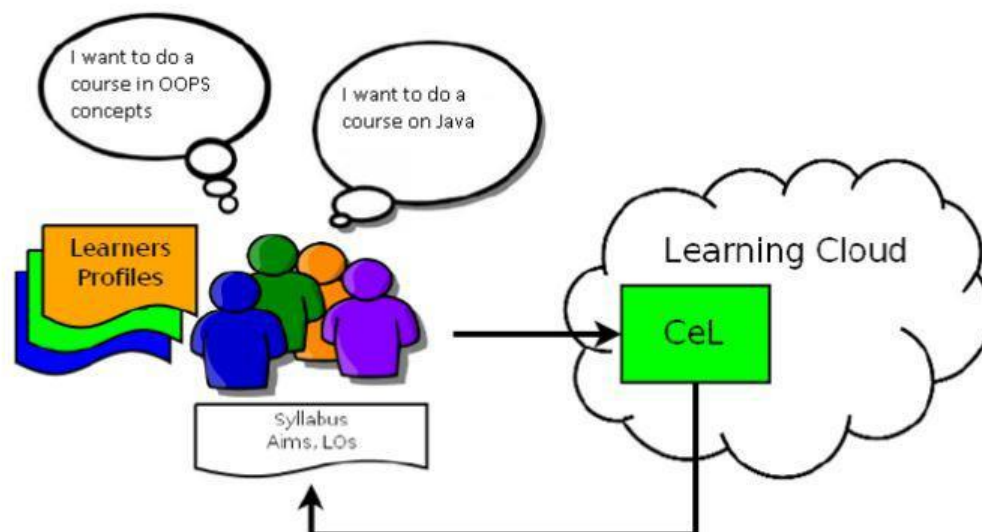


Figure 5. CeL identifies Preferences of Learners and Creates Individual Syllabi

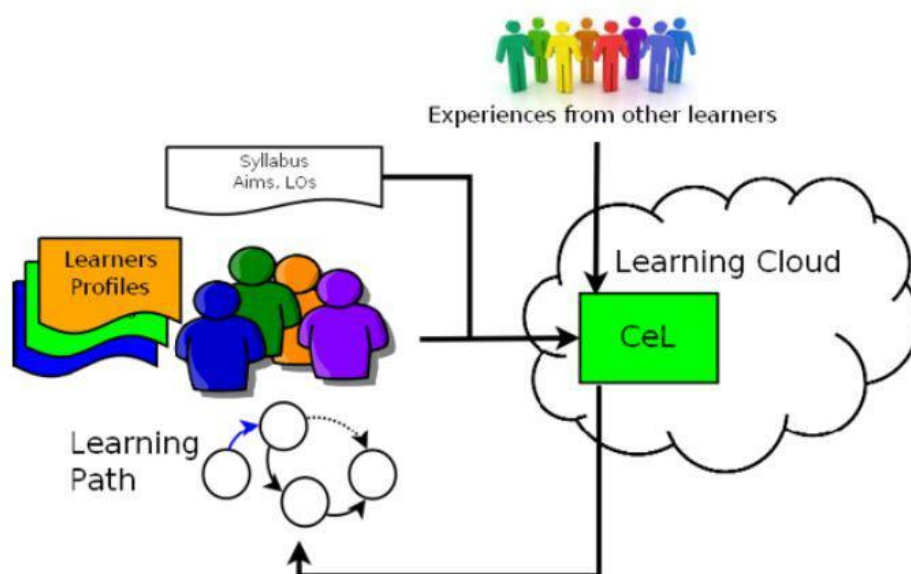


Figure 6. The Enhancement of Syllabi with Abstract Learning Paths for Particular Learners

In Figure 6, learners choose their preferred learning techniques, tailor their syllabus based on prior knowledge, select the desired learning methods, and tools, choose topics from various teachers, and always align their choices with the specific course's intended learning outcomes. As shown in Figure 6, CeL suggests a certain route for the learners to create course syllabuses. The customized learning path created by an automated planner draws on knowledge gleaned from past learners' experiences while also accounting for the learner's profile, completed courses, and enhancement of the system's overall usability in a variety of scenarios involving learners with comparable profiles. By incorporating user feedback on whether or not they liked the generated plan, the particular learning object, and so forth, the integration of user experiences will help to improve the generated personalized learning paths, which have a tendency to get better over time.

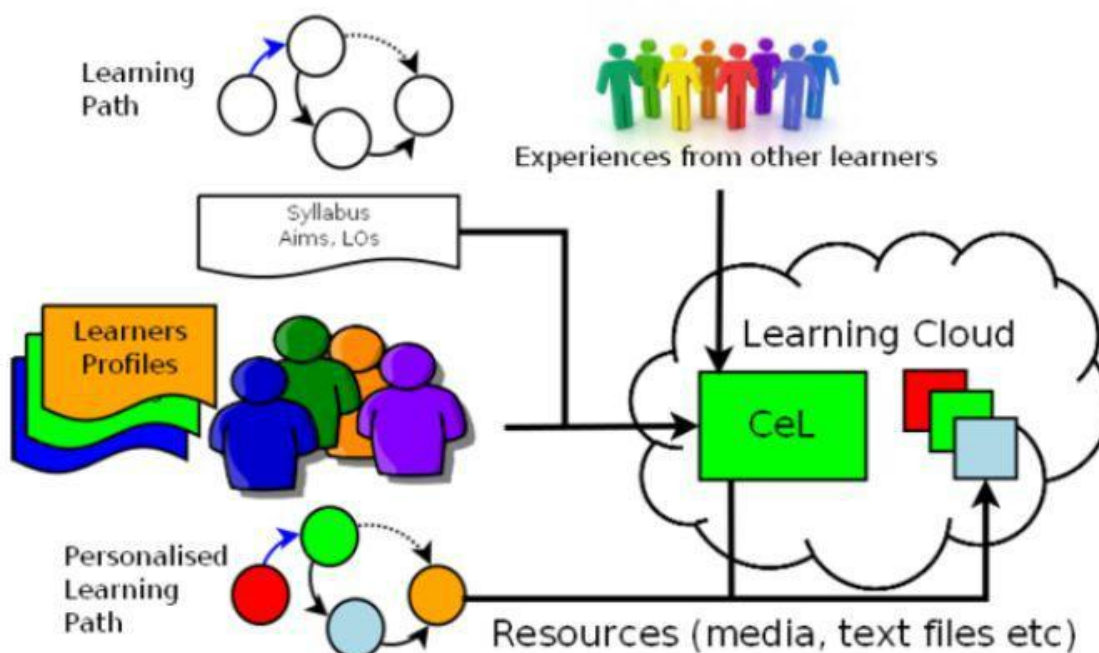


Figure 7. The Enhancement of the Abstract Learning Path with Resources of the Learning Cloud

As shown in Figure 7 the system automatically suggests a learning path based on the knowledge of the learners; nonetheless, it needs to be adaptable to the preferences of individual learners.

Finally, the user will have a list of courses with a personalized learning path, learning pace, learning tools, learning methodology, and also the process of assessment when following different courses within a Personal Learning Environment. Depending on how the learners use the cloud eLearning throughout time, the communication within these phases may vary each time they follow a specific course.

4. Materials and Method

In this section, the methodology used for evaluating the new proposed Cloud eLearning system is presented. The research instrument gathered both quantitative and qualitative data by going through the following three phases: 1) Using Cloud eLearning prototype functionalities, 2) user evaluation, and 3) an examination of the outcomes of (1) and (2) using the mixed approaches. The questionnaire instrument used in the second phase consisted mostly of closed-ended questions, along with one open-ended question. The combination of structured responses and open feedback justifies our approach of using both quantitative and qualitative analysis in this study.

4.1. Data Collection

Undergraduate and graduate students with different knowledge backgrounds were randomly selected from five different Computer Science courses. Three postgraduate students and fourteen undergraduate students made up the student participation list, which resulted in a total of seventeen (17) participants. The inclusion criteria required that participants be enrolled in a Computer Science course and willing to engage with new educational technologies; no specific exclusion criteria were applied. All 17 learners followed the 60-minute session protocol listed in Table 1, initially by using Cloud eLearning and ending up by evaluating its efficacy using an online questionnaire.

Table 1. The learners' Script Used in the Experimental Phase.

Instruction of using and evaluating the CeL	
Open CeL.	Run the CeL application on the desktop.
Register as a new user and create a profile	Follow the steps to be registered as a new user for CeL. Complete a questionnaire for the system to categorize user learning style.
Search for a specific topic in Java	Search for the topic or subtopic within the Java and algorithm domain, in the CeLRS.
Go through the generated path	Analyze the list of CeLLOs responses from the CeLRS, the ranking of the CeLLOs, and the required prerequisites.
Rate the proposed list of CeLLOs	Check the ranked and recommended CeLLOs from the CeLRS for the user and rate them.
Rate CeL learning objects	Rate the CeLLOs as a standalone object
Complete the survey process	Complete the online questionnaire to assess CeL activities.

The questionnaire served as the primary data collection instrument and was structured to gather both quantitative and qualitative data. It consisted primarily of closed-ended questions, supplemented by one open-ended question. The questionnaire was organized into five sections: (i) general questions, then continued with (ii) personalization learning process questions, (iii) CeL Recommender System questions, (iv) CeL personalized Learning Path questions, and (v) concluding with open-ended comments and suggestions from the learners. The instrument was only reviewed by domain experts for content relevance. The combination of closed and open-ended responses allowed for a mixed-methods approach to data analysis, with quantitative data analyzed using descriptive statistics and qualitative data analyzed through thematic analysis

5. Results

The evaluation of the Cloud eLearning proposal involved two phases: the first involved using a throwaway prototype to confirm the functionality of the proposed Cloud eLearning system, and the second involved a user-evaluation approach.

The experimental showcase results are presented in this section, along with a full explanation of every step of the process—from data collecting to the analysis of the final findings. Furthermore, the authors outlined in detail three different categories of learners that we identified while interacting with the Cloud eLearning prototype. Finally, is discussed the Cloud eLearning prototype's perspective and how it automatically created a personalized learning path for each category of users.

5.1. CeL Prototype Results

In the first twenty minutes of the session, participants created their profiles and enrolled as new learners see (Figure 8). After that, they searched for a specific topic and looked over the results.

User Name :

Password : Confirm :

Name : Sur Name :

Institute :

Background : -- Select One -- Experience : -- Select One --

Knowledge Level : -- Select One --
 -- Select One --
 -- Select One --
 -- Select One --

Interests :

Next

Figure 8. The registration of the User in Cloud eLearning Prototype

An explicit technique using Felder, Soloman, et al. (2000) learning styles model was utilized to get to know learners by asking questions that they had to explicitly respond to in order for the system to become familiar with them (i.e., construct a learner profile, example: knowledge level in a specific topic, current interest, to mention a few).

Active	11	9	7	5	3	1	1	3	5	7	9	11	Reflective
Sensing	11	9	7	5	3	1	1	3	5	7	9	11	Intuitive
Visual	11	9	7	5	3	1	1	3	5	7	9	11	Verbal
Sequential	11	9	7	5	3	1	1	3	5	7	9	11	Global

Figure 9. Results of Participants Located in Category 5 - Based on Felder and Soloman Index of Learning Styles.

Time restrictions and simplicity led to the decision to utilize an explicit technique rather than an implicit one, which would have taken a long time for the system to develop a learner profile.

The Felder and Soloman model has four dimensions related to learning style. Each dimension has two poles, such as active and reflective, sensing and intuitive, visual and verbal, and sequential and global (see Figure 9). The Felder and Soloman index learning style result shows that the participant prefers one of these poles across all categories.

Table 2. Three Selected Representatives of Different Learners.

	Category 1	Category 2	Category 3
Faculty	Computer Science	Information System	Computer Science
Level of study	Bachelor	Bachelor	Master
Knowledge Level in programming using scripting language	2	0	4
Knowledge Level in programming using object-oriented programming	2	0	3
Knowledge Level in Java language	2	1	4
Knowledge Level in Algorithms	2	0	2
Learning style	strong visual	moderate verbal	strong visual

The result shown in Table 2 presents the data of three chosen representatives of different student categories. It demonstrates that each of group members has a different educational background and varying degrees of expertise in specific topic, in our case: with a focus on Java programming and algorithms. We came across their degree of understanding in these particular courses because, as previously mentioned, the experiment includes Cloud eLearning Learning Objects related to Java course, and we believe that these courses will have an impact on the experiment's flow. Therefore, when learners express interest in learning a particular topic of the Java programming language (example: while loops), the CeL prototype generates different learning paths based on the learners background (see Table 3).

To provide you an example, for students of group "Representative 1" Cloud eLearning system prompted initially to Watch the video c24 (CeLLO) containing learning material for topic "if statement". At the end, after completing the requested task the learners are invited to rate the recommended Cloud eLearning Learning Objects.

Table 3. Cloud eLearning Results.

Representative 1	Representative 2	Representative 3
1. Watch the video c24 on "if statement";	1. Study text c1 on "introducing control flow" ;	1. Watch the video c14 on "multiple ifs";
2. Take the test t4;	2. Take the test t1;	2. Take the test t14;
3. Watch the video c12 on "else statement";	3. Study text c2 on "decision making";	3. Watch the video c15 on "loop counters";
4. Take the test t12;	4. Take the test t2;	4. Take the test t15;
5. Watch the video c14 on "while loops";	5. Listen podcast c41 on "if statement";	5. Watch the video c30 on "switch statement";
6. Take the test t14;	6. Take the test t4;	6. Take the test t30;
	7. Listen podcast c23 on "logical operators";	7. Watch the video c14 on "while loops";
	8. Take the test t23;	8. Take the test t14
	9. Study text c27 on "nested if statements";	
	10. Take the test t27;	
	11. Watch the video c14 on "while loops";	
	12. Take the test t14	

Lastly, the learners (crowd) feedback improves the ranking and the prediction of the most appropriate CeLLOs for each learner. However, we believe that in the following three to five years, as more learners provide feedback to the CeL, performance results will show that the personalization of learning paths will continue to rise.

User Name: ema

Materials Category: Learning

Key Words Search Learning Materials: data types

Features: ☒ All ☒ Catalog ☒ Context ☒ Credibility ☒ Crowd Rating ☒ Crowd Rating Sequence ☒ Description ☒ Difficulty ☒ Format Type ☒ Granularity ☒ Keywords ☒ LeO ☒ Prerequisite ☒ Title ☒ Topic

Search

Sr. No.	Recommended Materials	Rating	Difficulty Level	Score	LO	Prerequisite	Cluster	C. Score
1	C:\Users\Sony\Desktop\AI_Planner_01_15_Shtator_2017\AIPlanner...	★★★★★	Level-1 (reme...	2.51977...	I2_1_introducing_control_flow			
2	C:\Users\Sony\Desktop\AI_Planner_01_15_Shtator_2017\AIPlanner...	★★★★★	Level-1 (reme...	2.48585...	I5_1_introduction			
3	C:\Users\Sony\Desktop\AI_Planner_01_15_Shtator_2017\AIPlanner...	★★★★★	Level-1 (reme...	2.41361...	I11_intro			
4	C:\Users\Sony\Desktop\AI_Planner_01_15_Shtator_2017\AIPlanner...	★★★★★	Level-1 (reme...	2.38670...	I4_1_alarm			
5	C:\Users\Sony\Desktop\AI_Planner_01_15_Shtator_2017\AIPlanner...	★★★★★	Level-1 (reme...	1.68349...	instance variables			
6	C:\Users\Sony\Desktop\AI_Planner_01_15_Shtator_2017\AIPlanner...	★★★★★	Level-1 (reme...	1.57208...	nivalrate			

Have You Read and Learn Whole Materials?

Figure 10. A List of the CeLLOs Ordered According to Learner Interest

5.2. User Evaluation Results

The user evaluation of the system through the final survey groups the questions into the following categories: (i) related to learner's background, (ii) the personalization services that could

have been used or are currently being used to support the learning process, (iii) the performance of the Cloud eLearning Recommender System in inter-acting with the learners, and lastly (iv) the learner's satisfaction with the personalized learning path that the Cloud eLearning Planner generated. The correlation between these variables is shown in Table 4.

Table 4. Relationships Between Learner Satisfaction, Learner Background, Personalization Services, and System Performance

		CeL Perf.	Initial learner back	Personal. in learning process	Satisf. of learner
Pearson Correlation	CeL Performance	1.000	.321	.715	.516
	Initial learner background	.321	1.000	.383	0.16
	Personalization in learning process	.715	.383	1.000	.685
	Satisfaction of learner	.516	0.16	.685	1.000
Sig. (1-tailed)	CeL Performance	1.000	.104	.001	.017
	Initial learner background	.104	1.000	.065	.476
	Personalization in learning process	.001	.065	1.000	.001
	Satisfaction of learner	.017	.476	.001	1.000

Based on our analysis shown in Table 4, the authors conclude that there is a significant correlation of 90% between "performance of the system" and "learner initial background," 99% between "performance of the system" and "learner satisfaction," and 99% between "performance of the system" and "personalization services." Additionally, there is a 95% correlation between "personalization services" and "initial learner background" and a 99% correlation between "personalization services" and "learner satisfaction" when using CeL.

6. Discussion

The findings from the two-phase evaluation reveal that CeL significantly enhances personalization and learner satisfaction.

First, the high correlation between the CeL system's performance and personalization services (99%), learner satisfaction (99%), and initial learner background (90%) validates the system's effectiveness in adapting learning experiences to individual needs. These results directly address the two research questions: (i) How is the generation of personalized learning paths affected when compared to Cloud eLearning system performance, and (ii) whether the AI-driven automated personalization of learning paths impacts learners' satisfaction. Personalized learning paths clearly increased engagement, motivation, and perceived system effectiveness.

These outcomes are consistent with earlier research presented in the literature review, which emphasized the importance of moving away from "one-size-fits-all" eLearning models toward learner-centred approaches. The use of Learning Objects (LOs) tagged with semantic metadata, as discussed in previous work, supports con-tent re-use and personalized path generation, addressing long-standing challenges around adaptability and scalability in eLearning environments, see Duval et al. (2002); Hodgins (2006).

Moreover, the CeL system expands upon the personalized eLearning frameworks described in the literature, such as in Gligorea et al. (2023), Hooshyar et al. (2024), Munir et al. (2022), Pesovski

et al. (2024), Pireva, Kefalas, and Cowling (2017) by offering an integrated technical architecture—combining knowledge representation, intelligent recommendation, and automated planning. This represents a notable advancement compared to earlier systems that typically relied either on rule-based as in Wu et al. (2015) personalization or simple learner profiling without dynamic path adaptation.

However, several limitations remain. The sample size (17 participants) limits the generalizability of the findings. Future studies should involve a broader, more diverse participant pool across different disciplines. Additionally, while significant correlations were found, longitudinal studies are needed to assess the long-term impact of personalized learning paths on learning outcomes.

Finally, the practical implementation of CeL highlights important institutional and pedagogical implications. Institutions adopting similar systems must invest in infrastructure, provide training for teachers, and adapt administrative frameworks to support flexible, AI-driven learning environments. Furthermore, future iterations of CeL should explore enhancing user-to-user interactions, as social learning components were noted as an area for further strengthening.

7. Conclusion

This study addresses ongoing challenges in the personalization of eLearning environments, a field that has evolved since 2014 with a growing emphasis on tailoring learning services to individual learner characteristics. Despite advancements, issues remain in the personalization of learning content and in facilitating intuitive interactions between users and content, as well as among users themselves. To contribute to this domain, this research proposes the Cloud eLearning (CeL) system—an open, AI-driven approach designed to deliver personalized learning paths in a fully automated manner.

The CeL system advances the eLearning paradigm by emphasizing five key components: learner-center, transparency, personalization, self-motivation, and collaboration. By leveraging Artificial Intelligence techniques, CeL empowers learners to choose what, when, and from whom to learn, drawing from a wide range of educational resources across institutions. From the student perspective, CeL adapts learning paths to individual needs and interests, fostering a more engaging and efficient learning experience. From the teacher perspective, CeL encourages cross-institutional collaboration and peer evaluation, motivating teachers to elevate the quality of their work and share best practices. From the institutional perspective, the system promotes the continuous improvement of educational services and the development of clearer, more effective guidelines for both teaching and learning.

Future work should focus on further validating the CeL system through broader pilot studies across diverse academic disciplines, refining the AI algorithms to enhance personalization, and exploring strategies to strengthen user-to-user interaction within the learning environment. Additionally, institutions implementing CeL should prioritize professional development programs that help teachers adapt to collaborative and AI-enhanced educational models.

References

- Armbrust, M., Fox, A., Griffith, R., Joseph, A. D., Katz, R. H., Konwinski, A., & others. (2009). *Above the clouds: A Berkeley view of cloud computing*. University of California, Berkeley. Retrieved from <https://www2.eecs.berkeley.edu/Pubs/TechRpts/2009/EECS-2009-28.pdf>
- Barker, P. (2005). What is IEEE learning object metadata/IMS learning resource metadata? CETIS Standards Briefing Series, JISC (Joint Information Systems Committee of the Universities' Funding Councils), Retrieved from <https://standict.eu/standards-repository/ieee-1484121-2020-ieee-standard-learning-object-metadata?utmsource=chatgpt.com>

- Brika, S. K. M., Chergui, K., Algamdi, A., Musa, A. A., & Zouaghi, R. (2022). E-learning research trends in higher education in light of covid-19: a bibliometric analysis. *Frontiers in Psychology*, 12, 762819, <https://doi.org/10.3389/fpsyg.2021.762819>
- Clark, R. C., & Mayer, R. E. (2023). E-learning and the science of instruction: Proven guidelines for consumers and designers of multimedia learning. John Wiley & sons. Retrieved from <https://onlinelibrary.wiley.com/doi/book/10.1002/9781119239086>
- Conole, G., & Oliver, M. (2006). Contemporary perspectives in e-learning research. Routledge London. Retrieved from <https://doi.org/10.4324/9780203966266>
- Core, D. (2004). Dublin core metadata initiative. <http://www.dublincore.org>
- Duval, E., Wason, T., & Hodgins, W. (2002). IEEE standard for learning object metadata. *IEEE Standards Document*, 1484 (1), 1-10, Retrieved from <https://standards.ieee.org/ieee/1484.12.1/7699/>
- Fan, H., & Poole, M. S. (2006). What is personalization? perspectives on the design and implementation of personalization in information systems. *Journal of Organizational Computing and Electronic Commerce*, 16(3-4), 179–202, <https://doi.org/https://doi.org/10.1080/10919392.2006.9681199>
- Felder, R. M., & Soloman, B. A. (2000). *Learning styles and strategies*. North Carolina State University. Retrieved from: https://engr.ncsu.edu/wp-content/uploads/drive/1WPAfi3_j5o5OuJMiHorJ-lv6fON1C8kCN/styles.pdf
- Gandhi, B. (2011). Business process as a service (bpaas) delivered from the cloud. *IBM Cloud Computing News*, 435–440, https://doi.org/10.1007/978-3-319-25013-7_35
- Gligorea, I., Cioca, M., Oancea, R., Gorski, A. T., Gorski, H., & Tudorache, P. (2023). Adaptive learning using artificial intelligence in e-learning: a literature review. *Education Sciences*, 13(12), 1216, <https://doi.org/10.3390/educsci13121216>
- Gupta, M. (2016). A study on the impact of ICT (information and communication technology) in higher education with special reference to higher education institutions in Nagpur city. *EDUCATE: Journal of Educational Research* ISSN 2394-9422, 24, 41,
- Hodgins, H. W. (2006). The future of learning objects. *Educational Technology*, 49–54, Retrieved from <https://www.jstor.org/stable/44429269>
- Hooshyar, D., Azevedo, R., & Yang, Y. (2024). Augmenting deep neural networks with symbolic educational knowledge: Towards trustworthy and interpretable ai for education. *Machine Learning and Knowledge Extraction*, 6(1), 593–618, <https://doi.org/10.3390/make6010028>
- Jena, K. K., Bhoi, S. K., Malik, T. K., Sahoo, K. S., Jhanjhi, N., Bhatia, S., & Amsaad, F. (2022). E-learning course recommender system using collaborative filtering models. *Electronics*, 12(1), 157, <https://doi.org/10.3390/electronics12010157>
- King, F. B., Young, M. F., Drivere-Richmond, K., & Schrader, P. (2001). Defining distance learning and distance education. *AACE Review (Formerly AACE Journal)*, 9(1), 1–14, Retrieved from <https://www.learntechlib.org/primary/p/17786/>
- Klašnja-Milićević, A., Vesin, B., Ivanović, M., Budimac, Z., & Jain, L. C. (2016). E-learning systems: Intelligent techniques for personalization (Vol. 112). Springer. Retrieved from <https://link.springer.com/book/10.1007/978-3-319-41163-7>

- Koohang, A., Riley, L., Smith, T., & Schreurs, J. (2009). E-learning and constructivism: From theory to application. *Interdisciplinary Journal of E-Learning and Learning Objects*, 5(1), 91–109, <https://doi.org/10.28945/66>
- Martinez-Garcia, A., Horrach-Rossell'o, P., & Mulet-Forteza, C. (2023). Evolution and current state of research into e-learning. *Heliyon*, 9(10), 2405–8440. Retrieved from: <https://doi.org/10.1016/j.heliyon.2023.e21016>
- Miranda, J., Navarrete, C., Noguez, J., Molina-Espinosa, J. M., Ramírez-Montoya, M. S., Navarro-Tuch, S. A., & Molina, A. (2021). The core components of education 4.0 in higher education: Three case studies in engineering education. *Computers & Electrical Engineering*, 93, 107278. Retrieved from: <https://doi.org/10.1016/j.compeleceng.2021.107278>
- Moore, J. L., Dickson-Deane, C., & Galyen, K. (2011). e-learning, online learning, and distance learning environments: Are they the same? *The Internet and higher education*, 14(2), 129–135, <https://doi.org/10.1016/j.iheduc.2010.10.001>
- Munir, H., Vogel, B., & Jacobsson, A. (2022). Artificial intelligence and machine learning approaches in digital education: A systematic revision. *Information*, 13(4), 203, <https://doi.org/10.3390/info13040203>
- Naidu, S. (2006). E-learning: A guidebook of principles, procedures and practices. Commonwealth Educational Media Centre for Asia (CEMCA). Retrieved from <https://oasis.col.org/handle/11599/53>
- Noesgaard, S. S., & Ørngreen, R. (2015). The effectiveness of e-learning: An explorative and integrative review of the definitions, methodologies and factors that pro-mote e-learning effectiveness. *Electronic Journal of E-learning*, 13(4), 278–290, Retrieved from <https://eric.ed.gov/?id=EJ1062121>
- Oye, N. D., Salleh, M., Iahad, N. A. (2012). E-learning methodologies and tools. *International Journal of Advanced Computer Science and Applications*, 3(2), 48–52, <https://doi.org/10.14569/IJACSA.2012.030208>
- Pesovski, I., Santos, R., Henriques, R., & Trajkovic, V. (2024). Generative ai for cus-tomizable learning experiences. *Sustainability*, 16(7), 3034, <https://doi.org/10.3390/su16073034>
- Pireva, K., & Kefalas, P. (2013). An innovative web application for managing academic documents. *International Journal of Business and Technology*, 1(2), 39–46, <https://doi.org/10.33107/ijbte.2013.1.2.04>
- Pireva, K., & Kefalas, P. (2018). A recommender system based on hierarchical clustering for cloud e-learning. *Intelligent Distributed Computing XI*, 235–245, https://doi.org/10.1007/978-3-319-66379-1_21
- Pireva, K., Kefalas, P., & Cowling, A. (2017). A review of automated planning and its application to cloud e-learning. *Work in progress, Paper Submitted*, 1–14,
- Pireva, K., Kefalas, P., Dranidis, D., Hatziapostolou, T., & Cowling, A. (2014). Cloud e-learning: A new challenge for multi-agent systems. Agent and multi-agent systems: Technologies and Applications: Proceedings of the 8th international conference kes-amsta 2014 Chania, Greece, June 2014 (pp. 277–287). Retrieved from https://doi.org/10.1007/978-3-319-07650-8_28
- Pireva, K., Kefalas, P., & Stamatopoulou, I. (2017). Representation of learning objects in cloud e-learning. *2017 8th international conference on informa-tion, intelligence, systems & applications (iisa)* (pp. 1–6). Retrieved from <https://doi.org/10.1109/IISA.2017.8316435>

- Ruttenbur, B. W., Spickler, G. C., & Lurie, S. (2000). elearning: The engine of the knowledge economy. Morgan Keegan.
- Sharma, S., Gautam, S., & Agarwal, A. (2023). E-learning: Research and applications. *AITC-2023 and CSSP-2023*, 23,
- Stamatis, D., Kefalas, P., & Kargidis, T. (1999). A multi-agent framework to assist networked learning. *Journal of computer assisted learning*, 15(3), 201–210, <https://doi.org/10.1046/j.1365-2729.1999.153094.x>
- Sultan, N. (2010). Cloud computing for education: A new dawn? *International Journal of Information Management*, 30(2), 109–116, <https://doi.org/10.1016/j.ijinfomgt.2009.09.004>
- Teixeira, C., Azevedo, R., Pinto, J. S., & Batista, T. (2010). User pro-vided cloud computing. 2010 10th ieee/acm international conference on cluster, cloud and grid computing (pp. 727–732). Retrieved from <https://doi.org/10.1109/CCGRID.2010.104>
- Trafford, P., & Shirota, Y. (2011). An introduction to virtual learning environments. *Gakushuin Econ. Pap*, 48(10), 143–151,
- Triacca, L., Bolchini, D., Botturi, L., & Inversini, A. (2004). Mile: Systematic usability evaluation for e-learning web applications. *Edmedia+ innovate learning* (pp. 4398–4405). Retrieved from <https://core.ac.uk/download/pdf/20638806.pdf>
- Tuževljak, M., Majcen, L., Mervar, L., Stepankina, T., & Cater, B. (2016). E-learning in higher education: Focus groups and survey among students in central europe. *Journal of Educational Technology*, 13(2), 11–20, Retrieved from <https://files.eric.ed.gov/fulltext/EJ1131833.pdf>
- Villegas-Ch, W., & García-Ortiz, J. (2023). Enhancing learning personalization in educational environments through ontology-based knowledge representation. *Computers*, 12(10), 199. Retrieved from: <https://doi.org/10.3390/computers12100199>
- Wilen-Daugenti, T. (2009). edu: Technology and learning environments in higher education. *Peter Lang*. Retrieved from <https://doi.org/10.30829/vis.v17i2.1153>
- Wiley, D. A. (2008). The learning objects literature. *Handbook of research on edu-cational communications and technology* (pp. 345–353). Routledge. Retrieved from <https://doi.org/10.4324/9780203880869-32>
- Wu, D., Lu, J., & Zhang, G. (2015). A fuzzy tree matching-based personalized e-learning recommender system. *IEEE transactions on fuzzy systems*, 23(6), 2412–2426, <https://doi.org/10.1109/TFUZZ.2015.2426201>
- Zhang, J. (2015). Research on e-learning in college education: A model on personalized resource recommendation based on learning situation. *2015 IEEE 12th intl conf on ubiquitous intelligence and computing and 2015* (pp. 1264–1268). Retrieved from <https://doi.org/10.1109/UIC-ATC-ScalCom-CBDCom-IoP.2015.230>

About the Contributor(s)

Krenare Pireva Nuci, has been the architect behind the EU project PhDICTKES.eu and Tkaedite.eu, were she served as national coordinator during the implementation phase. She works very closely with schools; she has led as a coordinator the Ministry of Education (MESTI) funded research project, onlineclasses.cloud. Under the same project schema, Krenare is coordinating the ongoing project var4stem.net, which aims to analyse the impact of Virtual and Augmented technology in STEM-related fields. Krenare is very passionate about the digital transformation processes and the benefits

that our community could have when going digital. In this regard, through HERAS+ she has designed a number of national systems that contributes directly to the Education System: Kosovo Research Information System and EduSupport System. The first one serves as a repository for scientific research data in Kosovo whereas the second one is an internal database for MESTI which records all scholarships, grants and other financial support from MESTI and all the donators. Dr Pireva Nuci, while serving as a board member of Kosovo Accreditation Agency designed also the Kosovo Accreditation System eKAA version 2, after conducting successful feasibility research under the guidance of Fulbright expert supported by US Embassy.

Email: krenare.nuci@uni-pr.edu

ORCID: <https://orcid.org/0000-0002-8128-8557>

Publisher's Note: *The opinions, statements, and data presented in all publications are solely those of the individual author(s) and contributors and do not reflect the views of Universitepark, EDUPIJ, and/or the editor(s). Universitepark, the Journal, and/or the editor(s) accept no responsibility for any harm or damage to persons or property arising from the use of ideas, methods, instructions, or products mentioned in the content.*
