The application of Artificial Intelligence in Recommendation Systems reinforced through Assurance of Learning in personalized environments of e-Learning

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Abstract. Learning environments unquestionably enable learners to develop their pedagogical and scientific processes efficiently and effectively. Thus, considering the impossibility of not having conditions of autonomy over the routine underlying the studies and, consequently, not having guarantees of the learning carried out makes the learners experience gaps in the domain of materials adequate to their actual needs. The paper's objective is to present the relevance of the applicability of Artificial Intelligence in Recommendation Systems, reinforced through the Assurance of Learning, oriented towards adaptive-personalized practice in corporate e-learning contexts. The research methodology underlying the work fell on Design Science Research, as it is considered adequate to support the research, given the need to carry out the design phases, development, construction, evaluation, validation of the artefact and, finally, communication of the results. The main underlying results instigate the development of an Adaptive-Personalized Learning framework for corporate e-learning, provided with models (methods and algorithms) of Artificial Intelligence and guided using the Assurance of (the) Learning process. It becomes central that learners can enjoy adequate academic development. In this sense, the framework has an implicit structure that promotes the definition of personalized attributes, which involves recommendations and customizations of content per profile, including training content that will be suggested and learning activity content that will be continuously monitored, given the specific needs of learners.

Keywords: Artificial Intelligence, Recommendation Systems, Assurance of Learning, Adaptive-Personalized Learning, Learning Analytics.

1 Introduction

The development and launch of new training and qualification technologies are supporting organizations in optimizing the quality of the teaching and learning process, benefiting employees and collaborators, either in reducing costs and training time or in compensating for the lack of opportunities for initial and continuing improvements.

Furthermore, it is a fact that professional qualification enables the development of skills to highlight learning and to privilege opportunities for innovation, which responds to the restructuring demanded of corporations, as a rule, especially in a knowledge-based society [1].

Furthermore, through Adaptive Learning (AL), it is possible to offer Personalized Learning (PL) and an experience stimulated by Digital Technologies [2]. Equally boosted by Information & Communication Technology (ICT) tools, e-learning is successfully used in multiple forms of corporate interaction. The benefits range from establishing ways of communicating and interacting to taking exams and evaluating progress. However, most of these environments are designed on a one-size-fits-all approach. Although effective, such environments are sometimes quickly abandoned by learners [3, 4].

In the evolution of this perspective, it is observed that the learner is utterly devoid of autonomy and control over the study routine. The experience starts to be imposed by predetermined contents and times, segmented tasks/jobs and codes of conduct. There are differences in the instruction process from learner to learner, as the interests and paces of learning differ. After his school cycle, the reality of the classical learner lies in the difficulty of mobilizing his acquired knowledge. Such setbacks will extend from personal to professional experience.

Planning to simplify intelligent learning, mechanisms and Recommendation Systems / Recommender Systems (RS) are designed to perform unique tasks where conveniences are proven relevant to learning outcomes. The challenges of e-learning are primarily because of the progressions in Content-Based (CB), Collaborative (CF), Hybrid (HF) filtering. Also, difficulties with Cold-Start, Sparsity, First Rater, Popularity Bias, Accuracy, Scalability. Some proposed solutions are considered to solve the problems, such as Cross-Domain recommendations, Context-Aware recommendations and Deep Learning (DL) techniques, among others [5–7].

Regarding the relationships between RS and e-learning tools, the references on performance indicators are reduced, including the lack of reports associated with student and faculty feedback [8]. Thus, to resolve the problems, the following actions are proposed: a) Identify Adaptive-Personalized Learning contexts; b) Plan metrics for the different contexts (indicators: performance, development, monitoring, satisfaction, training); c) Identify Artificial Intelligence (AI) methods and algorithms that enable content recommendations; d) Design a framework that explores the skills of employees.

1.1 Contribution

This document registers the intention to implement an Adaptive-Personalized Learning framework for corporate e-learning, provided with AI models (methods and algorithms) and guided using the learning management process [9–12]. Therefore, multiple attributions can be established, such as a) Investigations into the advantages and disadvantages of AI for RS and/or Adaptive-Personalized Systems, reinforced through *Assurance of Learning* (AoL); b) Checks of the leading AI algorithms and metrics, integrated with RS and/or Adaptive-Personalized Systems, currently used in e-learning platforms – Learning Management Systems (LMS) / Learning Content Management

Systems (LCMS); c) Use of a framework and/or reference model for the application of AI in RS and/or Adaptive-Personalized Systems, reinforced through AoL in e-learning contexts; d) Findings of differentials in the practice of AoL in the application of AI in RS and/or Adaptive-Personalized Systems in e-learning environments.

According to the strategy adopted for the execution of the phases of this work, it appears that the research methodology to be applied is Design Science Research (DSR), which comprises a rigorous process to design artefacts in solving problems, making contributions, project evaluation and communication of results [13]. The methodology will support the research work due to the possibility of carrying out the design phases (distributed in different stages of the project), development, construction, evaluation and validation of artefacts, among others. Consequently, will be used the method proposed by Alturki and co-authors [14], in which the 3 (three) Hevner cycles [15] – Rigor, Relevance and Design - are considered, in addition to the recommendation of 14 (fourteen) activities foreseen in the process.

1.2 Motivation

E-learning has transformed educational didactics as an alternative to traditional teaching-learning processes, providing innovative trends and methodologies daily, which extensively influences and favours the education sector [16]. In terms of training, online learning becomes significantly profitable for employees to acquire knowledge, allowing them to learn at any time, at any pace – based on the student profile – and from anywhere. However, how to configure the appropriate content for learning applications (?) becomes an exceptional question, especially when each trainee has a distinct learning profile and, surprisingly, when the training material must also suit this work [17].

The following will be considered about the identified problem: a) Adaptive-Personalized Teaching: the teaching-learning process is static because "a single type of teaching" is offered. There is no adaptation and/or personalization according to the individual needs of the learners; b) Recommendation Systems: there are still specific weaknesses in traditional RS through filtering methods. Resources and content classifications are used, in which the learner's context is not contemplated; c) Learning Analytics: the systematic use of data and training indicators, which have been partially implemented and present summarized metrics (feedback, assessment); and d) Artificial Intelligence: the existing algorithms are, until now, insufficiently developed and minimally used to enable the recommendations of training content for learners.

In the understanding that systems involving AI almost always end up as protagonists in the context of adaptive and personalized learning and in the relevance of offering the employee/learner intelligent learning, this work aims to answer the following questions: (**RQ1**) What are the advantages and disadvantages of Artificial Intelligence for Recommendation Systems and/or Adaptive-Personalized Systems, reinforced through the Assurance of Learning? (**RQ2**) What are the leading Artificial Intelligence algorithms and metrics, integrated with the Recommendation Systems and/or Adaptive-Personalized Systems, currently used in e-learning platforms (LMS / LCMS)? (**RQ3**) What characteristics should a framework and reference model have for applying Artificial Intelligence for Recommendation Systems and/or Adaptive-Personalized, reinforced

through the Assurance of Learning in corporate e-learning contexts? (**RQ4**) What are the differentials in using Assurance of Learning in applying Artificial Intelligence for Recommendation Systems and/or Adaptive-Personalized Systems in corporate e-learning contexts?

2 Related Works

Concerning related works, Adaptive-Personalized Learning – in different environments – and Assurance of Learning and Solutions/Frameworks are presented according to the study's pertinence.

2.1 Adaptive-Personalized Learning

The learning contents are analyzed in multiple, adaptive and personalized environments through recommendation methods, evaluation metrics, usability tests and attributes and cognitive aspects of learners [18]. An adaptive learning system, composed of an interactive and dynamic pedagogy, consists of several key features, with enough autonomy to keep learners engaged and motivated towards the objectives [19]. Furthermore, e-learning platforms include tools that adapt learning materials according to the learner's profile. The purpose is to offer unique learning materials in which it is possible to find solutions that support tutors in creating pedagogical content and learning objects adapted to the student's abilities and preferences [13].

The pedagogical model of adaptive learning can enable personalized and individualized learning. Continuous data collection on the user's general activities and actions release feedback that adapts to his pace and needs. By carrying a data-driven approach, it provides individualized learning paths. In this way, the information analysis mechanisms customize – in real time – the offer of e-learning materials according to the learners' performance level [20]. Furthermore, Peng and co-authors point out that "the development of current technologies has made Personalized Learning increasingly adaptive and Adaptive Learning increasingly personalized" [21].

2.2 Assurance of Learning

The appropriation of the Assurance of Learning (AoL) [22] process – in the precaution in quality education – is perceived by the systematic process of collecting and reviewing data on the results of training and qualifications, as well as in the adequacy of methodologies of learning (active, agile, immersive and analytical). It is continually used in developing and improving training and educational programs [12, 22]. Furthermore, using Learning Outcomes (LO) – through Bloom's Taxonomy or Taxonomy of Educational Objectives [23] –ensures the execution of the proposed learning. Similar to the 5 (five) steps of the Association to Advance Collegiate Schools of Business (AACSB) aimed at the learning management process [12, 22].

In some cases, Learning Objectives and Learning Outcomes are used interchangeably. However, in practice, the purposes are different. The 'objectives' indicate the

purpose of the learning activity and the desired results. In the case of 'results', they show what the learner can accomplish when completing the proposed activities. Similarly, it is understood by statements of what is achieved and evaluated at the end of a cycle of studies [24]. According to Libba and coauthor-res [25], the expositions of learning – mission, objectives, outlines – in formations and programs are commonly disparate, even within the same study area. Such dissimilarity contributes to a difference in teaching materials and methodologies [24].

2.3 Solutions/Frameworks

According to a literature review, an expressive part of e-learning solutions and frameworks was identified, and used in this work, based on Recommendation Systems. However, most of the different solutions that this work seeks are to provide AI models. Specific frameworks are focused on Adaptive Learning, others on Personalized Learning, but limited frameworks are targeted explicitly at Adaptive-Personalized Learning. Likewise, about assurance of learning and corporate education. The details of each structure, including name, year and reference, are summarized and listed in Table 1.

Table 1. Summary of solutions and frameworks based on e-learning Recommendation Systems. The structure, year and reference details. The author.

Framework	Year	Reference
Recommender Systems in E-learning	2022	[26]
A Survey of Recommendation Systems: Recommendation Models, Techniques, and Application Fields	2022	[27]
Review and classification of content recommenders in an E-learning environment	2021	[28]
Adaptive E-Learning System	2021	[29]
A hybrid recommendation model in social media based on deep emotion analysis and multi-source view fusion	2020	[30]
Toward a Hybrid Recommender System for E-learning Personalization Based on Data Mining Techniques	2018	[31]
Personalized recommender system for e-Learning environment based on student preferences	2018	[32]
Good and Similar Learners' Recommendations in Adaptive Learning Systems	2016	[33]

3 Model Design

Below are the details of the DSR, as well as the draft of the model under development.

3.1 Design Science Research

The application of the DSR will allow the development of an artefact to support corporations in optimizing the quality of the teaching and learning process – reducing costs and training time for employees and collaborators. Table 2 illustrates the objective of this research work on the relevance of the applicability of Artificial Intelligence in Recommendation Systems, reinforced through Assurance of Learning, oriented towards adaptive-personalized practice in business e-learning contexts. A mechanism to promote the definition of personalized attributes involves recommendations and customizations of content by profile, including training content that can be recommended and content of learning activities that will be monitored, using the model developed by Alturki and co-authors [14].

Table 2. Alturki and co-authors' framework for the application of DSR. [14].

	Activity	Description
1.	Document the spark of an idea/problem	After the identified problems, it is recalled that the investigation's idea is to apply Artificial Intelligence in Recommendation Systems for personalized e-Learning environments.
2.	Investigate and evaluate the importance of the problem/idea	In addition to the listed problems, a Systematic Literature Review (SLR) will be made to verify and compare the work carried out with the proposed work.
3.	Evaluate the new solution feasibility	A paper (position paper) will be prepared to evaluate and verify the feasibility of the theme.
4.	Define the research scope	The constitution of an Adaptive-Personalized Learning framework with features for corporate e-Learning. Identified Adaptive-Personalized Learning contexts; To be projected metrics for the different contexts (indicators: performance, development, follow-up, satisfaction and training); To identify Artificial Intelligence methods and algorithms that enable content recommendations, and conceived, a framework that explores the abilities of the collaborators.
5.	Resolve whether within the DS paradigm	The work adheres to the DS perspective.
6.	Establish type (IS DS versus IS DSR)	The Assurance of Learning process is accredited by AACSB [22]. Furthermore, he remembers the use of DSR for the research methodology, which comprises a rigorous process for designing artefacts in problem-solving, making contributions, evaluating projects and communicating results [34] and adopting the 3 (three) Hevner cycles [15]. For the SRL, the guideline proposed by Kitchenham [35] will be used, which brings a careful analysis of the quality of the literature to be selected.
7.	Resolve the theme (construction, evaluation or both)	The investigation will be about the construction and evaluation of an artefact.

8. Define requirements	Tools, including the Word or Writer text editor, should be used to elicit the requirements. The investigation technique will be the interview for data collection (qualitative).
9. Define alternative solutions	Not applicable at this point in the project.
10. Explore knowledge Base support of alternatives	Not applicable at this point in the project.
11. Prepare for design and/or evaluation	The development and/or evaluation plan must be prepared concurrently with the evolution of the project.
12. Develop (construction)	It will be carried out concurrently with the evolution of the project.
13. Evaluate	
"Artificial" evaluation	Initial tests should be conducted in a laboratory context, as the intention is to prepare the framework for the most varied contexts.
"Naturalistic" evaluation	Other tests in different contexts are necessary to prove the structure's robustness and acquire confidence in what is proposed. A company or several actual companies will be needed for the tests of the developed proposal (data collection and validation of what the research is coming to contribute, with a particular distinction to existing works.
14. Communicate findings	It will be informed to the scientific community through the publication of articles.

Table 2 emphasizes the activities and descriptions underlying the authors' views framed in the DSR.

3.2 Proposed Model

Figure 1 presents the draft of the model under development, demonstrating the flow of actions to be undertaken implicit in the learning process.

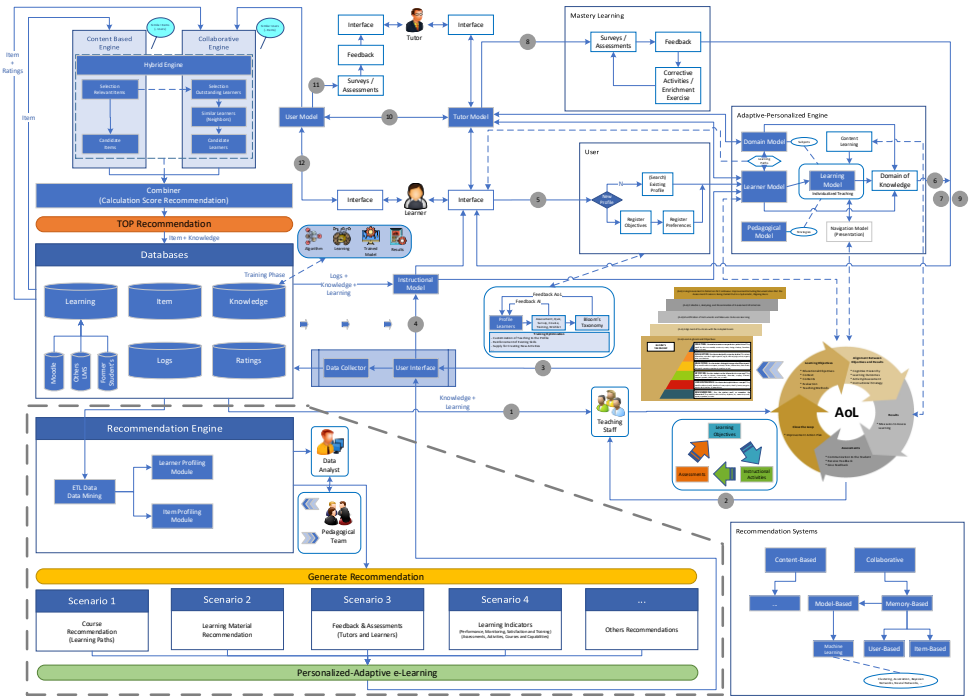

Fig. 1. The proposed models for corporate e-learning are based on solutions and/or frameworks by Bourkoukou & Bachari [31], Fazazi et al. [32], Jiang et al. [30], Joy & Pillai [28], Ko et al. [27], Nurjanah [33], Zhang et al. [26].

In summary, the learning process, shown in Figure 1 contains: a) Processes and mechanisms: user, adaptive-personalized learning, learning mastery (learners must reach a level to advance), including compliance with the AoL process cycle; b) Learner interface: presents the result of course and material recommendations, according to the profile. Handles logic and events during training (surveys, quizzes, feedback, assessments, etc.); c) Tutor interface: presents contents and tips to guide and clarify doubts about the studies. Partial performances and events during training (surveys, feedback, etc.); d) Databases: storage of learning information (behaviors used in building/conducting the learning profile. Sources: Moodle, other LMS, former students), items (information on materials, objects and learning activities), logs and mainly knowledge extracted from the list of materials, learning path and performance. The 'combiner' (relevant recommendations) retrieves data from the recommendation's engine (of types) (content-based, collaborative, hybrid) and later ETL and DM; d) Recommendation engine: the central part, where the device trains the recommendation methods for knowledge generation. Contains the learner and item profile modules. Implements recommendation methods (involving the pedagogical team and the data analyst). The results (classification, measurement and combination: learners or items) are generated as a sorted list of items for decision-making. Recommendations: a) Scenario 1 - Course Recommendation (Learning Paths): a learner who is looking for a course and the skills he would like to improve; b) Scenario 2 - recommendation of learning material: learners who are enrolled in one or more courses, however, looking for learning materials that help them advance in knowledge; c) Scenario 3: feedback and evaluations (tutors and students); d) Scenario 4: Learning Indicators (performance, monitoring, satisfaction and training: assessments, activities, courses and training); e) Other Recommendations: Different data about students/items are used by the RS, depending on the recommendation scenario. It is stressed that ethical and privacy issues should be taken into consideration when considering such recommendation frameworks, in particular involving AI. Mechanisms must ensure the security of user information.

4 Future Work

In this context, however, it is possible to highlight the strategic planning of organizations, which can guarantee the practical success of e-learning – in some instances, transformed into corporate academies/universities – listed as one of the means to achieve the business goals. The domains to be addressed, as are-as of challenges, in future works are i) Training (training), competence (skill) and awareness (experience) of tutors in the preparation and use of digital technologies; ii) Appropriation process for adaptability and customizable intelligent learning systems (digital pedagogy and educational or instructional design); and iii) Acceptance of intelligent learning, as well as active methodologies (innovative education) in general, by learners and tutors.

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