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Alexandros Papadimitriou
School of Humanities, Hellenic Open University, Greece
https://orcid.org/0000-0002-7661-731X

Adaptive and Intelligent MOOCs: How They Contribute to the Improvement of the MOOCs' Effectiveness

Abstract

Several traditional MOOCs have been developed utilizing particular traditional approaches for distance learning. The main objective of this article is to examine numerous studies and research about the provision of adaptive and intelligent MOOCs to address issues, such as dropout rate, for improving their efficiency compared to conventional MOOCs. Important issues that have been the essential study interests of MOOC scholars in recent years, including dropout rate, completion rate, loneliness, and other topics, were studied. Finally, the research questions posed on the effectiveness of Adaptive and Intelligent MOOCs, the learner's characteristics used for adaptation, the adaptive and intelligent methods and techniques used, and the improvements they bring to traditional MOOCs as a compass for designing Adaptive and Intelligent MOOCs in the coming years, are discussed.

K e y w o r d s: distance education, adaptive and intelligent MOOCs, personalized learning, MOOC challenges

1. Introduction

The aim of this paper is to highlight the progress made in enhancing the effectiveness of traditional MOOCs by researchers using Adaptive and Intelligent MOOCs to address critical issues like dropout, loneliness, engagement, user collaboration, and the validity of methods for assessing learners' knowledge, among others.

Kentnor (2013) asserts that technology facilitates the educational process. The advancement of online assistive technologies and the opportunities they present allow us to improve on the conventional methods of instruction and learning. Massive Open Online Courses (MOOCs) have been used to implement this capability in the domain of traditional distance learning (MOOCs).

A new and potent method of gaining access to knowledge and education, MOOCs, is characterized by the integration of traditional digital teaching tools (videos, sounds, graphics, or slides), personalized tools for knowledge acquisition and validation, and the appropriate use of private social networks (Dillenbourg, Fox, Kirchner, Mitchell, and Wirsing, 2014).

Ardchir, Talhaoui, and Azzouazi (2017) assert that MOOCs are associated with the idea of openness in learning and that their main characteristics include having an infinite number of participants with free Internet access, delivering instruction via the Internet, and basing their courses on a set of goals in a particular field of study. The target audience for MOOCs is an unspecified number of participants with a very diverse profile, a range of learning preferences and methods, and a variety of online learning environments.

Widespread acceptance of distance learning has increased as a result of MOOC evolution. Due to their abundance of free, open online courses that are available to everyone and that also have interactive user forums to foster community connections between students and educators, MOOCs are very appealing and have excellent accessibility.

The effectiveness of MOOCs as teaching resources is a crucial concern for scholars. According to Sonwalkar (2012), a significant reason for concern about the long-term success, effect, and sustainability of MOOCs is the high dropout rate of participants who initially enroll in a MOOC (about 90%). In addition, the lack of participant collaboration outside of peer review raises concerns about their efficacy (Blanco, García-Peñalvo, and Sein-Echaluce, 2013). The diversity of the students and the necessity to individualize the content and delivery method is a big concern with MOOCs. One size no fits all is the idea based on personalized learning. Learning styles, knowledge levels, interests, learning rates, and other variables vary among learners (Qaffas, Kaabi, Shadiev, and Essalmi, 2020).

The conclusion made by Daniel, Cano, and Cervera (2015) was that "*Implementing adaptive learning techniques to make MOOC courses more individualized* *is a potential, albeit currently underdeveloped, solution that will probably be accessible shortly.*" Additionally, according to Shpolianskaya, and Seredkina (2020), using intelligent technology in MOOCs enables us to create tailored learning pathways for every student, each with their techniques, forms, and rates of his learning.

The first stage is to develop the learning content into finely-grained and clearly labeled knowledge units to enable future MOOC students to personalize their learning routes (Yu, Miao, Leung, and White, 2017).

There are numerous sorts of MOOCs. Connectivist MOOCs (cMOOCs) and xMOOCs are two of the most significant MOOCs categories (eXtended MOOCs). Incorporating the de-schooling concept of Illich (1971) and the connectivism pedagogical principles put forward by Siemens (2005), cMOOCs are among the most accessible platforms for promoting self-directed learning. With a highly planned, content-driven course created for several students working primarily on their own, quiz-like examination procedures, and lectures, xMOOCs use a remarkably linear approach with well-defined outcomes.

The hybrid MOOC paradigm (hMOOC) lowers the dropout rate and encourages collaborative learning by combining aspects from cMOOCs and xMOOCs (Anders, 2015).

Instead of everyone following the same course, personalized learning is encouraged by adaptive learning. In terms of developing Web-based educational courseware, adaptive and intelligent Web-based educational systems (AIWBES) offer an alternative to the conventional "just-put-it-on-the-Web" method (Brusilovsky & Miller, 2001 as cited in Brusilovsky & Peylo, 2003). By creating a model of each student's goals, preferences, knowledge, learning styles, etc., and using this model during the engagement with the student, AIWBES aims to be more adaptable (Brusilovsky & Peylo, 2003). These include Adaptive and Intelligent MOOCs.

To provide tailored learning experiences based on dynamic assessment and data collecting for the course, adaptive MOOCs (aMOOCs) employ adaptive methodologies. They are prerequisite-based and cater to students' various, personalized pathways through the material (Ardchir et al., 2017). Additionally, MOOCs and Intelligent Tutoring Systems typically use complementary instructional strategies, although combining the two is uncommon (Aleven et al., 2016). Thus, in recent years, Intelligent or Smart MOOCs have been established.

According to Gynther (2016), adaptive learning systems, such as adaptive MOOCs, should include the following design criteria when creating adaptive learning plans in general:

- The learner should be modeled using reported outcomes.
- The development of an adaptive learning system should follow a preemptive rule that advises against using tired methods for modeling the learner.
- Modeling should take into account the learner's professional abilities, as well as their knowledge and ability to retain information in a MOOC format.

- A specialized framework's non-transparent algorithm-based adaptation cannot function by itself.
- A learner and a teacher must negotiate using one or more created data sets.
- The adaptation process ought to be prescribed and straightforward and beneath the learner's control.
- The learner ought to control his learning model.

The challenges of conventional MOOCs have led to the development of adaptive and intelligent MOOCs, which are the subjects of this article.

The remaining part of the article is structured as follows. The second section covers the methodology of the research. The third section covers relevant research on the benefits and uses of Adaptive and Intelligent MOOCs and the improvement of the efficiency they offer over conventional MOOCs, the learner characteristics they use for adaptation, and the applications that have been used to date. In the fourth section, the results of the research are presented, and in the fifth section, a discussion about the results takes place. Finally, conclusions about the effectiveness of Adaptive and Intelligent MOOCs are formed.

2. Methodology of Research

This work supplies a thorough review of the literature on adaptive and intelligent MOOCs to guide researchers, designers, and developers in planning future Adaptive and Intelligent MOOCs to achieve significant efficacy over traditional MOOCs. Thus, MOOC designers or developers might use the findings of this research for their MOOC design to avoid or minimize shortcomings, manage the challenges systematically, and form valid research questions for their study on related topics. Moreover, they might use the corresponding report for general information on innovations of MOOCs on the Adaptive and Intelligent MOOCs. They may also be used for educational purposes.

To find the methods and techniques used by the Adaptive and Intelligent MOOCs that increase their efficiency over traditional MOOCs, a thorough literature review regarding this case was conducted. For the quality of research studied sixty-eight bibliographic sources and papers that reported empirical evidence concerning the developed Adaptive and Intelligent MOOCs, and how they affect student performance, engagement, dropout rate, and other factors.

The fundamental factors adopted for deciding which research methodology will be used are the factors of the Adaptive and Intelligent MOOCs that contribute to the enhancement of efficiency of traditional MOOCs, the learner traits they used, and the adaptive and intelligent methods and techniques that have been used for the improvement of the efficacy of conventional MOOCs.

Consequently, the critical keys that have been used for the research questions are Adaptive MOOCs, Intelligent MOOCs, Personalized MOOCs, effectiveness, performance, engagement, dropout rate, completion rate, loneliness, learning styles, course material or content, competence, learning experience, satisfaction, isolation, motivation, learning outcome, Adaptive and Intelligent MOOC techniques.

Taking into consideration the referred above, the following research questions (RQ) were posed:

RQ1: What improvements have been made to the Adaptive and Intelligent MOOCs to overcome the low effectiveness of conventional MOOCs?

RQ2: Which learner traits have Adaptive and Intelligent MOOCs used so far to adapt to the many roles they provide?

RQ3: What adaptive and intelligent methods and techniques have been used so far to improve the effectiveness of conventional MOOCs?

The systematic literature review methodology was used to investigate traditional MOOCs' challenges and shortcomings and find solutions from research on Adaptive and Intelligent MOOCs by searching the bibliography to answer the research questions. Furthermore, as much research as possible was conducted to reduce inaccuracy, increase efficiency and reliability, and eliminate biases and errors. Prerequisites for the study include the selection of a bibliography and studies that meet the following inclusion and exclusion criteria:

Inclusion criteria: Peer-reviewed high-quality scientific journals and conferences articles and books about Adaptive and Intelligent MOOCs with a significant number of citations from 2011 to 2022; methodology/technology/procedure/findings that address challenges or shortcomings of MOOCs, fewer and shorter primary studies are considered to avoid population restrictions when considering the practical implications of the systematic review.

Exclusion criteria: Articles should be limited to English-language articles from 2011 to 2022, articles in the non-MOOC context, articles that do not meet the inclusion criteria.

The papers were collected from Scopus and Google Scholar databases according to critical keys and taking into account the inclusion and exclusion criteria.

3. Literature Review on Adaptive and Intelligent MOOCs

3.1. The efficiency of Adaptive and Intelligent MOOCs

As was indicated before, Siemens (2005) suggests connectivism as a learning theory for the digital age. The principles of chaos, network, complexity, and self-organization theories, which were influential in the early creation of cMOOCs, are incorporated into connectivism. Similar to Carneiro (2013), who proposed the generativism theory, which lays the groundwork for a new philosophy of lifelong learning, seeks to describe collaborative learning using digital technologies and open educational resources.

Adaptive MOOCs are based on notions of brain-based learning. Examining brain cells is necessary to comprehend brain-based learning. The brain's central energy is a sort of structure called a neuron. Neurons are connected among them. The creation of new connections between neurons is called neuroplasticity and the production of new neurons is called neurogenesis. Also, neuroplasticity allows for changes in neuronal structure and pathways within the brain, as well as its physical shape. The connections between the neurons also form and break, and the brain occasionally loses and gains neurons. The average brain has 100 billion neurons, along with a vast number of connections.

When two neurons communicate, learning happens. The dendrites expand as the neuron gathers information. Dendrites are pursuing out constantly new information or stimuli because the brain is trying continuously to learn, and the brain is searching for significance in that information or stimulation. When data is conveyed to the brain, a synapse is a gap between cells that enables the communication between neurons. A neural network is created when neurons communicate with each other continually (Sprenger, 2010).

Slavkin (2002) defines brain-based learning as any instructional strategy or technique that uses knowledge about the human brain to set up lessons in such a way that promotes learning by how the brain learns.

There are notable suggestions for incorporating brain-based learning into the classroom that also applies to online courses. Based on the results of neuroscience research, Braidic (2011) suggested online faculty which uses brain-based learning techniques should provide a safe, comfortable, flexible, interactive, and supportive asynchronous learning environment by engaging students in activities and collaborative learning groups, offering flexibility, making resources available, providing feedback, and so on.

Boromo (2017) asserts that the principles that maximize information acquisition and retention are at the core of brain-based learning theory. Techniques for distance learning may be utilized to decrease interruptions and improve focus. Students' interest in online courses will grow from the discussion. Materials and teaching must be learner-centered and presented in a fun, relevant, and personally enriching way in brain-based learning settings (Lucas, 2010). It has been theorized and demonstrated through related studies that interaction is paramount for adequate online courses (Roblyer & Wiencke, 2003).

Research by Boulton, Hughes, Kent, et al. (2019) indicated a positive interaction between engagement and happiness, with an unexpected negative relationship between engagement and academic outcomes.

Conventional MOOCs face many difficulties, including learner dropout, loneliness, engagement, low completion rates, user collaboration, low satisfaction, diversity of learners, and trustworthy techniques for assessing students' knowledge. As other variables impacting MOOC dropouts, Chiappe and Castillo (2020) emphasize the importance of collaboration, community, and the necessity for certification and standardization.

To develop new approaches meant to lower dropout rates and other shortcomings of conventional MOOCs, understanding what makes MOOCs successful has emerged as a critical research challenge. The participation of the students in the course activities and the reported outcomes are used to define successful MOOCs (Niman, 2014).

According to Sonwalkar (2012), a significant reason for concern over any long-term viability, impact, and sustainability of MOOCs is the high dropout rate of individuals who enroll initially in them. Itani, Brisson, and Garlatti (2018) discovered through their research that the high dropout rate is caused by the lack of time, family obligations, lack of online abilities, lack of prior experience, the course's structure and complexity, the poor quality of the lessons, and the pedagogical approaches that have been used. According to a study by Hew and Cheung (2014), looking at the difficulties professors and students have in typical MOOCs, the plurality of students lacks orientation and motivation, and lack of communication and connection with peers and/or teachers causes dropout rates.

Sonwalkar (2012) asserts that conventional MOOC courses rely heavily on video lectures and discussion forums and are predicated on the principle that "one size fits all." A MOOC course that uses an adaptive system based on inductive, deductive, and exploratory pedagogy, when adapted to each learner's preferred learning style may have a substantially better completion rate. Completion rates can be significantly increased with adaptive MOOCs, which offer information with diverse learning methodologies and timely, intelligent feedback.

According to Miloud, Soukaina, Salma, and El Hassan (2020), a MOOC's design should be centered on an adaptive online learning system that boosts course completion rates. This will ensure that the suggested course corresponds to the most effective manner for the learner to finish the learning process.

Many classic MOOCs are created as a collection of texts and videos utilizing typical distance learning concepts, but they do not support adaptive and personalized learning. The diverse educational levels, educational objectives, learning styles, interests, and preferences of learners influenced the development of adaptive MOOCs for individualized learning. Personalisation has a significant impact on how successful MOOCs are.

MOOCs must, among other things, employ various pedagogical approaches and offer some category of accreditation or certification if they are to support personalized learning. If we look at MOOCs from five angles–the teaching model, monetization, certificate, adaptive learning, and MOOCs for underdeveloped nations–the future will be theirs. The primary problems in the upcoming years must be these dimensions and the standard of the educational process (Daniel, Cano, and Cervera (2015).

According to Sein-Echaluce, Fidalgo-Blanco, and García-Peñalvo (2017), adaptive MOOCs should provide participants with learning methodologies that cover their learning objectives and profiles, learning preferences, etc.

Rosen, Rushkin, Federicks, Tingley, and Blink (2017) assert that engagement, adaptability to learning outcomes, and lower dropout rates result in more effective learning as students move through the course more quickly and encounter fewer issues since they are dealt with in a targeted manner. There is a definite need for research-based educational approaches that foster the best conditions for students with various backgrounds, aptitudes, and goals to thrive in MOOCs.

Gynther (2016) found that learners who want to keep their professional skills current and to collaborate with peers who have already taken a formal exam on a topic covered by the MOOC would wish to have access to the MOOC after their exams. Colleagues who also want access to the most recent information in a field and ongoing professional growth the MOOC might provide through regular updates.

3.2. Applications of the Adaptive and Intelligent MOOCs

Personalized learning systems have been developed using a variety of adaptive and intelligent techniques, such as artificial intelligence educational systems (from the 1970s) based on artificial intelligence languages, knowledge simulation, and modeling, adaptive control systems (from 1980 to 2010) based on artificial intelligence languages, object-oriented languages, and multimedia and adaptive cloud-based systems (from 2010 and later) that use server virtualization hardware and a cloud computing platform (Semantic Web, intelligent network agents, robots, etc.).

The first adaptive MOOC platform was created by Synaptic Global Learning and offers a personalized learning environment within a MOOC learning environment while emphasizing an educational foundation.

Birari (2014) used ITS approaches in MOOCs to create suggestions and modify the material and learning routes. Additionally, Lafifi, Y., Boudria, Lafifi, A., and Cheraitia (2020) offer a fresh perspective on how an intelligent tutoring process might be applied in human learning systems in general and MOOCs, in particular, to prevent learner dropout, isolation, and motivation loss based on learner behaviors and competencies.

Instead of using sequential modules, Blanco et al. (2013) built an adaptable MOOC utilizing a variety of functions. The design for the proposed adaptive MOOC is based on non-sequential modules, but on the different MOOC thematic sections, when each module is applied. The modules act as a spiral along the development of the course and include gathering and analyzing data, working together, and managing resources. The modification takes place as follows:

- For each profile, the knowledge management system selects the best learning resources. Every learner in the community receives a unique program thanks to the adaption mechanism.
- During the formative assessment, the results of interactions and activities are taken into account.
- New knowledge is produced by the learning community, as a result of collaborative efforts. The newly created knowledge is assessed regularly and incorporated into the system (social knowledge produced by the educational community).

Ewais and Samara (2020) provided a system that facilitates learning by modifying the learning content through the adaptive MOOC utilizing the Nave Bayesian classification algorithm, allowing the student to attain many learning outcomes. The learner can take an automatically generated course based on anticipated learning outcomes and pedagogical relationships.

Lin et al. (2021) took into account the fact that the current techniques for course suggestions in MOOCs typically presuppose that users' choices are unchanging. They disregard the user's changing interests in consecutive learning practices. To increase the adaptability of the recommendation model, they suggest a new lesson recommendation framework called Dynamic Attention and Hierarchical Reinforcement Learning (DARL). In every contact between a profile reviewer and a referral model, DARL automatically records user preferences, enhancing the efficacy of the suggestion. According to experimental findings, the DARL performs much better than more sophisticated methods of course recommendation on important assessment parameters.

Open edX (Sanchez-Gordon & Luján-Mora, 2015) was created to increase the accessibility of course materials for individuals with disabilities. By tailoring the course material to the requirements, preferences, abilities, and students' circumstances, the edX extension aims to increase the accessibility of MOOCs. The user should update their profile with their preferred methods of access. Based on the adaptive engine controls, the Open edX plugin automatically applies all necessary settings and feeds the presentation layer with the user-optimized material.

Aleven et al. (2016) integrated the Cognitive Tutor Authoring Tools (CTAT) and the Generalized Intelligent Framework for Tutoring (GIFT) into the edX MOOC platform. For adaptive training, GIFT offers a framework and authoring tools (Goldberg, Hoffman, and Tarr, 2015). According to Aleven et al. (2016), the combination of GIFT and CTAT enhances the adaptability of edX to learner characteristics and enables the extension of learning-by-doing activities. In this situation, GIFT and CTAT each have unique responsibilities to perform, but both increase the adaptability of MOOCs.

Conversational pedagogical agents can be utilized to successfully promote and enhance student collaboration in MOOCs (Tomar, Sankaranarayanan, Wang, and Rosé, 2017), boost student engagement, lower dropout rates, increase the availability of peer assistance resources (Ferschke, Yang, Tomar, and Rosé, 2015), and increase students' collaboration (Caballé and Conesa, 2018).

Tegos, Mavridis, and Demetriadis (2021) described the design of a prototype system named PeerTalk that uses a conversational agent service designed to support students' online collaboration and provide helpful guidance. It might be organized by course instructors, scaled with faculty support, and incorporated simply into MOOC platforms, resulting in more sophisticated opportunities for authentic social engagement between students.

González-Castro, Muñoz-Merino, Alario-Hoyos, and Delgado-Kloos (2021) introduced a conversational agent for the adaptive learning module for JavaPAL that enhances a MOOC for learning Java programming by altering how students audit important topics offered by the MOOC. Item Response Theory (IRT) is used in this module to adjust the questions' difficulty based on the student's prior knowledge and provides suggestions for videos taken from the MOOC when students are unskillful to answer questions.

Pang et al. (2018) suggested an adaptive recommendation for the MOOCs (ARM) method to deal with learners' low satisfaction (a dropout cause) and feelings of isolation. ARM provides adjustable features following the needs for user happiness. Collaborative filtering enables collaborative learning to decrease loneliness by supplying information about matching learners. Additionally, ARM cleverly blends time scheduling with collaborative filtering to increase the accuracy of proposals. Experiments using data from the actual world show how well ARM can offer recommendations for reducing dropout rates.

An adaptive hybrid MOOC (ahMOOC) paradigm that combines hMOOC and aMOOC was presented by Sein-Echaluce et al. (2017). When corresponding to conventional MOOCs, the ahMOOCs model has the lowest dropout rate (much like hMOOCs). The model's qualitative analysis demonstrated the ability of its diversely profiled participants to jointly produce knowledge that will improve the course material and then apply it to their specific work environments. The study also seemed to show that the participants were conscious of how an ahMOOC may tailor the learning experience to their profiles and interests.

More trustworthy techniques are needed for evaluating learner knowledge in MOOCs. Rossano, Pesare, and Roselli (2017) experimented with an adaptive computer-based test that permits the test's energy content to be adjusted depending on the user's skill. Additionally, this keeps the user from losing interest because a question is too challenging for their profile. To gain experience creating an algorithm for assigning grades, a prototype of the CAT was integrated into an adaptive MOOC that used a quiz game.

The learner's progress toward precisely stated objectives is consistently evaluated in tailored adaptive systems. When the student is ready to exhibit their abilities, the assessment takes place so that the reinforced content can be customized to their needs. Rosen et al. (2017) utilized the functionality for adaptive learning available in edX in the ALOSI (Adaptive Learning Open Source Initiative) platform. They investigated the effects of two different approaches on developing knowledge and expertise for adaptive problems and concluded that ALOSI's adaptive assessment, with a focus on recovery, is associated with a notable increase in learning gains while having no significant effect on dropout.

Hasmaini, Salam, Nurul, and Syafiatun (2018) focused on using appropriate adaptive self-assessment tasks in MOOC-based learning. The results of this study have two main implications: (1) the dimension of learner characteristics (learning style and cognitive style) to enhance learner performance in learning through MOOCs; and (2) appropriate self-assessment activities, which consider learners' prerequisites or adapt to the characteristics of their prerequisites, to enhance learner performance in the MOOC. Based on the adaptation's findings, visual, active, reflective, and intuitive learners outperformed all others.

Teixeira, Garcia-Cabot, García-Lopéz, Mota, and de-Marcos (2016) described the so-called iMOOC (intelligent MOOC) platform, which customizes the course material based on the participant's existing knowledge and the device they use to access it.

Shpolianskaya and Seredkina (2020) used a MOOC framework and described how to select online resources and incorporate them into students' learning paths. The system was developed as a collection of personal agents and services that effectively update user characteristics in the knowledge base, enhancing the potency of suggestions.

To enable adaptation in real-time in MOOCs that use logged interaction information to remember which user behavioral or activity patterns ought to trigger and provide support, Lall'e and Conati (2021) suggested the Framework for User Modeling and Adaptation (FUMA). The association rules will shed light on which behavioral patterns can forecast poor learning performance, allowing for the communication of adaptation to challenging such habits.

Sun, Guo, and Zhao (2020) developed a theoretical framework based on adaptive structuration theory that recognizes three contextualized characteristics, namely collaborative spirit, task interdependence, and social interaction links, as prototypes for appropriation consensus. According to the results of their study, collaborative nature, task interdependence, and social interaction linkages are all positively connected with the comprehension of appropriation, which can promote commitment and learner engagement in MOOCs.

Nicholas and Francis (2017) suggested the Adaptive MOOC Design Framework (AMDF), which exemplifies how a MOOC should be put together to satisfy the plurality of personalisation requirements. Additionally, they offered Felder and Silverman's learning style model to attain the required level of adaptivity and personalisation because learning style is one of the crucial personalisation characteristics.

Sun et al. (2015) offered a system that tries to deliver personalized micro-learning materials while bearing into account the specific needs, learning preferences, and context of story learners.

Pham and Wang (2016) suggested the Attentive Review innovation for mobile MOOC learning, which determines a learner's perceived difficulty levels of the relevant learning materials and recommends personalized review sessions through a user-independent model. This innovation makes it possible to improve mobile MOOC learning by suggesting review materials.

Using a deep neural network for question and confusion classifiers and a content-based recommender to provide answers to the learner's question, Trirat, Noree, and Yi (2020) proposed IntelliMOOC, a system for MOOCs that makes use of learners' online behaviors in addition to content information to respond to student questions.

Sun, Cui, Yong, Shen, and Chen (2018) described an intelligent micro-learning environment, namely MLaaS (Micro-Learning as a Service), using educational data mining (EDM) methods that seek to adjust micro-learning content and learning path identifications fit for each student. They created a dynamic learner model to account for the internal and external aspects that may affect learning experiences and outcomes to personalize the micro-learning necessities.

Li and Zhou (2018) described a hybrid Neural Network (NN) model that has been coupled to anticipate learners' learning methods and educate them with information about their behavior. The potential of the MOOC platform is substantially increased when a learner's preferred learning style is identified, enabling students to raise their course productivity and quality successfully.

Amarasinghe, Hernández-Leo, Manathunga, and Jonsson (2018) suggested an intelligent agent classify MOOC participants based on their actions in a structured collaborative learning environment that promotes the development of ongoing, essential collaboration learning flows.

Assaf, Ramírez-Hernández, and Glasserman (2018) developed a model based on the ROI economic model of terminal effectiveness for estimating the effective completion rate to assess MOOC completion rates.

Recently, on the idea of making systems like MOOCs more intelligent, Yilmaz et al. (2022) offered a conceptual and systematic framework for the development of an adaptive, dynamic, and intelligent tutoring system (SMIT) supported by learning analytics, which is a product of the project that attempts to merge LMS and ITS.

El Emrani, Merzouqi, and Khaldi (2021) created the intelligent adaptive cMOOC known as "IACM" to increase learner engagement while bearing into account individual preferences and learning styles.

To address the problem of high dropout rates in MOOC platforms, El Emrani, Palomo-Duarte, Mota, and Dodero (2022) suggested an adaptive cMOOC based on the ideas of adaptation, connectivism, and social constructivism. The system can also enhance learning performance and student engagement by reducing restrictions and inspiring learners.

By simultaneously developing the following elements: adaptive and personalized content, the ideal educational path, an intelligent selection system, and recommendations for interested students, Parfenov and Zaporozhko (2018) created a multifaceted, holistic, self-organizing cloud environment SMART based on MOOCs that will enable learners to maximize their potential.

By taking into account the diversity of learner profiles and providing each learner with a path customized to their needs through the exploitation of their interactions with the learning environment, Smaili, Khoudda, Sraidi, Azzouzi, and Charaf (2022) aimed to personalize the MOOC content for each learner to advance their academic performance and to enhance the effectiveness of the online platform.

Hamal and El Faddouli (2022) present an intelligent system built on cutting-edge developments in artificial intelligence, mainly deep learning applications, that may assist the learner by responding to all of his/her queries on the topics covered in the MOOC in the area of Natural Language Processing (NLP).

Using big data and artificial intelligence (AI) technologies, Tzeng, Lee, Huang, Huang, and Lai (2022) designed a MOOC assessment system that can accurately predict student satisfaction even in case of low questionnaire response rates. As a result, instructors might use a more satisfactory approach to estimate student satisfaction during and after the course.

The EduEdge project seeks to develop and launch a cloud-based Intelligent Adaptive e-Learning MOOC Platform that uses 4S Technologies to customize the learning experience for each learner. This individualized instruction will help students learn more quickly and retain it. Boosting the efficiency of the learning process and engagement also raises the quality of the learning outcomes.

4. Results of Research

The analysis of the research ends up with a conclusion that the researchers contribute with alternative solutions for enhancing the effectiveness of conventional MOOCs in response to the high dropout rate of students, which is one of the biggest challenges, as well as diverse educational levels, completion rates, interests and preferences, educational goals, and other learner characteristics. For individualized learning, two of them are Adaptive and Intelligent MOOCs.

This article's analysis of adaptive and intelligent MOOCs brings to light the most critical problems they addressed. Both innovations boost the effectiveness of conventional MOOCs by addressing some of their shortcomings or difficulties and outlining them below.

The response to the first research question (RQ1) posed for the improvements the Adaptive and Intelligent MOOCs provide to the effectiveness of MOOCs are as follows: lowering the dropout rate and improving the quality of MOOCs; boosting learning gains; lessening loneliness; utilizing different learning styles for better academic performance; tailoring the course material to the student's needs, preferences, skills, and circumstances; creating learning itinerary recommendations tailored to each participant's competence profile; adjusting different learning strategies to distinct learning goals; adjusting content according to prior knowledge and the device they utilize to access the course, maximizing their potential, customizing the learning experience for each learner, gauging student satisfaction during and after the course, preventing isolation, and motivation loss; and choosing the intended learning outcome. The study also showed that reducing dropout rates boosts learning effectiveness.

The response to the second research question (RQ2) is that the following learner characteristics have been used by adaptive and intelligent MOOCs to date for adaptation to a variety of functions as follows: learning styles (primarily the learning style model developed by Felder and Silverman); participants' prior knowledge and the device they use to access the course; specific requests; preferences; knowledge level; learner circumstances; engagement and ability; needs; and heterogeneity of learners' profiles.

The response to the third research question (RQ3) is that the following adaptive and intelligent methods and techniques have been used by adaptive and intelligent MOOCs to date for adaptation to a variety of functions: educational data mining (EDM) methods; hybrid Neural Network (NN) model; intelligent agent to classify MOOC participants; ROI economic model of terminal effectiveness; methodical framework for the development of an adaptive, dynamic, intelligent tutoring system; multifaceted, holistic, self-organizing cloud environment; personal agents and services that effectively update user characteristics in the knowledge base; adaptive assessment; algorithm for assigning grades; adaptive recommendation for reducing dropout rates; conversational agent service; conversational pedagogical agents to successfully promote and enhance student collaboration; adaptation of the course material to the requirements, preferences, abilities, and circumstances of the students; Nave Bayesian classification algorithm for attaining learning outcomes; personalized learning environment.

5. Discussion

This paper aims to highlight the progress made in enhancing the effectiveness of conventional MOOCs by researchers using Adaptive and Intelligent MOOCs to address critical issues such as dropout, loneliness, engagement, user collaboration, and the validity of methods for assessing learner knowledge, and others.

To meet this goal, appropriate research questions were posed, the relevant research method was chosen to increase the credibility and quality of the article, and the inclusion and exclusion criteria were set to select the most relevant articles from journals, conferences, and books. From the study of the most relevant articles, the above results emerged that prove the improvement of the effectiveness of the Adaptive and Intelligent MOOCs as well as the highlighting of the new technologies used by them.

Let us hope that it will help for further study and research by MOOC platform designers regarding Adaptive and Intelligent MOOCs to solve their problems and address challenges. Several important issues were analyzed to answer the research questions, and notable information emerged about the effectiveness of the Adaptive and Intelligent MOOCs using various learner characteristics and what adaptive methods and techniques have been used.

Conclusions

The above information was collected through in-depth literature research up to date. According to the research, an improvement in the effectiveness of conventional MOOCs by the Adaptive and Intelligent MOOCs in several of their challenges and shortcomings was encountered. Various characteristics of learners have been used so far for adapting to different functions of MOOCs using several diverse adaptive and intelligent methods and techniques of Adaptive and Intelligent MOOCs. All of them are important for the additional development of Adaptive and Intelligent MOOCs by coming designers.

The main challenges in the evolution of Adaptive and Intelligent MOOCs in the upcoming years should be the adaptability to the unique characteristics of the learner, along with the quality of the education or training provided, the pedagogical effectiveness, and the effective treatment of challenges of conventional MOOCs.

The examination and application of several strategies and techniques used in online adaptive educational hypermedia systems, which have made significant contributions to learning through contemporary learning theories, is one avenue that this work suggests for increasing the effectiveness of MOOCs in the future.

These methods will significantly benefit MOOCs concerning their efficacy and capacity to handle the challenges and shortcomings of conventional MOOCs.

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Alexandros Papadimitriou

**Adaptacyjne i inteligentne kursy MOOC:
jak przyczyniają się do poprawy skuteczności kursów MOOC**

S t r e s z c z e n i e

Opracowano kilka tradycyjnych kursów MOOC, wykorzystując określone podejścia do nauczania na odległość. Głównym celem tego artykułu jest przeanalizowanie licznych badań dotyczących zapewniania adaptacyjnych i inteligentnych kursów MOOC w celu rozwiązania problemów, takich jak wskaźnik rezygnacji w celu poprawy ich efektywności w porównaniu z konwencjonalnymi kursami MOOC. Zbadano kwestie, które stanowiły główne zainteresowanie badaczy MOOC w ostatnich latach, w tym wskaźnik rezygnacji, wskaźnik ukończenia studiów, samotność. Dyskutowane pytania badawcze dotyczą: skuteczności adaptacyjnych i inteligentnych kursów MOOC, cech ucznia stosowanych w adaptacji, adaptacyjnych i inteligentnych metod i technik nauczania oraz ulepszeń, jakie wnoszą do tradycyjnych kursów MOOC jako podstawy do projektowania adaptacyjnych i inteligentnych kursów MOOC w najbliższych latach.

S ł o w a   k l u c z o w e: kształcenie na odległość, adaptacyjne i inteligentne MOOC, spersonalizowane nauczanie, wyzwania MOOC

Александрос Пападимитриу

**Адаптивные и интеллектуальные МООК:
как они способствуют повышению эффективности МООК**

А н н о т а ц и я

Несколько традиционных МООК были разработаны с использованием конкретных традиционных подходов к дистанционному обучению. Основная цель этой статьи — изучить многочисленные исследования и исследования, посвященные предоставлению адаптивных и интеллектуальных МООК для решения таких проблем, как процент отсева, для повышения их эффективности по сравнению с обычными МООК. Были изучены важные вопросы, которые были основными исследовательскими интересами ученых МООК в последние годы, включая процент отсева, процент завершения, одиночество и другие темы. Наконец, исследовательские вопросы, касающиеся эффективности адаптивных и интеллектуальных МООК, характеристик учащихся, которые они используют для адаптации, адаптивных и интеллектуальных методов и техник, которые они используют, и улучшений, которые они привносят в традиционные МООК в качестве компаса для разработки адаптивных и интеллектуальных МООК в ближайшие годы, обсуждаются.

К л ю ч е в ы е   с л о в а: дистанционное образование, адаптивные и интеллектуальные МООК, персонализированное обучение, вызовы МООК

MOOC adaptativos e inteligentes: cómo contribuyen a mejorar la eficacia de los MOOC

Resumen

Se han desarrollado varios MOOC tradicionales utilizando enfoques tradicionales particulares para el aprendizaje a distancia. El objetivo principal de este artículo es examinar numerosos estudios e investigaciones sobre la provisión de MOOC adaptativos e inteligentes para abordar problemas, como la tasa de abandono, para mejorar su eficiencia en comparación con los MOOC convencionales. Se estudiaron temas importantes que han sido los intereses de estudio esenciales de los académicos de MOOC en los últimos años, incluida la tasa de deserción, la tasa de finalización, la soledad y otros temas. Finalmente, las preguntas de investigación planteadas sobre la efectividad de los MOOC adaptativos e inteligentes, las características del alumno que utilizan para la adaptación, los métodos y técnicas adaptativos e inteligentes que utilizan, y las mejoras que aportan a los MOOC tradicionales como brújula para el diseño de MOOC adaptativos e inteligentes en los próximos años, se discuten.

Palabras clave: educación a distancia, MOOC adaptativos e inteligentes, aprendizaje personalizado, desafíos MOOC