IMPROVING ONLINE LEARNING USING DEEP LEARNING AND STUDENT'S INTELLIGENCES

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ABSTRACT

The emergence of online learning has sparked increased interest in predicting learners' academic performance to enhance teaching effectiveness and personalized learning. In this context, we propose a complex model APPMLT-CBT which aimes to predict learners' performance in online learning settings. This systemic model integrates cognitive, social, emotional, contextual, and normative aspects to predict the learners' performance in online learning environment. This model, based on Competency-Based Learning Traces, takes a holistic approach by integrating various data reflecting knowledge acquisition and skills development. By Taking into account the exchanges among the learners, as well as the interactions with their teachers and the complexity of their online learning environment, the model aims to provide accurate and informed predictions of academic performance. This study provides a detailed overview of the APPMLT-CBT model, its data collection methodology, and discusses its potential implications for online teaching. Results suggest that the model can serve as a robust framework for improving online teaching and learning while offering a deep understanding of the underlying mechanisms of online learning.

Keywords: Learner's intelligences, predicting academic performance, competency-based learning, deep learning, online learning.

INTRODUCTION

Digital learning has revolutionized education, introducing new learning modalities such as online teaching. This evolution has sparked growing interest in utilizing data generated by online learning platforms, aiming to enhance teaching effectiveness and personalization (Larabi-Marie-Sainte et al., 2021). At the heart of this transformation lies the need to predict learners' academic performances, a crucial task to anticipate their individual educational needs and guide the development of tailored pedagogical strategies (Fahd et al., 2021). In this work that we propose the APPMLT-CBT model: Academic Performance Prediction Model based on Competency-Based Learning Traces. In contrast to traditional approaches such as (Haseena & Peter, 2017), (Xu et al., 2019), and (Tormon et al., 2023), often focused on quantitative measures like test scores, our model adopts a comprehensive approach. Indeed, APPMLT-CBT mobilizes multi-modal data reflecting both knowledge acquisition and skills development, aiming to provide a more accurate and informed prediction of online learners' academic performances.

Our model incorporates an analysis of digital traces across four dimensions: cognitive, social, emotional, contextual, and normative intelligence, resulting from complex interactions among learners, as well as between learners and the online learning environment. Our objective is to establish an integrated framework to predict and enhance learners' academic performance while gaining a deeper understanding of online learning mechanisms.

In this contribution, we will introduce the Academic Performance Prediction Model based on Competency-Based Learning Traces (APPMLT-CBT), emphasizing its key components and data collection methodology. This article will also report the effectiveness of the model in predicting learners' academic performance, as well as its potential implications for enhancing online teaching and personalized learning.

LITERATURE REVIEW

In the emerging field of digital education, the understanding and application of predictive models of academic performance benefit from the integration of the multiple facets of human intelligence. The evolution of the conceptualization of intelligence, as explored in studies such as (Quilez-Robres et al., 2022), highlights the importance of different forms of intelligence - emotional, social, cognitive, contextual, and normative -in predicting academic outcomes. In particular, the studies (Sanchez-Alvarez et al., 2020) and (Antonio-Agirre et al., 2019) shed light on the pivotal role of emotional intelligence and social support in the academic success of secondary education students, indicating a positive correlation with performance.

The analysis of online learning traces, enriched by indirect measures of cognitive intelligence, offers considerable potential for predicting academic performance, as demonstrated in (Otero et al., 2022). This perspective is complemented by the works of (Li et al., 2022) and (Hongsuchon et al., 2022), which reveal the significant impact of instructional interactions and normative intelligence on academic success in online learning environments. The studies by Xing Li et al., as well as Tanaporn Hongsuchon et al., underline the crucial importance of navigating and optimizing technical, communication, and academic interactions to achieve academic success.

Furthermore, research (Arnaiz-Sanchez et al., 2020) suggests that innovative learning strategies, such as collaborative and cooperative learning, can significantly improve language and mathematics skills, thereby offering paths to enhancing academic performance. These studies collectively illustrate the importance of a multidimensional approach to intelligence in designing predictive models of academic performance, suggesting that integrating these various dimensions could provide more nuanced and precise insights into academic performance in online learning environments.

The integration of deep learning into predictive models of academic performance has shown considerable potential for improving forecasting accuracy. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been particularly effective in extracting relevant features from online interactions, as shown by the research in (Li & Liu, 2021). Furthermore, moblizing deep neural networks to analyze online learning behaviors enables the identification of complex patterns tthan traditional methods can (Ghazvini et al., 2024). In this sense, (Deng et al., 2024) have emphasized the importance of integrating multidimensional models in education, showing how emotional, social, and cognitive intelligence can influence academic outcomes.

Thus, this literature review underscores a convergence towards recognizing the complexity of human intelligence and its direct impact on academic success, particularly in the context of online learning. By accounting for the multiple dimensions of intelligence, our research aims to develop a richer and more inclusive predictive model, capable of capturing the diversity of learning experiences and more accurately predicting the academic performance of learners in online learning platforms.

THE PROPOSED MODEL

Our model presents a systematic approach to predicting academic performance in an online learning environment. It is based on dynamic analysis of learners' skills development, integrating multiple data reflecting not only knowledge acquisition but also the evolution of specific and transferable competencies. As shown in Figure 2, the architecture of our online competency-based academic performance prediction model relies on a systematic and integrated approach designed to capture the complex interactions among learners, the online learning environment, and competencies development processes. Rooted in a learning environment, our model encompasses the various stages of this dynamic process. This learning environment is shaped by active pedagogical methods such as problem-based learning, project-based learning, among others, and is enriched by interaction with the teacher as well as the use of various disciplinary resources such as declarative, procedural, and conditional knowledge. Each learner starts their learning process with an initial skills profile and evolves by interacting with course activities, peers, and teachers.

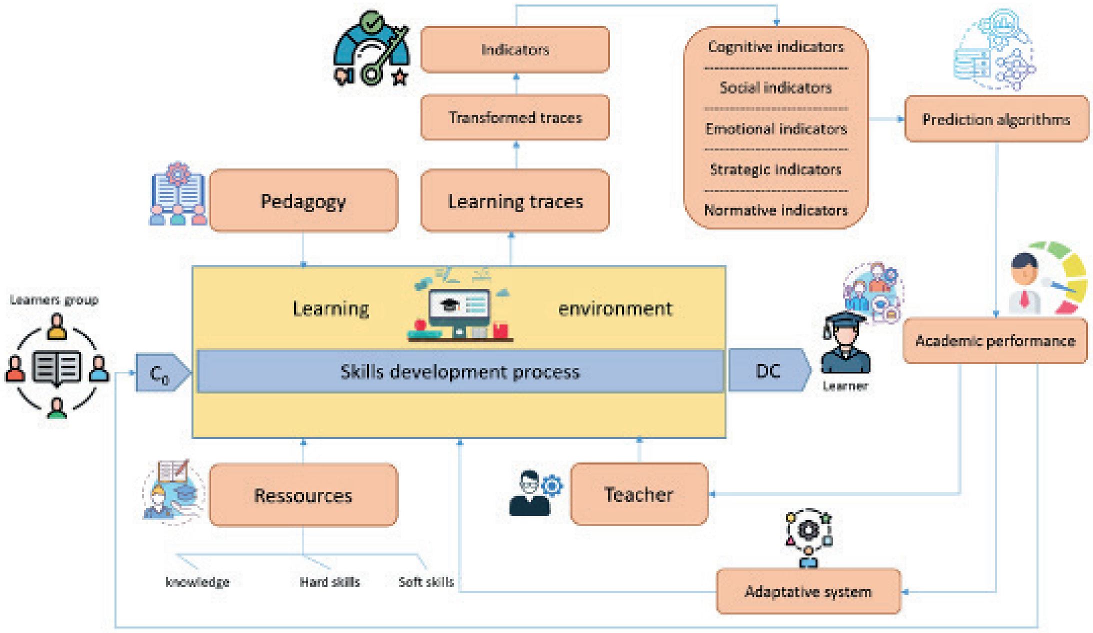

Figure 1. (APPMLT-CBT) Model for Academic Performance Prediction based on Competency-Based Learning Traces

The first step involves collecting learners' learning traces. These traces are then processed to extract various indicators representing cognitive, social, emotional, contextual, and normative aspects. These indicators serve as input data to a prediction system based on machine learning while using a hybrid approach. The output of this predictive system is the academic performance of each learner.

Competency-Based Learning as Pedagogical Framework

According to Franz E. Weinert, competence can be defined as an acquired cognitive disposition specific to demands, encompassing the knowledge, skills, and motivational attributions necessary to perform tasks and meet environmental requirements (Weinert, 2001). Consistent with De Landsheere Viviane, competence goes beyond the isolated application of cognitive, affective, or psychomotor abilities and involves an integrated combination of these different dimensions (Amraouy et al., 2022). In practice, several discrete abilities are combined into structures adapted to the contingencies of the situation. Competency-based learning is a pedagogical approach that emphasizes the practical application of knowledge and skills. Instead of focusing solely on theoretical knowledge, this approach aims to equip learners with the tools and abilities they need to solve problems, make decisions, and succeed in professional life, thus promoting their success in their careers (Bergsmann et al., 2015). By emphasizing competencies, this learning promotes a deeper understanding and practical application of concepts, preparing learners to face real-world challenges (Perrenoud, 1994). Furthermore, this approach encourages autonomy and responsibility by allowing learners to take charge of their own learning and progress at their own pace while developing essential skills such as critical thinking, collaboration, and problem-solving (Collazos, M. A., Hernandez, B., Molina, Z. C., & Ruiz, 2020). Through this approach, the learner develops the ability to mobilize internal resources (knowledge, skills, and attitudes) and external resources (dictionaries, books, media, etc.) to solve problems from the same family, thus reinforcing adaptability and overall competence (Moreira et al., 2023).

Online learning in the competency-based approach provides a flexible and adaptable platform, allowing learners to develop not only knowledge but also essential practical and cross-cutting skills. Through interactive tools, multimedia resources, and personalized assessments, learners can progress at their own pace, focusing on the skills they wish to acquire. Online learning also promotes autonomy and empowerment, encouraging learners to take ownership of their learning process and develop skills such as problem-solving, communication, and collaboration (Jacobs et al., 2023). Additionally, this approach allows for increased personalization by adapting content and activities to individual learners' needs and interests, thereby promoting more effective and motivating learning.

Competencies Development Process

Competencies development process begins at an initial stage designated by C0, where the targeted competency is in an embryonic state. This competency gradually develops through the dynamic interaction of multiple elements within the learning environment. Resources play a crucial role in this context, as they provide the necessary knowledge and expertise (hard skills) as well as interpersonal and behavioral skills (soft skills) that serve as the foundation for the developing skill. Furthermore, the tutor acts as a catalyst in this process. Their role is to guide, encourage, and adjust teaching methods and resources according to the specific needs of the learners, thereby facilitating the transformation of C0 into a developed and applicable competency DC. The tutor also plays a crucial role in interpreting learning traces and various indicators (cognitive, social, emotional, strategic, and normative) to tailor teaching to each individual. Ultimately, the acquired skill is assessed through the learner's academic performance, and the entire process is supported by adaptive systems that ensure the continuous optimization of learning.

Academic Performance

Academic performance refers to the assessment of a student's performance and outcomes within the educational context. It typically involves measuring a student's success in their studies, taking into account various criteria such as grades in courses, exam results, participation in academic activities, quality of work completed, progression in the courses, etc. Academic performance is often used as an indicator of competence and mastery of the knowledge and skills required in a specific field of study (Mason, 2017).

Prediction Algorithms

Academic performance prediction techniques constitute a valuable tool in the field of education, where a diverse range of statistical methods and machine learning models such as Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), Logistic and Linear Regression (L/LR), Decision Tree (DT), Naïve Bayes (NB), K-Nearest Neighbor (KNN), ensemble/hybrid algorithms (Issah et al., 2023), (Saba Batool, Junaid Rashid, Muhammad Wasif Nisar, Jungeun Kim, 2023), as well as other analytical approaches, are utilized. According to the findings of research conducted by (Albreiki et al., 2021), among the algorithmic methods frequently used by researchers to assess student performance, Multiple Regression (MR), Artificial Neural Networks (ANN), Random Forest (RF), and hybrid algorithms are commonly employed.

The Multiple Regression Algorithm

Multiple regression is a statistical method used to model the relationship between a continuous dependent variable Y and multiple continuous independent variables X1, X2, ..., Xn. It employs a linear model to estimate the coefficients β1, β2, ..., βn, representing the impact of each independent variable on the dependent variable, according to the formula:

$$Y = \beta 0 + \beta 1\ X1 + \beta 2\ X2 + \ldots + \beta n\ Xn + \varepsilon$$

The parameters are estimated using techniques such as ordinary least squares (OLS), where the objective is to minimize the sum of squared residuals (errors) between the observed and predicted values of the dependent variable. The coefficients obtained are interpreted in terms of the variation of the dependent variable for each unit change in the corresponding independent variables.

The Random Forest Algorithm

Random Forest is a versatile machine learning algorithm used for classification and regression tasks. It is capable of handling both classification and regression problems. It operates by constructing an ensemble of many decision trees, with each tree trained on a random subset of the training data and features. Each decision tree in the forest provides an independent prediction. For a regression task, the predictions from individual trees are then aggregated to obtain a final prediction. Mathematically, the prediction process in Random Forest can be represented as follows:

$$\hat{Y} = \frac{1}{N}\sum_{i=1}^{n} f_i(X)$$

This translates to the average of predictions from each tree, where $\hat{Y}$ represents the final prediction, N is the total number of trees in the forest, and fi(X) is the prediction of tree i for the features X. The parameters of individual decision trees in Random Forest are adjusted to minimize a measure of error, such as the mean squared error for regression problems. Once trained, the forest of trees can be used to make predictions on new data with high accuracy and robustness.

The Artificial Neural Network Algorithm

Artificial neural networks are machine learning algorithms inspired by the functioning of the human brain. They consist of interconnected layers of neurons, with each connection having a weight determining its importance. Mathematically, the prediction process in a neural network can be represented as follows:

$$\hat{Y} = f(\sum_{i=1}^{n} W_i . X_i + b)$$

This formula shows how the input features Xi are weighted by the weights Wi, then summed and added to the bias b. The result is then passed through an activation function *f*, such as the sigmoid function, the Rectified Linear Unit (ReLU) function, or the hyperbolic tangent function, to obtain the final prediction $\hat{Y}$.

Hybrid Algorithms

The main challenge in prediction modeling lies in identifying effective techniques that can deliver acceptable prediction accuracy. To attain the utmost accuracy, numerous researchers have advocated for the use of hybrid techniques, which amalgamate multiple machine learning algorithms. Hybrid techniques entail combining various machine learning algorithms. Several studies, such as (Adejo & Connolly, 2018), (Saleem et al., 2021), (Yakubu & Abubakar, 2022), and (Niyogisubizo et al., 2022), have used hybrid algorithm techniques to assess at-risk students in a course and predict their success, thus demonstrating improved prediction accuracy.

The 5I

In this section, we explore the five intelligences (5I) that have a significant impact on learners' academic performance in online learning environments. These intelligences include cognitive, social, emotional, contextual, and normative intelligence. In the context of online learning, cognitive intelligence plays a crucial role in facilitating the understanding of concepts, problem-solving, and acquiring new knowledge through available digital resources (Otero et al., 2022). Similarly, social intelligence becomes essential for interacting with peers and teachers through online communication tools, thereby promoting collaboration and cooperative learning (Ramirez-mendoza et al., 2018). Emotional intelligence takes on particular importance in virtual environments, enabling learners to manage their emotions in the face of challenges and obstacles encountered in their online educational journey (Benesova et al., 2021), (MacCann, Carolyn Jiang, Yixin Brown, Luke E. R. Double, Kit S. Bucich, Micaela Minbashian, 2020). Contextual intelligence also becomes crucial as learners need to adapt their learning strategies to online teaching platforms and modalities while effectively utilizing available digital resources (Marishane, 2020). Finally, normative intelligence plays a role in adhering to academic standards and expectations in online learning, ensuring compliance with rules and policies established by educational institutions (Kier & Ives, 2022). By combining these five intelligences, learners are better equipped to succeed in online learning environments, leveraging technology opportunities to optimize their academic performance.

Digital Learning Traces

According to (Djouad et al., 2010), a Digital Learning Trace represents a sequence of observations collected from a Computer-Based Learning Environment (CBLE), also known as a trace source. These traces undergo various technical transformations, such as cleaning, rewriting, merging, and modeling, to generate new traces from which indicators can be extracted and utilized for Mirroring, Monitoring, or Guiding, as illustrated in Figure 1.

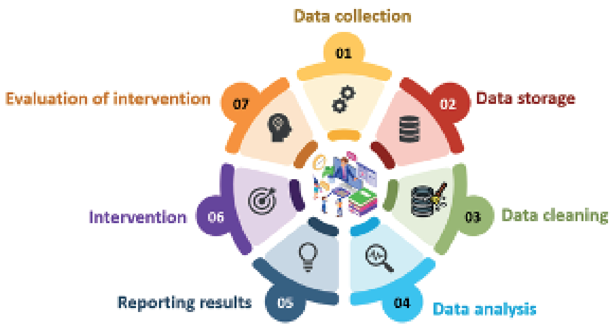

Figure 2. Lifecycle of Learning Traces

The processing of online learning traces, as illustrated in Figure 1, unfolds through several essential stages. Initially, it involves collecting data, which means gathering all user interactions with the educational platform, including qualitative data from learners such as responses to forms, tests, and obtained scores, as well as data collected from learner actions, such as explicit actions like platform logins, completed activities, help requests, participation in discussion forums, and resource allocation to learners, or implicit actions such as resource viewing time, inactivity time, and gestures. These pieces of information are subsequently recorded in a database in preparation for analysis. The third stage involves data cleaning, where errors and redundant data are removed. The purified data undergoes analysis to identify patterns and trends revealing individual learning dynamics. The results of this analysis are then summarized in a report that identifies the progress made as well as the strengths and weaknesses of the learner. This information serves as a foundation for the development of targeted interventions, such as personalized recommendations or modifications in pedagogical approach. The final phase involves evaluating the impact of these interventions and adjusting them as needed. This approach aims to provide effective support to the learner in their online learning experience, relying on concrete data to guide educational actions.

Academic Performance Prediction Approach

In this subsection, we consider key variables and characteristics, integrating the five intelligences as dimensions influencing learners' academic performance prediction, as well as factors of participation in discussion forums. The variables include previous standardized assessment results, learners' interactions with online educational resources, frequency and duration of learning sessions, level of participation in collaborative learning activities (Castillo et al., 2017), and demographic characteristics (YILDIZ & BOREKCI, 2020) such as age, gender, and socioeconomic status. Additionally, we examine specific factors associated with the five intelligences, as presented in the table 1.

Table 1. Grouping of traces collected by intelligence category

Category	Indicator	Meaning
Cognitive Intelligence	NW	The total number of words used in the posts of a learner on the forum.
	NC	The total number of characters used in the posts of a learner on the forum.
	NS	The total number of sentences used in the posts of a learner on the forum.
	TRC	Topic-relevant score counts the number of messages posted by a learner in discussion forums that are relevant to the course content.
Social Intelligence	NPD	Number of messages posted by each learner on the enriched discussion forum.
	NPR	Number of responses to other participants' messages posted by each learner on the forum.
	NV	The frequency with which other participants have viewed the content (posts) created by a learner.
Emotional Intelligence	ES	The emotional state expressed by each learner in their posts and comments on the enriched discussion forum.
Contextual Intelligence	FR	Frequency of consulting learning resources.
	EAR	Use of additional or external resources during learning sessions.
	RCP	Responsiveness to changes in content format or presentation.
	DEI	Level of engagement in collaborative activities.
	AC	Adaptability to challenges encountered in the learning process.
	CT	Overall connection time
Normative Intelligence	CRP	Compliance with institution's rules and policies.
	PA	Participation in academic activities.
	AI	Ability to follow instructions.
	TA	Time spent on specific activities related to content or topic.

The indicators were chosen based on their ability to capture different aspects of the five intelligences and their empirical relevance, validated by previous studies and exploratory tests in similar online learning environments. We chose forum interactions as key indicators because they provide rich and quantifiable data on learners' participation and engagement (Yang et al., 2022). These interactions capture not only the cognitive contribution through the relevance of messages but also the social and emotional dimensions by analyzing responses and peer interactions (Amraouy et al., 2020).

Cognitive intelligence is assessed through the calculation of the relevance score of messages. This is done by counting the number of relevant messages and comments posted by each learner in discussion forums. This approach allows for an objective evaluation of a learner's contribution to a given course. Latent semantic analysis (LSA) and machine learning methods used to classify forum messages based on their relevance to the course content (Yang et al., 2022). This approach provides insight into the degree of alignment of the learner's contributions with the course content, facilitating a more precise evaluation of their cognitive engagement.

To calculate the Social Intelligence Score (SIS), we use a formula that integrates the three indicators explained in Table 1: NPD, NPR, and NV. This formula, $(NPD+NPR)\times NV$, takes into account both the quantity and quality of the learner's social interaction in the discussion forums. Therefore, it reflects both the active participation of the learner and the engagement of other participants with their content.

We adopt a similar approach to that of study (that explained in) (Rafiq et al., 2023) to evaluate emotional intelligence by analyzing the emotional state expressed in the messages. To do this, we mobilize the Bidirectional Encoder Representations from Transformers model (BERT) as a natural language processing techniques. The messages will be preprocessed to remove punctuation, convert them to lowercase, eliminate stop words, and normalize words. Then, we will apply a pretrained multilingual BERT model for sentiment analysis.

To calculate contextual intelligence we proposed the following formula:. $\frac{FR+EAR+RCP+DEI+AC}{CT \times k}$ First, FR is evaluated by counting the number of times a learner accesses available learning resources. Then, EAR is measured by observing interactions with sources external to the educational material. RCP is assessed by assigning numerical values to each level of responsiveness. DEI is evaluated by observing participation and contribution to group activities. AC is assessed by observing the learner's ability to overcome obstacles and adapt to new situations. Finally, CT is taken into account to reflect the learner's overall engagement in the learning process. The coefficient k represents a normalization factor that adjusts the relative importance of each indicator relative to the total connection time (CT). By adjusting k, we can ensure that each indicator contributes fairly to the overall measure of contextual intelligence, taking into account the total connection time of the learner. By normalizing these indicators in a global formula, we obtain an overall measure of the learner's contextual intelligence.

To calculate normative intelligence, we use the weighted average of its four indicators: CRP, PA, AI, and TA. Each of these indicators will be quantified based on the learner's behavior and engagement with institutional rules, academic activities, adherence to instructions, and allocation of time for content-related activities. This score aims to assess the extent to which the learner adheres to established norms and directives in the educational context, providing insights into their ability to navigate effectively within institutional expectations and requirements.

Finally, the learner's overall score is calculated using the weighted average of the scores of the 5I. Each score is weighted according to its relative importance in the context of online learning. This overall score is used to predict learner performance.

$$\text{Score}_{\text{global}} = w_1 \text{ xScore}_{\text{cognitive}} + w_2 \text{ xScore}_{\text{social}} + w_3 \text{ xScore}_{\text{emotional}} + w_4 \text{ xScore}_{\text{contextal}} + w_5 \text{ xScore}_{\text{normative}}$$

In addition to learning traces and demographic data, we collect other relevant information to enrich our model. This include data on learners' prior experience in the course subject area, their learning preferences, personal goals, and any other qualitative or quantitative data that could impact their academic performance.

DISCUSSION

In the competency-based approach, learners not only acquire knowledge but also develop the ability to use various resources to solve real-world problems. When using computerized environments, learning traces become essential for establishing this link with the skills developed. Nowadays, with the proliferation of online learning tools such as MOOCs, LMSs, Intelligent Tutoring Systems (ITSs), Adaptive Learning Systems (ALSs), and many others, collecting and analyzing learners' traces becomes a necessity to predict and assess their performance in a competency-focused educational context.

Also, In the context of competency-based learning, it is relevant to emphasize that learning traces are closely linked to dimensions of intelligence, as demonstrated in the study (Kashkool, 2023) and (Quilez-Robres et al., 2022). Cognitive intelligence, for example, is manifested through actions such as problem-solving and knowledge acquisition, playing a crucial role in academic development, as suggested also by the study (Onditi et al., 2022) and (Tikhomirova et al., 2020). Similarly, social intelligence is essential for building a collaborative and supportive learning environment by facilitating interactions with peers and teachers, as discussed in the study (Rafiq et al., 2023). Emotional intelligence, another crucial aspect, is necessary for overcoming emotional challenges associated with online learning, thereby promoting learners' motivation and engagement, a perspective also supported by the study (Rehman et al., 2017) and by (Amraouy et al., 2023). Furthermore, contextual intelligence, illustrated when learners adapt to the specifics of the learning context, demonstrates their ability to adapt and innovate, a notion also emphasized by the study (Buchler et al., 2021). Lastly, the importance of normative intelligence is highlighted in adherence to rules and academic expectations specific to virtual learning environments, thereby fostering cohesion and ethics within the educational community, a dimension that can be further explored considering the findings of study (Kier & Ives, 2022). These interconnected dimensions of intelligence underscore the complexity and richness of online learning, emphasizing the importance of proposing a model for predicting online learners' performance that integrates all these dimensions to promote a comprehensive and effective learning experience.

Our online academic performance prediction model is grounded in this systemic approach that integrates the cognitive, social, emotional, contextual, and normative intelligence. Regarding the contextual aspect, research (Goedl et al., 2024) revealed a strong and significant correlation between the number of videos watched by learners and their performance. In terms of the social dimension, (Rafiq et al., 2023) demonstrated that engagement in discussion forums was associated with higher scores and greater retention in MOOCs. Regarding the normative dimension. According to the findings of (Kier & Ives, 2022), adherence to academic norms and expectations is a crucial element of online learning, and compliance with rules and policies established by educational institutions is essential. As for the TA indicator, study (Rafiq et al., 2023) indicated that the consistency of accessing the learning platform and the time spent by learners on specific activities related to a given content or subject are strongly correlated with achieving good academic results. Additionally, the data analyzed in research (Jiang & Peng, 2023) included three types of activities (videos watched, assignments submitted, and messages written) as indicators of learner engagement in online tasks. The results of the learning analytics approach from (Jiang & Peng, 2023) showed that all three indicators (videos watched as contextual dimension, assignments submitted as cognitive dimension, and messages posted as social dimension) of engagement in online tasks significantly predicted academic performance, with scores on the final exam serving as a measure of their academic performance. It is noteworthy that the exploration of academic performance as a multidimensional concept is insufficient in the analyzed literature, highlighting the necessity for research aimed at enhancing the validity and reliability of measuring learners' intelligence and performance in online learning environments. To address this, we identified specific indicators associated with each intelligence dimension, such as the number of words, characters, and phrases used in learners' messages to assess their cognitive intelligence, as well as their participation and interactions in discussion forums to measure their social intelligence. Furthermore, we developed advanced analysis methods, utilizing the Bidirectional Encoder Representations from Transformers (BERT) model and Latent Semantic Analysis (LSA), to evaluate learners' emotional state and the relevance of their contributions. Moreover, we included measures of learners' engagement in online activities, their adaptability to challenges encountered, and their compliance with institutional rules to capture the contextual and normative dimensions of their intelligence. By integrating these different dimensions of intelligence, our model aims to provide an accurate and comprehensive prediction of online academic performance, considering the diversity of learners' abilities and skills in a digital learning environment.

Conclusion and Future Work

Education is undergoing a profound transformation with the advent of digital learning, particularly with the rise of online education. The intent of this paper is to develop a conceptual framework, APPMLT-CBT model, offering an approach to predicting and enhancing learners' academic performance in the online environment. The proposed model should be interest to both online learning environment and academic community. For online learning environment, the model will enhance leaners' experience by taking into account the cognitive, social, emotional, contextual, and normative intelligence. A proposed model also serves as a foundation for understanding competency-based online learning processes and offers ample research opportunities for the academic community to validate, either supporting or disproving the proposed propositions. In the future, we will improve our model by exploring new deep learning techniques and refining criteria for predictive performance evaluation. Additionally, we plan to expand our model to support personalized online learning, providing individualized pedagogical recommendations based on academic performance predictions.

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REFERENCES

Adejo, O. W., & Connolly, T. (2018). Predicting student academic performance using multi-model heterogeneous ensemble approach. *Journal of Applied Research in Higher Education*, *10*(1), 61–75. https://doi.org/10.1108/JARHE-09-2017-0113

Albreiki, B., Zaki, N., & Alashwal, H. (2021). A systematic literature review of student' performance prediction using machine learning techniques. *Education Sciences*, *11*(9). https://doi.org/10.3390/educsci11090552

Amraouy, M., Bellafkih, M., Bennane, A., & Himmi, M. M. (2022). Online Competency-Based Assessment (OCBA): From Conceptual Model to Operational Authoring System. *International Journal of Interactive Mobile Technologies*, *16*(4), 46–57. https://doi.org/10.3991/ijim.v16i04.28373

Amraouy, M., Bellafkih, M., Bennane, A., & Talaghzi, J. (2023). Sentiment Analysis for Competence-Based e-Assessment Using Machine Learning and Lexicon Approach. *The 3rd International Conference on Artificial Intelligence and Computer Vision (AICV2023), March 5–7, 2023. AICV 2023*. https://doi.org/10.1007/978-3-031-27762-7_31

Amraouy, M., Bennane, A., Himmi, M. M., Bellafkih, M., & Benomar, A. (2020). Detecting the Learner's Motivational State in Online Learning Situation towards Adaptive Learning Environments. *ACM International Conference Proceeding Series*, 127–132. https://doi.org/10.1145/3419604.3419760

Benesova, A., Tupa, J., Kerroum, K., Khiat, A., Bahnasse, A., Aoula, E. S., Khiat, Y., Antonelli, D., D'Addona, D. M., Maffei, A., Modrak, V., Putnik, G., Stadnicka, D., Stylios, C., Cadavieco, J. F., Goulão, M. de F., Costales, A. F., Pena-Ayala, A., Weber, A., … Beckett, R. C. (2021). Aligning Education for the Life Sciences Domain to Support Digitalization and Industry 4.0. *Procedia Computer Science*, *36*(5), 237–248. https://doi.org/10.1016/j.compedu.2015.03.016

Buchler, J. P., Bruggelambert, G., de Haan-Cao, H. H., Sherlock, R., & Savaneviciene, A. (2021). Towards an integrated case method in management education—developing an ecosystem-based research and learning journey for flipped classrooms. *Administrative Sciences*, *11*(4). https://doi.org/10.3390/admsci11040113

Deng, J., Huang, X., & Ren, X. (2024). A multidimensional analysis of self-esteem and individualism: A deep learning-based model for predicting elementary school students' academic performance. *Measurement: Sensors*, *33*(April), 101147. https://doi.org/10.1016/j.measen.2024.101147

Djouad, T., Mille, A., Reffay, C., & Benmohammed, M. (2010). A new approach based on modelled traces to compute collaborative and individual indicators' human interaction. *Proceedings - 10th IEEE International Conference on Advanced Learning Technologies, ICALT 2010*, 53–54. https://doi.org/10.1109/ICALT.2010.21

Ghazvini, A., Sharef, N. M., & Sidi, F. B. (2024). Prediction of Course Grades in Computer Science Higher Education Program Via a Combination of Loss Functions in LSTM Model. *IEEE Access*, 1–23. https://doi.org/10.1109/ACCESS.2024.3351186

Goedl, P. A., Mallaa, G. B., & Sanders, M. G. (2024). Impact of Video Lectures on Students' Performance and Analysis of Viewer Demographics in Online Courses. *American Journal of Distance Education*, *1–18*. https://doi.org/https://doi.org/10.1080/08923647.2024.2303346

Issah, I., Appiah, O., Appiahene, P., & Inusah, F. (2023). A systematic review of the literature on machine learning application of determining the attributes influencing academic performance. *Decision Analytics Journal*, *7*(February), 100204. https://doi.org/10.1016/j.dajour.2023.100204

Jiang, Y., & Peng, J. E. (2023). Exploring the relationships between learners' engagement, autonomy, and academic performance in an English language MOOC. *Computer Assisted Language Learning*, 1–26. https://doi.org/https://doi.org/10.1080/09588221.2022.2164777

Kashkool, H. S. (2023). *Iraqi EFL University Students' Strategic Intelligence and its Relation to Language Proficiency: A Correlational Study Hind Salim Kashkool*. *1*, 363–388.

Kier, C. A., & Ives, C. (2022). Recommendations for a balanced approach to supporting academic integrity: perspectives from a survey of students, faculty, and tutors. *International Journal for Educational Integrity*, *18*(1), 1–19. https://doi.org/10.1007/s40979-022-00116-x

Li, S., & Liu, T. (2021). Performance Prediction for Higher Education Students Using Deep Learning. *Complexity*, *2021*. https://doi.org/10.1155/2021/9958203

MacCann, Carolyn Jiang, Yixin Brown, Luke E. R. Double, Kit S. Bucich, Micaela Minbashian, A. (2020). Emotional intelligence predicts academic performance: A meta-analysis. *Psychological Bulletin*, *146(2)*, *15*. https://doi.org/https://doi.org/10.1037/bul0000219

Marishane, R. N. (2020). Contextual Intelligence for Student Learning. In *Contextual Intelligence in School Leadership* (pp. 147–177). https://doi.org/https://doi.org/10.1163/9789004431263_006

Niyogisubizo, J., Liao, L., Nziyumva, E., Murwanashyaka, E., & Nshimyumukiza, P. C. (2022). Predicting student's dropout in university classes using two-layer ensemble machine learning approach: A novel stacked generalization. *Computers and Education: Artificial Intelligence*, *3*(March), 100066. https://doi.org/10.1016/j.caeai.2022.100066

Onditi, W. O., Nzioki, S., & Murithi, S. (2022). Effect of knowledge sharing on academic performance of postgraduate students of private Universities in Kenya. *International Journal of Professional …*, *2*.

Otero, I., Salgado, J. F., & Moscoso, S. (2022). Cognitive reflection, cognitive intelligence, and cognitive abilities: A meta-analysis. *Intelligence*, *90*, 101614. https://doi.org/10.1016/j.intell.2021.101614

Quilez-Robres, A., Usan, P., Lozano-Blasco, R., & Salavera, C. (2022). Types of Intelligence and Academic Performance: A Systematic Review and Meta-Analysis. *Journal of Intelligence 10:*, *10*. https://doi.org/https://doi.org/10.3390/jintelligence10040123

Rafiq, J. E., Zakrani, A., Amraouy, M., Namir, A., & Bennane, A. (2023). Optimizing Learning Performance through AI-Enhanced Discussion Forums. *2023 14th International Conference on Intelligent Systems: Theories and Applications (SITA)*. https://doi.org/10.1109/SITA60746.2023.10373689

Ramirez-mendoza, R. A., Morales-menendez, R., Iqbal, H., & Parra-saldivar, R. (2018). *Engineering Education 4.0 - Proposal for a new Curricula*. 1273–1282.

Rehman, R., Tariq, S., & Tariq, S. (2017). Emotional intelligence and academic performance of students. *Journal of the Pakistan Medical Association*, *71*(12), 2777–2781. https://doi.org/https://doi.org/10.29086/2519-5476/2017/sp20a9

Saba Batool, Junaid Rashid, Muhammad Wasif Nisar, Jungeun Kim, H.-Y. K. (2023). Educational data mining to predict students' academic performance: A survey study. *Educ Inf Technol 28*, 905–971. https://doi.org/https://doi.org/10.1007/s10639-022-11152-y

Saleem, F., Ullah, Z., Fakieh, B., & Kateb, F. (2021). Intelligent decision support system for predicting student's e-learning performance using ensemble machine learning. *Mathematics*, *9*(17), 1–22. https://doi.org/10.3390/math9172078

Tikhomirova, T., Malykh, A., & Malykh, S. (2020). Predicting academic achievement with cognitive abilities: Cross-sectional study across school education. *Behavioral Sciences*, *10*(10). https://doi.org/10.3390/bs10100158

Yakubu, M. N., & Abubakar, A. M. (2022). Applying machine learning approach to predict students' performance in higher educational institutions. *Kybernetes*, *51*(2), 916–934. https://doi.org/10.1108/K-12-2020-0865

Yang, B., Tang, H., Hao, L., & Rose, J. R. (2022). Untangling chaos in discussion forums: A temporal analysis of topic-relevant forum posts in MOOCs. *Computers and Education*, *178*(June 2021), 104402. https://doi.org/10.1016/j.compedu.2021.104402