THE FUTURE OF LEARNING ENVIRONMENTS WITH ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

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Abstract

E-Learning and online education have become inseparable parts of the world's education systems due to the rapid growth of technology and its positive effects on education quality and accessibility. The social implications caused by the COVID-19 outbreak (e.g., closure of educational institutions) have further contributed to the wide adoption of e-learning solutions, especially learning management systems (LMSs), which make up the largest segment of the e-learning market. The effectiveness of online education strongly depends on the learning environment that LMS provides for students, as the most important user group. LMS should sit at the heart of learning strategies to give students an interactive and engaging learning experience. This requires significant research and development (R&D) by service providers to understand students' needs, learning styles, and learning patterns in order to improve learning environments such that they will be endorsed and welcomed by the students. Artificial intelligence (AI) and machine learning are the most powerful processing technologies that have transformed many sectors, including education, in the past decade. AI and machine learning have huge potentials to aggregate, curate, and personalize the learning experience and content to realize state-of-the-art e-learning at its finest. In this paper, we first review various scenarios regarding students' learning experiences in an LMS, which can be improved by data-driven approaches. Then, we present examples of machine learning-based solutions that can effectively extract insights from students' behaviors to improve and personalize their learning experiences. These solutions are the results of the R&D conducted by the TechClass AI Team to implement such features into the TechClass Next-generation Learning Environment.

Keywords: e-learning, online education, learning management system, learning environment, artificial intelligence, machine learning, data-driven solutions.

1 INTRODUCTION

1.1 Online education: a global trend

The 21st century began with a paradigm shift in attitudes towards e-learning and online education [1], which has been further developed due to the technological advances that have increased the ease of learning at a distance [2]. Online education has brought several advantages over traditional education, such as flexibility, affordability, pacing options, easy documentation, and most importantly, accessibility to a wide range of learning materials regardless of location. These advantages have led to a rapidly growing adoption of online and distance learning over the past two decades. Massive open online courses (MOOCs) have become popular than ever, universities are expanding their online learning programs and resources, and overall, education systems are being transformed due to such advantages. All of these have started a new era for higher education.

While this paper is being written, another global reason has further contributed to the wide adoption of online learning, and it is the COVID-19 outbreak. The social implications caused by the COVID-19 pandemic, such as stay-at-home restrictions and the widespread closures of schools and universities [3], have caused an exponential growth in online and distance learning. As argued by many, learning management systems (LMSs) has been, by far, the most suitable solution for the realization of online learning platforms [4]. An LMS provides an integrated learning environment that offers the learning content and other functionalities such as management and tracking, documentation, reporting, and collaboration across the system [5]. Today's LMSs sit directly at the intersection of the latest e-learning trends – personalized (adaptive) learning, microlearning, mobile learning, and gamification. Using such technologies, an LMS can duplicate its teaching force in an unlimited way by eliminating the need to make teachers and academic staff present in every classroom [6].

The increased popularity of online learning has introduced some new issues regarding student interactions and engagement, course content design and delivery, types of assignments, performance expectations, and assessments and evaluations [2]. These issues have attracted a great deal of attention from the research community as addressing them will improve the online learning quality. Studies have shown that, in contrast to traditional classroom settings, providing online teaching requires different pedagogy and a specific set of skills [7]. For an LMS, most of the issues are centered around its learning environment as it is the heart of an LMS [6]. There has been an increased demand for learning environments that encourage social interaction, cooperation, and collaboration in the classroom [8]. Recently, the emphasis is also on analyzing students' interactions to gain insights into the collaborative learning process [2].

1.2 Development of TechClass Online Learning Community

Constructivism and social learning theory are two fundamental theories in education that recognize the contribution of learners' own experiences and their social behavior in the learning environment, respectively, to their understanding and knowledge [9], [10]. Closely related to each other, these two theories present an integrated view of learning and give ideas about how our mind works. Other significant theories inspired this integrated view of learning (e.g., Albert Bandura's social cognitive theory) as well, and they have shared an important idea: learning is a cognitive activity within a social context, and an individual's active engagement with content and others is directly related to his/her knowledge acquisition [11].

In 2018, TechClass felt the need to adjust its mindset with such ideologies, and embrace the recent advancements in online learning to realize an interactive, social, and engaging learning environment. By fully understanding the integrated ideology of constructivism and social learning, TechClass developed the 3rd generation of its LMS called "Smart Online Learning Community" (see Figure 1) to replace the traditional version of its e-learning portal [12]. The purpose was to address a common limitation of most e-learning platforms: not existing communication channels between students of the same class, which prevents them from learning from each other. An ocean of possibilities will be visible by shifting the attitude from an e-learning platform to an online learning community where students are more connected to each other [12]. By relying on the "Community-first" approach, TechClass reinvented its LMS to realize an effective online learning community [13].

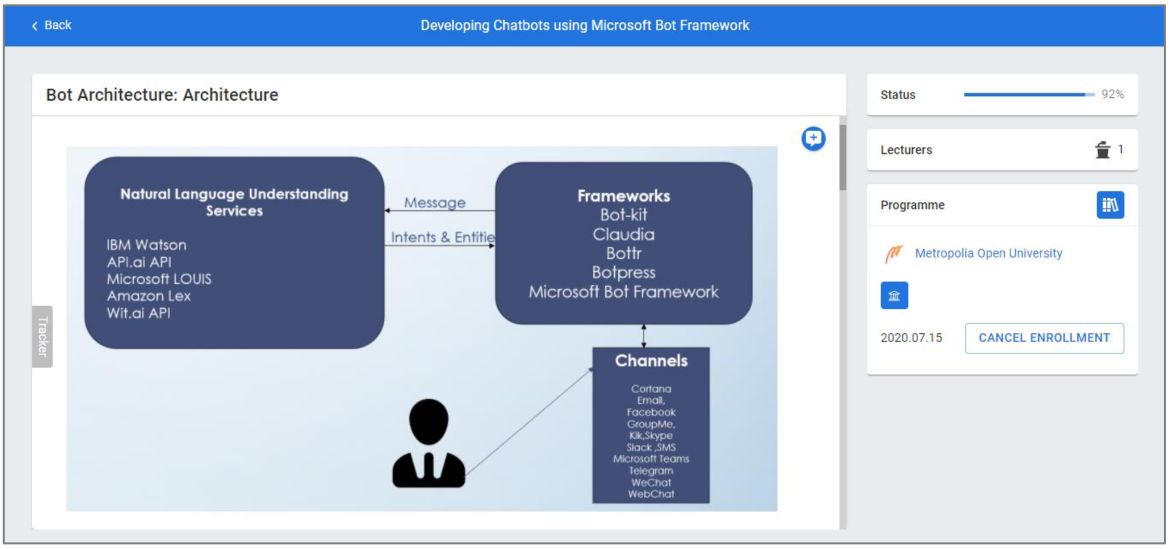

Figure 1. TechClass Smart Online Learning Community: Learning Environment

1.3 Next step: entering the world of AI

As the next step towards developing an interactive, social, and engaging learning environment based on the community-first approach, TechClass is willing to expand its horizons and employ today's most advanced processing technologies: artificial intelligence (AI) and machine learning. Modern AI and machine learning methods use observed data of a system or process to create models for capturing its interactions and characteristics. AI, machine learning, and data-driven solutions in general, have revolutionized our lives in many ways. They have transformed many sectors including education which is currently experiencing another paradigm shift because of AI. AI can help us better understand students' personal needs and desires, the way they learn, how to personalize their learning experience, and how to model the dynamic relationship between student learning, the knowledge domain, and the resources that allow them to interact with the domain [14]. Over the past decade, the role of AI in learning has been recognized by several education institutions, the government, and numerous funding entities within the industry, not to mention various research groups that are working on educational research problems through data-driven methodologies.

This paper is our contribution to the continuous efforts of the research community to further enhance online education using AI. This paper will review different scenarios of students' learning experiences in an LMS, which can be improved by data-driven approaches. Then, we present AI- and machine learning-based features that can be implemented into LMSs as data-driven solutions to enhance the platform capabilities. We will specifically focus on the TechClass next-generation LMS and present the solutions regarding its learning environment. The primary goal of these features is to provide an enjoyable, productive, and fruitful experience of TechClass learning environment to students. The second most important goal is to extract insights and business strategies based on data-driven analyses.

2 METHODOLOGY

The paper is organized as follows: Section 2 describes the methodology of presenting the ideas. In section 3, the AI- and machine learning-based features that are directly applicable to the LMS learning environment will be presented. Section 4 will discuss several more AI- and machine learning-based features (not necessarily related to the learning environment) that can gain insights into students' behaviors and predict their actions. Section 5 presents some suggestions and outlooks to continue this research path. Finally, section 6 concludes the paper.

To provide a comprehensive view over each AI- and machine learning-based feature in terms of its applicability and usefulness, we will describe the followings for each feature that will be presented in the next two sections:

1. Scenario (use case): the reason for using the feature and the possible value that it can bring
2. Feature description: information about the feature's functionality, capability, and possible input/output
3. Sample solution(s): sample AI- or machine learning-based solution(s) (necessary data and applicable algorithms)

3 LEARNING ENVIRONMENT FEATURES

3.1 Course recommendation system

Students who enroll in classes aligned with their personalities and interests will most likely accomplish more than those who take their courses by following a general curriculum. Using a general curriculum for every student of a program can be susceptible to error, negatively affecting the students' performance and learning experiences. After all, not all students have the same talents, interests, characteristics, or personalities.

Even though LMSs have facilitated the course selection process to some extent, there is still space to accomplish more. As the next step, an LMS can be equipped with features to provide students with personalized suggestions about which course, program, or study (learning) path to take, and in this way, offer them a customized study curriculum. Such a personalized recommendation system can be developed to suggest the followings to the students:

1. Study paths or programs that are aligned with their past activities, interest, and personal preferences
2. Online courses (classes) that are aligned with their study path and learning preferences
3. Other courses in which their classmates (or other students with similar preferences) are enrolling
4. Courses that students can benefit from according to their specific characteristics. For example, by finding their skill gaps (based on their performance in other courses), the system can suggest some courses which can strengthen their weaknesses

The solution to offer such personalized recommendations are *recommender systems,* a type of machine learning algorithms that perform information filtering. Recommender systems analyze various types of information related to a user's past behavior as well as similar decisions made by other users to predict the user's preference or his/her interest in an item or product. There are four main types of these algorithms: collaborative, content-based, knowledge-based, and hybrid recommender systems [15].

As an initial study on recommender systems for online course enrollment, O'Mahony and Smyth analyzed and highlighted the factors that affect the students' choices, and proposed solutions for some of the identified primary factors [16]. In another research, Gulzar et al. proposed a hybrid recommender system to guide a learner in selecting his/her courses as in a personalized curriculum [17].

3.2 Course hyper-personalization

Personalized learning (PL) is defined as instruction in which the pace of learning and teaching methods are tailored to each learner's needs. Learning goals, instructional methods, and instructional material (and the order of their presentation) will change depending on the learner's needs. Furthermore, learning activities are meaningful and relevant to learners in such instruction as they are driven by their interests and often self-initiated [18].

Fig. 2 presents a general model of learning theories and learning augmentation principles by personalizing a learning environment to individual students. PL and adaptivity theories suggest using the data of a student's past performance and preferences in order to adapt the features and settings of the learning environment to improve the student's learning experience. Thus, in the case of LMS, PL design leads to changes in the LMS's learning environment. These can involve PL technologies that enable instructional activities to utilize students' characteristics to adjust the instruction, or classroom PL implementations that allow them to select and direct their learning, often along study paths aligned with their personal goals and interests.

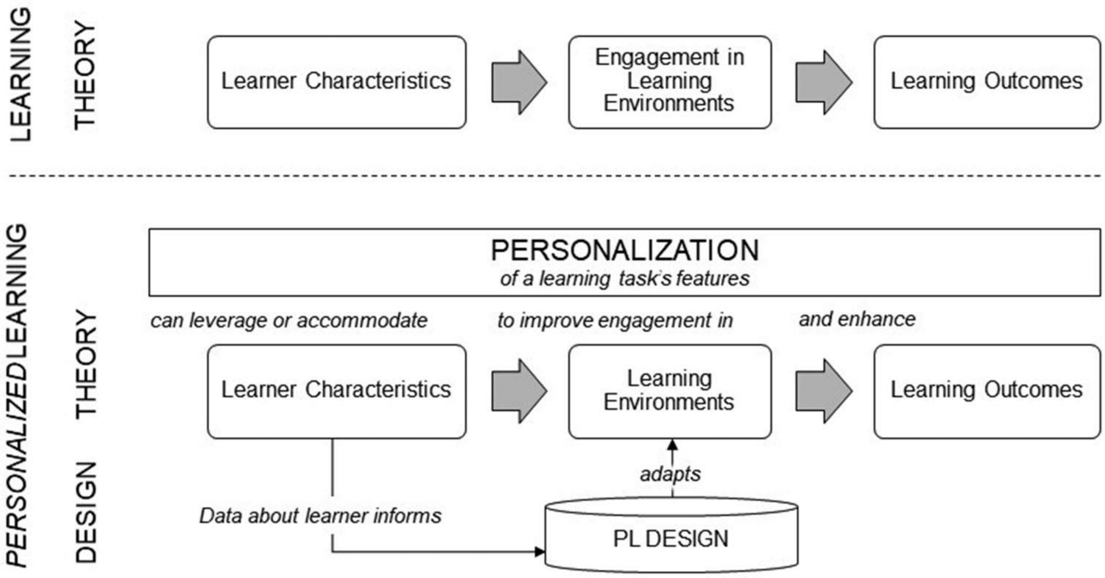

Figure 2. General model of a personalized learning environment [19].

Through the power of machine learning-based hyper-personalization, it is possible to develop a custom learning profile for each student and customize the learning materials for each student based on his/her learning profile. A learning profile should be a complete picture representing a student's interests, preferences, aspirations, background, strengths, weaknesses, and preferred learning style. PL can empower an LMS to leverage a student's learning profile to offer him/her a customized study path (curriculum) as well as the customized versions of the followings during a course enrollment:

1. Learning style
2. Pace of learning
3. Learning environment design
4. Level of the learning content and material
5. Type and level of assessments

Adaptive machine learning models are the solutions to realize PL in an LMS. Adaptive learning models can evolve and tune themselves with changing contexts; such models can support struggling students or challenge gifted ones. For example, the authors of [20] proposed a machine learning model for learning path recommendation. This model first clusters students into several groups to train a long short-term memory (LSTM) model to predict students' learning paths and performances. Personalized learning full paths are then selected from the results of path prediction [20]. LSTM is a type of artificial neural networks well-suited for processing and learning long term dependencies in time series and sequential data.

As another related study, Rad et al. presented *Cloud-eLab*, an AI-thinking platform that enables highly personalized learning based on the manual and perceptive feedback obtained from the students. Cloud-eLab's learning environment can customize the learning contents from the beginner level to the advanced level, and it can accept additional, new modules as well. A block diagram of Cloud-eLab's components and structure is illustrated in Fig. 3.

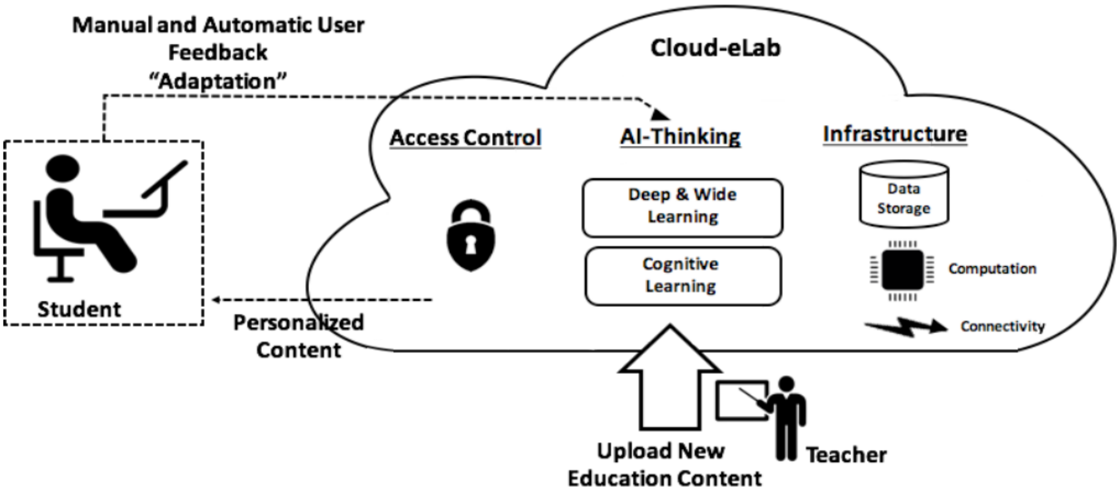

Figure 3. Cloud-eLab AI-Thinking block diagram.

3.3 Smart class groups

Collaborative or community learning is a mechanism where team members support and rely on each other to accomplish defined goals. The advantages of group work and community learning are well established in pedagogy. Collaborative learning helps students develop critical thinking skills, reinforce socialization, improves attitudes towards learning, and promote moral and ethical values [21]. Therefore, using such collaborative learning strategies in LMS design can further improve their effectiveness.

LMSs can be equipped with the necessary features to facilitate collaborative learning for classes that require students to work in groups. Grouping students can be done smartly based on their similarities and differences. An effective group is one with diversity in terms of member's backgrounds and skills. Clustering algorithms are suitable to build such smart class groups. Clustering is a type of unsupervised machine learning strategy in which a population or a set of data points is divided into several groups (i.e., *clusters*) where the members in the same groups share similar (or pre-defined) characteristics.

An LMS can provide group competitions, quizzes, or projects based on such collaborative learning features. Groups can compete against each other to have a passion for improving themselves, and students help each other in each group get a higher rank in the competition. The results can be analyzed to see whether group work can enhance the learning experience.

3.4 Student chatbot assistant

A smart and personalized assistant in the form of a chatbot can help students with FAQs or simple questions related to the course material. The chatbot can be designed to interact with each student based on his/her personality, interests, and past performance. Fig. 4 presents a sample architecture of an education support system chatbot.

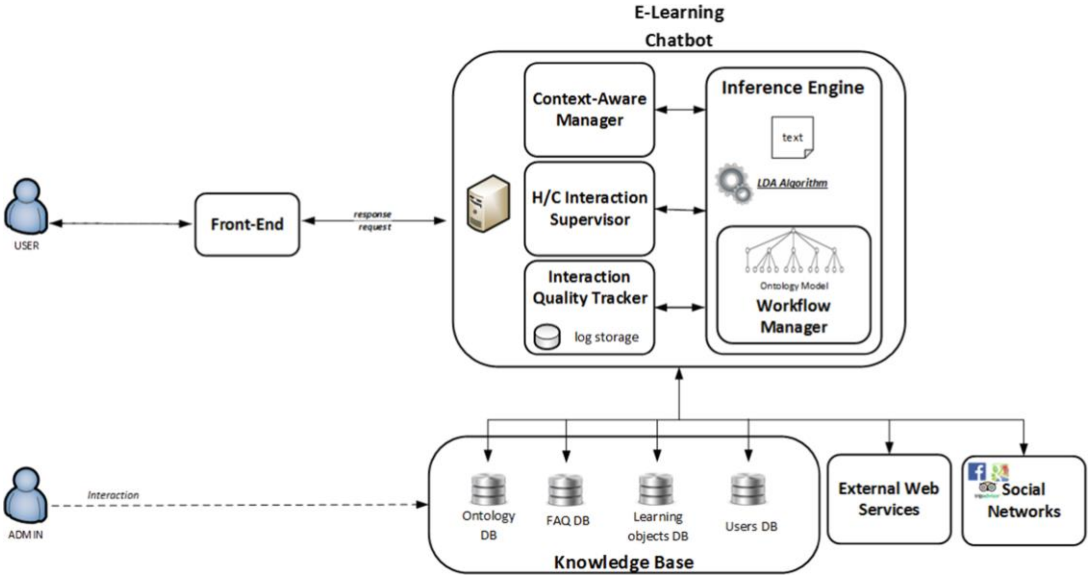

Figure 4. Architecture of an education support system chatbot [22].

The chatbot can be designed to be a smart and friendly assistant in the initial phase. By leveraging deep learning and natural language processing (NLP) technologies, it can be trained to answer students' typical questions (e.g., FAQs, technical issues regarding the platform) or even questions related to the course topics. Usually, each course has a primary reference book. One can equip the chatbot with a question-answering (QA) engine tuned for each course's reference book to provide the student with more detailed information on a specific topic.

The recent Generative Pre-trained Transformer 3 (GPT-3) model works dramatically well on the QA task. GPT-3 is an autoregressive language model that uses deep learning to produce human-like text. Thus, one can consider it as a possible solution to implement the support chatbot. It is worth noting that several other language models can be applied as well, such as Bidirectional Encoder Representations from Transformers (BERT). One can use such models and fine-tune them on the preferred text, most likely making them generate more accurate responses due to their considerable, precise, and broad knowledge about every topic.

As another useful capability, the support assistant may also check the student's progress to see whether it is normal. If abnormal progress is detected, it may check up on the student regularly. This can be done using anomaly detection algorithms. These algorithms can identify rare data observations that differ significantly from most of the data.

3.5 Course section summarization

Text summarization methods produce a concise, simplified version of a text with the most relevant details included. A summarization of course content can be very beneficial to students as it helps them effectively and efficiently capture the information from the text. For example, students can use a course summary to determine the course's essential ideas and details. A course summary also enables students to concentrate on keywords and phrases that are worth noting and recalling.

LMS service providers can manage to implement a feature in their learning environments to automatically find the most important sentences and details in a course section and summarize them to give a general idea about that section to a student. The results can be presented at the beginning or the end of each section as a quick briefing.

Although automatic text summarization is very challenging, some machine learning methods have been developed to perform it with acceptable results. Automatic summarization methods are often categorized into two general types: *extractive* and *abstractive* methods. Extractive summarization methods identify important parts of the original text and put them together word for word to generate the summarized version. On the other hand, abstractive summarization methods analyze the text using advanced NLP techniques to construct a new paraphrased and shorter text that conveys the most crucial information from the original text [23]. See [23] for a more detailed review of automatic text summarization techniques.

3.6 Presenting industry trends

It is possible to scrape raw data from job search websites, news articles, and technology blogs and analyze it to extract insights related to the latest industry trends. One should use NLP methods (e.g., keyword extraction) and data mining techniques to achieve more useful results. The results can then be categorized according to the available courses in the platform, and then related industry trends can be presented to students when they start a course (or a chapter of a course). This will make students familiar with the applications of the course in the industry as well as related job positions. Furthermore, they will know the goals and intentions of different topics discussed in a course that might help them learn the concepts smoother.

For example, when the student reaches a new chapter of a course related to “recommender systems,” he/she can be informed of how many companies are wanting to hire people specialized in recommender systems. Displaying real-time statistics of job opportunities related to the course will hopefully make students more passionate about their path.

4 ADDITIONAL FEATURES

4.1 Student dropout prediction

Although online education is appealing to many students, it still suffers from the major issue of high dropout rates compared to traditional education. Students enroll in a course with some motivations and expectations, which might degrade gradually due to various factors such as debilitation or lack of satisfaction, leading them to disengage or drop out.

Being able to predict student dropouts can add both short-term and long-term values. In the short-term, predicting dropouts helps lecturers and program managers be aware of students who might not complete their courses, to intervene and prevent possible dropouts. In the longer term, dropout prediction will provide useful insights into how course design and students learning factors can affect each other [24].

One can conduct a series of predictive analyses on the students previously enrolled in courses to develop binary classification models for finding the students who are at the risk of dropout. It is possible to build a dataset of previous students’ cumulative records and analytics extracted from their behaviors and performances during the semester and use it to develop predictive models to predict which ones are more likely to drop out because of academic failure or other reasons. Such a dataset can also be used to develop regression models to predict a student’s score on a standardized exam, his/her final GPA in a course, or any other performance metric.

What makes dropout prediction challenging is the “imbalanced data” issue; the frequency of dropout students is much less than that of students who did not drop out. Imbalanced datasets pose a problem for predictive modeling, as most learning algorithms were developed for cases with an approximately equal number of examples for each class. Lykourentzou et al. attempted to overcome this issue using an ensemble model of neural networks, support vector machines, and fuzzy ARTMAP [25]. Xing and Du also proposed a deep neural network architecture to address the issue, which predicted the dropouts and estimated dropout probabilities for each student [26].

4.2 Automatic assignment evaluation

Giving instant feedback is a critical component for improving the interactivity of the e-learning systems. The instant feedback helps the students find their weaknesses and strengths immediately and provides them with the opportunity to identify and resolve their mistakes. Developing a system that automates the process of student evaluation can address this problem. Instant evaluation can be done through different approaches for different types of assessment methods.

Unlike multiple-choice questions and analytical exercises with single, unique answers that are easy to evaluate instantly, exercises requiring descriptive answers are challenging to evaluate automatically. In this type of question, the students explain their answers in their own words; therefore, there is no unique answer to each question. One can use NLP methods such as the one presented in [27] to find the semantic similarity between a reference answer and the students’ answers. In recent years, advancements in NLP have enabled us to capture the semantics and concepts of a text into a numerical framework called “embedding.” Two texts with similar semantics and concepts would usually have similar embeddings. This enables us to compare them using mathematical similarity measures, which facilitates the similarity detection process.

4.3 Student-teacher matching

Studies show that the cultural and personal fit between a student and teacher can improve the student's academic and non-academic performance [28]. One can deduce that this is also the case for online education settings where the teacher (lecturer) is present and has a direct connection with students. Assuming there will be courses presented by multiple lecturers in some LMSs, matching a student with the teacher best aligned with the student's academic background and interests will most likely result in improved learning performance.

To this end, one can develop a recommender system to link the student to the lecturer, who is the best fit for the student regarding his/her academic background, preferences, and past performance. Training such a recommender system needs data that can be collected by adding a survey at the end of each course and asking students to rate specific aspects of the lecturer's performance. A dataset can then be built based on this data and several more features such as student learning style, student pace, and any other useful, related feature that can be collected. Such a recommender system can be trained on this dataset, and the final model can be actively retrained to adapt to the changes over time.

4.4 Plagiarism detection

Plagiarism is a serious issue growing among students in academic institutions, mostly because of the wide availability of electronic resources online (e.g., text, exercise solutions, articles). Plagiarism is the act of copying someone else's work (e.g., from other students or sources) without acknowledging the source. In addition to courses that require essays and descriptive answers for exercises, plagiarism is also a problem for programming courses where students copy each other's source code.

Automatic and computer-aided plagiarism detection has drawn significant academic interest in the past two decades. Various plagiarism detection systems have been developed to detect cheating in students' work. These systems have reduced the academic workload by eliminating the manual detection process.

It is possible to extract lexical, syntactic, and semantic features from a student's submitted assignment and use sentence-level and passage-level approaches to investigate the similarity of his/her answer to other submissions. In [29], the author presented machine learning methodologies as an effective solution for textual plagiarism detection. He proposed several feature extraction techniques and evaluated several classification methods such as Naïve Bayes, Decision Tree, and Random Forest. Ullah et al. also proposed a source-code plagiarism detection technique for the similarity between C++ and Java source-codes.

5 FUTURE WORK

Future work for this R&D direction should concern more in-depth analysis of the mechanism of each feature presented in the paper to evaluate its performance under various conditions that affect its final results, such as students' country and culture, area of the course, the population of the students (overall or in a class), and level of education. Each of the features needs to go through many different adaptations, tests, and experiments to validate their effectiveness for real-life scenarios. TechClass AI Team has already started this phase of the R&D, and the results will hopefully be published in the next paper.

6 CONCLUSIONS

The learning environment is the heart of a learning management system (LMS) and directly affects the students' understanding and knowledge acquisition in online learning. Understanding students' needs, preferences, and learning styles is necessary to improve online learning environments to give students an interactive, engaging, and personalized learning experience. Artificial intelligence (AI) and machine learning have proved huge potentials to personalize students' learning experience and course content to realize state-of-the-art e-learning at its finest. This paper reviewed several AI- and machine learning-based features to analyze and even predict students' acts and behaviors to improve and personalize their learning experiences in online learning settings. The presented ideas are the results of the R&D conducted by the TechClass AI Team to implement such features into the TechClass Next-generation Learning Environment.

ACKNOWLEDGEMENTS

We want to thank our friends in Microsoft USA, especially Mr. Baldwin Ng, for guiding us regarding technical affairs related to integrations between TechClass and Microsoft systems. Also, for having their trust in TechClass to get entered into Microsoft for Startups program. Microsoft Teams and Microsoft Azure services enabled us to focus on implementing state-of-the-art features and capabilities more freely.

REFERENCES

[1] L. Harasim, "Shift happens: online education as a new paradigm in learning," *Internet High. Educ.*, vol. 3, no. 1–2, pp. 41–61, 2000.

[2] G. Pisoni, M. Marchese, and F. Renouard, "Benefits and Challenges of Distributed Student Activities in Online Education Settings: Cross-University Collaborations on a Pan-European Level," in *2019 IEEE Global Engineering Education Conference (EDUCON)*, 2019, pp. 1017–1021.

[3] A. Aristovnik, D. Keržič, D. Ravšelj, N. Tomaževič, and L. Umek, "Impacts of the COVID-19 Pandemic on Life of Higher Education Students: A Global Perspective," *Sustain.*, vol. 12, no. 20, pp. 1–34, 2020.

[4] B. Davis, C. Carmean, and E. D. Wagner, "The Evolution of the LMS: From Management to Learning," *eLearning Guild Res.*, pp. 1–21, 2009.

[5] W. R. Watson and S. L. Watson, "An argument for clarity: What are learning management systems, what are they not, and what should they become?," *TechTrends*, vol. 51, no. 2, pp. 28–34, 2007.

[6] F. Eftekhari, H. Nikram, A. Beshkar, S. R. Chokami, B. Nafardavoodi, and J. Gharibshah, "Implementing the Future of Learning Environments," in *14th International Technology, Education and Development Conference (INTED2020)*, 2020, pp. 4437–4447.

[7] A. P. Rovai and J. R. Downey, "Why some distance education programs fail while others succeed in a global environment," *Internet High. Educ.*, vol. 13, no. 3, pp. 141–147, 2010.

[8] M. Oztok, D. Zingaro, C. Brett, and J. Hewitt, "Exploring asynchronous and synchronous tool use in online courses," *Comput. Educ.*, vol. 60, no. 1, pp. 87–94, 2013.

[9] M. R. Matthews, *Constructivism in science education: A philosophical examination*. Springer Science & Business Media, 1998.

[10] A. Bandura and R. H. Walters, *Social learning and personality development*. New York, Holt, Rinehart and Winston, 1963.

[11] J. V. Boettcher and R. M. Conrad, *The online teaching survival guide: Simple and practical pedagogical tips*. John Wiley & Sons, 2016.

[12] F. Eftekhari, "Progressing from an Elearning Portal To a Smart Online Learning Community," in *12th International Technology, Education and Development Conference (INTED2018)*, 2018, pp. 1997–2005.

[13] F. Eftekhari, "Techclass Smart Online Learning Community: Community Features," in *13th International Technology, Education and Development Conference (INTED2019)*, 2019, pp. 6427–6437.

[14] K. Ahmad *et al.*, "Artificial Intelligence in Education: A Panoramic Review," 2020.

[15] D. Jannach, M. Zanker, A. Felfernig, and G. Friedrich, *Recommender systems: an introduction*. Cambridge University Press, 2010.

[16] M. P. O'Mahony and B. Smyth, "A recommender system for on-line course enrolment: an initial study," in *Proceedings of the 2007 ACM conference on Recommender systems*, 2007, pp. 133–136.

[17] Z. Gulzar, A. A. Leema, and G. Deepak, "Pcrs: Personalized course recommender system based on hybrid approach," *Procedia Comput. Sci.*, vol. 125, pp. 518–524, 2018.

[18] U. S. Department of Education, "Future Ready Learning: Reimagining the Role of Technology in

Education," Washington, D.C., United States, 2016. [Online]. Available: http://tech.ed.gov/files/2015/12/NETP16.pdf.

[19] C. Walkington and M. L. Bernacki, "Appraising research on personalized learning: Definitions, theoretical alignment, advancements, and future directions," *J. Res. Technol. Educ.*, vol. 52 2020, no. 3, pp. 235–252, 2020.

[20] Y. Zhou, C. Huang, Q. Hu, J. Zhu, and Y. Tang, "Personalized learning full-path recommendation model based on LSTM neural networks," *Inf. Sci. (Ny).*, vol. 444, pp. 135–152, 2018.

[21] A. Hassanien, "Student experience of group work and group assessment in higher education," *J. Teach. Travel Tour.*, vol. 6, no. 1, pp. 17–39, 2006.

[22] F. Clarizia, F. Colace, M. Lombardi, F. Pascale, and D. Santaniello, "Chatbot: An education support system for student," in *International Symposium on Cyberspace Safety and Security*, 2018, pp. 291–302.

[23] M. Allahyari *et al.*, "Text summarization techniques: a brief survey," *arXiv Prepr. arXiv1707.02268*, 2017.

[24] S. Halawa, D. Greene, and J. Mitchell, "Dropout prediction in MOOCs using learner activity features," *Proc. Second Eur. MOOC Stakehold. summit*, vol. 37, no. 1, pp. 58–65, 2014.

[25] I. Lykourentzou, I. Giannoukos, V. Nikolopoulos, G. Mpardis, and V. Loumos, "Dropout prediction in e-learning courses through the combination of machine learning techniques," *Comput. Educ.*, vol. 53, no. 3, pp. 950–965, 2009.

[26] W. Xing and D. Du, "Dropout prediction in MOOCs: Using deep learning for personalized intervention," *J. Educ. Comput. Res.*, vol. 57, no. 3, pp. 547–570, 2019.

[27] C. D. Corley and R. Mihalcea, "Measuring the semantic similarity of texts," in *Proceedings of the ACL workshop on empirical modeling of semantic equivalence and entailment*, 2005, pp. 13–18.

[28] C. Redding, "A teacher like me: A review of the effect of student--teacher racial/ethnic matching on teacher perceptions of students and student academic and behavioral outcomes," *Rev. Educ. Res.*, vol. 89, no. 4, pp. 499–535, 2019.

[29] R. B. Kalleberg, "Towards detecting textual plagiarism using machine learning methods," University of Agder, 2015.