Predicting academic performance: toward a model based on machine learning and learner's intelligences

Jamal Eddine Rafiq[1], Zakrani Abdelali[1], Mohammed Amraouy[2], Said Nouh[3], Abdellah Bennane[4]
[1]Laboratory of Artificial Intelligence and Complex Systems Engineering, Hassan II University, Casablanca, Morocco
[2]National Institute of Posts and Telecommunications, Mohammed V University, Rabat, Morocco
[3]Information Technology and Modeling, Hassan II University, Casablanca, Morocco
[4]Inspectors Training Center for Education, Mohammed V University, Rabat, Morocco

Article Info

Article history:

Received May 19, 2024
Revised Aug 20, 2024
Accepted Sep 3, 2024

Keywords:

Competency-based learning
Digital learning
Learning traces
Machine learning
Predicting academic
Performance

ABSTRACT

With the rapid evolution of online learning environments, the ability to predict students' academic performance has become crucial for personalizing and enhancing the educational experience. In this article, we present a predictive model based on machine learning techniques, designed to be integrated into online learning platforms using the competency-based approach. This model leverages features from four key dimensions: demographic, social, emotional, and cognitive, to accurately predict learners' academic performance. We detail the methodology for collecting and processing learning traces, distinguishing between explicit traces, such as demographic data, and implicit traces, which capture learners' interactions and behaviors during their learning process. The analysis of these data not only improves the accuracy of performance predictions but also provides valuable insights into skill acquisition and learners' personal development. The results of this study demonstrate the potential of this model to transform online education by making it more adaptive and focused on individual learners' needs.

Corresponding Author:

Jamal Eddine Rafiq
Laboratory of Artificial Intelligence and Complex Systems Engineering, Hassan II University
150 Avenue Nile Sidi Othman, Casablanca 20670, Morocco
Email: jamal.rafiq-etu@etu.univh2c.ma

1. INTRODUCTION

Digital learning has revolutionized education by offering new modalities, including online instruction. Despite these advances, it remains a crucial challenge to anticipate and effectively improve learners' academic performance using data generated by online learning platforms. Accurate prediction of academic performance is essential to meet individual educational needs and to adapt pedagogical strategies [1], [2]. Previous research has explored various methods to predict academic performance. Traditional approaches, such as those described in studies [3], [4], [5], primarily focus on quantitative measures like test scores. Although these methods have provided valuable insights, they often overlook the broader context of learning, including knowledge acquisition and skill development. The main contributors in this field have established fundamental techniques, but have not fully addressed the complexities of integrating multimodal data in online learning environments.

Current models often struggle to provide a comprehensive prediction of academic performance by neglecting the multidimensional nature of online learning. In particular, there is a gap in the use of data from various dimensions such as demographic, social, emotional, and behavioral factors, which are crucial for a holistic understanding of learners' progress. Addressing this gap could significantly enhance the accuracy of predictions and provide more personalized support for learners, thus fostering better academic outcomes.

In this study, we propose the academic performance prediction model based on competency-based learning traces (4I-CBT). Unlike traditional methods, 4I-CBT utilizes multimodal data to provide a more precise and nuanced prediction of learners' academic performance. Our model integrates analysis across four dimensions of digital traces, offering a more comprehensive approach compared to existing solutions.

The following sections will detail the 4I-CBT model, including its key components and data collection methodology. We will show how our model improves existing approaches and discuss its effectiveness in predicting academic performance. Additionally, the relevance of our results for enhancing online teaching and personalized learning will be highlighted.

2. METHOD

This work is exploratory research about how to predict academic performance in a complex online environment. The methodology adopted by our study, as illustrated in Figure 1. Encompasses four primary steps: literature review, model conception, solution development, and relevance evaluation.

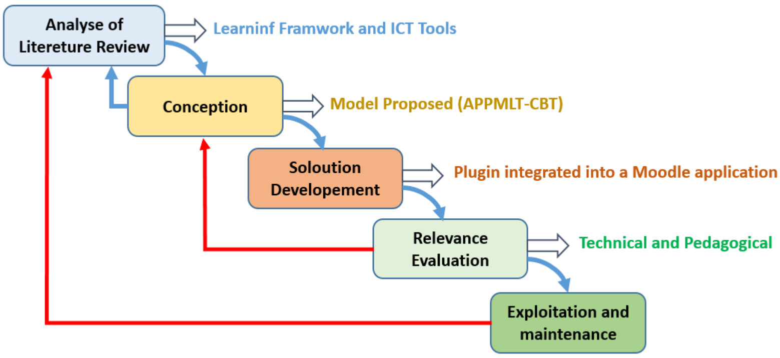

Figure 1. Methodology adopted

2.1. Literature review analysis

2.1.1. Research questions

This study initially aims to provide a comprehensive overview of research published from 2019 to 2024 on predicting academic performance based on competency-based learning traces. The analysis of these studies is guided by the four key research questions presented in Table 1. By focusing on these questions, the study seeks to highlight trends, gaps, and emerging methodologies in the field, providing valuable insights for future research.

Table 1. Research questions

ID	Review question	Main motivation
RQ1	What are the main factors influencing the academic performance of online learners?	Identify and understand the key variables that affect the success of online learners in order to develop targeted interventions and improve academic outcomes.
RQ2	What models for predicting academic performance have been proposed in the existing literature?	Evaluate the current approaches and techniques for predicting academic performance to identify effective practices and potential gaps in the literature.
RQ3	What are the advantages and limitations of the different prediction models?	Analyze the strengths and weaknesses of various models to inform the development of new, more accurate, and robust models suited to the current needs of education.
RQ4	How are competency-based learning traces collected and analyzed in existing studies, and what is their role in predicting academic performance?	Understand the methods of collecting and analyzing learning traces to determine their effectiveness and utility in improving models for predicting academic performance.

2.1.2. Search query

In order to obtain the largest number of articles addressing questions related to our study topic, we have used the keywords explained in Table 2. These keywords were carefully selected to cover a broad range of relevant themes and ensure comprehensive search results. This approach maximizes the relevance and scope of the articles included in the analysis, contributing to the overall rigor of the study.

2.1.3. Scientific databases

Using the previously established search string, we searched three major scientific databases: Scopus, Web of Science, and ScienceDirect. This yielded a total of 185 papers: 61 from Scopus, 71 from Web of Science, and 53 from ScienceDirect. The inclusion of these multiple databases ensured a comprehensive and diverse collection of studies, enhancing the robustness of our literature review.

Table 2. Initial search string

Topic	Search terms
Predicting academic performance	"Predicting academic performance" OR "academic performance prediction"
Advanced techniques	AND "machine learning" OR "artificial intelligence"
Learner intelligences and environmental indicators	AND "learning traces" OR "cognitive" OR "social" OR "emotional" OR "demographic"
Online learning	AND "online learning" OR "e-learning"
Competency-based learning	AND "Competency-Based Learning Traces" OR "competency-based education"
Interactions in learning	AND "interactions" OR "teacher-student interactions"

2.1.4. Study selection

In this pivotal step, our primary objective was to choose relevant studies that shed light on the research questions (RQs) at hand. In sense, have applied the inclusion and exclusion criteria outlined in Table 3. Based on these criteria, we have selected 18 relevant studies in our research field from the initially collected 185 articles. Table 4 presents the list of selected articles, categorized by type of indicators and by algorithm used for predicting academic performance.

Table 3. Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Published 2019–2024	Published before 2019
English	Not in English
Empirical, primary research Indexed	Not primary research (*e.g.*, review)
Indexed in Web of Science or Scopus	Not indexed WoS or Scopus
Journal or Conference Proceedings	Not a journal article
Use case of predicting academic performance	No IT of predicting academic performance
	Duplicate papers
	Papers available only as abstracts or PowerPoint presentations

Table 4. Relevant studies classified by type of indicators and predictive algorithm used

Type of indicators	Algorithms	Studies
Cognitive	LR, RF, SVM, NB, KNN, SVR, CNN, RL, ANN, FDN, DT, SVM	[6], [7], [8], [9], [10], [11], [12], [13]
Social	SVR, CNN, ANN, KNN, DT, RF, SVM, MR, DT, NB	[11], [14], [15], [16], [17], [18], [19]
Emotional	CNN, FDN, RF, DT, KNN	[14], [18], [20], [21]
Demographic	DT, VSM, NB, KNN, RF	[17], [8], [22], [23]

2.2. Conception and modelization

The analysis of the studies selected in the previous stage allowed us to propose a model for predicting academic performance in line with the principles of exploration theory and the four categories of learning traces: social, cognitive, emotional, and demographic dimensions. This model integrates these dimensions to provide a more holistic and accurate prediction of learners' academic success. The detailed description and analysis of the proposed model will be presented in the analysis and discussion section, offering further insights into its structure and effectiveness.

2.3. Solution development

The hybrid predictive model we developed combines multiple regression (ML), artificial neural networks (ANN), and random forest (RF) to maximize the accuracy of academic performance predictions. This model has been encapsulated in a plugin specifically designed for the Moodle online learning platform. The integration of this plugin into Moodle was achieved using the platform's APIs and programming interfaces, allowing seamless interaction between the predictive model and course data. Specifically, the plugin can retrieve learner data, such as their scores, forum participation, and assignment submission activities, to process and provide real-time predictions of their future performance. The prediction results are then accessible to instructors via the Moodle dashboard, thereby facilitating pedagogical decision-making and personalized learner support. This integration also ensures continuous updating of predictions as new data becomes available, thus maintaining the relevance and accuracy of the analyses provided by the model.

2.4. Relevance evaluation

During the code development and throughout the validation phases, tests were scheduled to ensure product quality control. In this regard, we aimed to assess the pedagogical and technical relevance of the proposed solution. The analysis and discussion section highlights the pedagogical quality of our model, while the technical relevance will be addressed in another paper.

2.5. Exploitation and maintenance

This phase allowed us to effectively monitor the operation of our predictive model based on the traces collected from interactions of learners with the course their teachers deployed on the Moodle online platform. Consequently, we were able to correct development bugs, fine-tune its operations, and adjust parameters. Ongoing use of the plugin also involved regular performance monitoring, gathering user feedback, and continuously implementing enhancements to ensure its effectiveness and robustness.

3. RESULTS AND DISCUSSION

The analysis of previous studies, particularly that of Vimarsha *et al.* [8], underscores the complexity of human intelligence and its direct impact on academic achievement, especially in the context of online learning. These works converge on the recognition of the importance not only of cognitive dimensions but also of socio-emotional and demographic factors. The studies in [24] have elucidated the evolution of intelligence constructs, emphasizing the plurality of intelligence forms and their role in predicting academic achievement. More specifically, studies [25] and [26] have demonstrated the critical importance of emotional intelligence and social support for the academic success of secondary school students, thereby corroborating the findings of [24]. The analysis of online learning traces [27] reveals a significant potential for predicting academic performance. By combining cognitive measures and innovative pedagogical strategies [28], such as collaborative learning, we can refine our prediction models. Our model in Figure 2 integrates a multidimensional approach, dynamically analyzing learners' skill development in a rich and interactive learning environment. This approach allows for a better understanding of the factors influencing online success. Firstly, we collect learners' learning traces, including both explicit traces (revealing cognitive, social, and emotional processes) and implicit traces (such as demographic data). This heterogeneous data is then processed to feed a hybrid prediction model, thereby enabling the estimation of each learner's academic performance.

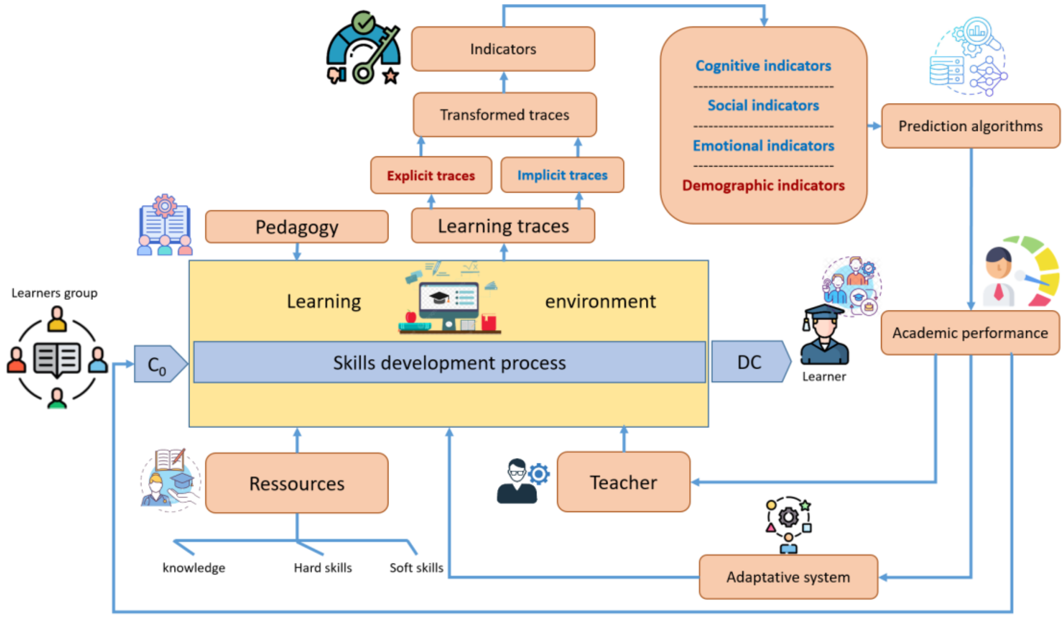

Figure 2. Academic performance prediction model based on competency-based learning traces

3.1. Competency-based learning as pedagogical framework

According to Weinert [29], competence is an integrated combination of knowledge, skills, and motivations, adapted to situations. De Landsheere emphasizes that it goes beyond the isolated application of abilities [30]. Competency-based learning, which focuses on practical application and problem-solving, promotes a deeper understanding and better preparation for real-world challenges [31]. It encourages autonomy, responsibility, and the development of transversal skills such as critical thinking and collaboration [32]. Online learning, in this perspective, offers a flexible and personalized platform, allowing learners to progress at their own pace and develop the necessary skills [33].

3.2. Competencies development process

The development of a competency, initially in an embryonic state (C0), is a dynamic process influenced by a confluence of factors. Resources, encompassing both hard and soft skills, serve as the bedrock for this development. The tutor plays a pivotal role in facilitating learner progress, adapting instruction based on the analysis of learning traces. Consequently, the competency evolves towards a developed state (DC), as evidenced by academic performance, within a framework of adaptive systems.

3.3. Academic performance

Academic performance, often operationalized as a proxy for competency, is derived from a multifactorial assessment of student outcomes [34]. It encompasses both quantitative measures (grades, examinations) and qualitative indicators such as participation and quality of work. This multifaceted assessment enables the evaluation of a student's capacity to mobilize the requisite knowledge and skills within their specific domain of study [35].

3.4. Prediction algorithms

Machine learning provides a diverse range of methodologies for predicting academic performance [36], [37]. As per the research conducted by Albreiki *et al.* [38], Models including random forests (RF), artificial neural networks (ANN), and multiple regression (MR) are frequently utilized. These models leverage sophisticated algorithms to analyze extensive datasets and uncover patterns associated with academic achievement. The MR algorithm uses the formula $Y = \beta 0 + \beta 1\ X1 + \beta 2\ X2 + \ldots + \beta n\ Xn + \varepsilon$ to evaluate the influence of each independent variable on the dependent variable. Random forest predicts academic performance by averaging the predictions of multiple decision trees according to $\hat{Y} = \frac{1}{N}\sum_{i=1}^{n} f_i(X)$. Artificial neural networks (ANN) use the formula $\hat{Y} = f(\sum_{i=1}^{n} W_i . X_i + b)$ to transform weighted input features through an activation function to obtain the final prediction.

3.5. The 4I

In this section, we explore the four types of indicators (4I) that have a significant impact on online academic performance. These indicators are derived from explicit traces (demographic indicators) and implicit ones (emotional, social, and cognitive intelligence). Cognitive intelligence is essential for understanding concepts, solving problems, and acquiring new knowledge through digital resources [39]. Similarly, social intelligence is key for interacting with peers and teachers via online tools, facilitating collaboration and cooperative learning [40]. Emotional intelligence is crucial online, helping learners manage their emotions in the face of educational challenges [41]. Finally, demographic characteristics play a crucial role in learners' academic performance, directly influencing their success in online learning [42]. By combining these four types of indicators, our model enhances the accuracy of online academic performance predictions, enabling more personalized and targeted interventions to support each learner.

3.6. Digital learning traces

A digital learning trace, as defined by [43], is a sequence of actions performed by a learner within a computer-based learning environment (CBLE). After cleaning and transformation, these traces allow for the extraction of key indicators that can be used to personalize the learning experience. Figure 3 illustrates how these indicators are utilized to tailor educational interventions based on individual learner behaviors.

The processing of online learning traces follows a rigorous multi-step process. Firstly, data is collected from learner interactions with the learning platform, including both explicit actions (logins, submissions) and implicit actions (time spent on tasks, navigation paths). This data is then cleaned and structured to facilitate analysis. Once prepared, the data is analyzed using statistical tools and machine learning techniques to identify patterns and trends in learning behaviors. The results of this analysis are summarized in reports that assess learners' progress, identify their strengths and weaknesses, and highlight areas for improvement. This information serves as the basis for personalizing learning paths by offering activities tailored to individual learner needs and adjusting pedagogical strategies accordingly.

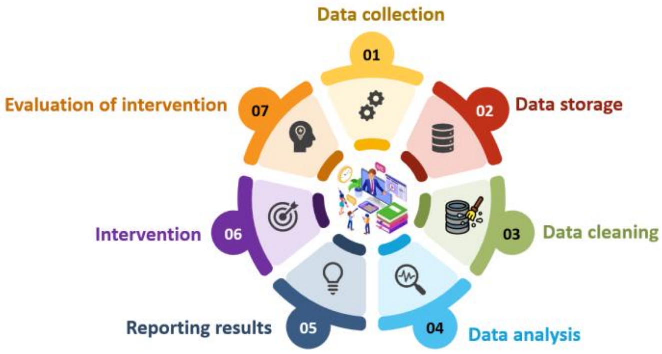

Figure 3. Lifecycle of learning traces

3.7. Academic performance prediction approach

In this study, we explore the factors influencing online academic performance by integrating indicators derived from learners' explicit and implicit traces. We consider a set of variables, including previous academic results, engagement in learning activities (discussion forums, online resources), demographic characteristics, and dimensions related to the three intelligences. This comprehensive approach allows us to analyze the multifaceted nature of online learning and identify the key elements that impact learners' success.

To assess cognitive intelligence in online learning, we can analyze learners' cognitive activities. Problem solving, knowledge acquisition, and participation in online discussions are key indicators. Onditi *et al.* [44] showed that analyzing forum content can evaluate learning outcomes. Text analysis methods can measure how well learners' contributions align with learning objectives. Social intelligence, crucial for online collaboration [45], is measured by the social intelligence score (SIS). This score integrates the number of posts (NPD), replies (NPR), and views (NV). The formula $SIS = (NPD + NPR) \times NV$ assesses a learner's social engagement. To evaluate emotional intelligence, essential for online motivation [46], we analyze emotions expressed in messages. We use the bidirectional encoder representations from transformers (BERT) model, as in Rafiq *et al.* [47], for sentiment analysis. Messages are preprocessed. Messages are preprocessed before analysis. To calculate the demographic score, we integrate several significant environmental characteristics: geographic region, neighborhood poverty level, prior education, age, gender, and disability status. These indicators are combined to assess the overall impact of the socio-economic environment on learners' academic performance. The proposed formula is:

$$\begin{aligned} Demographic\ score = {} & w_1 \times Region + w_2 \times\ Poverty\ Level + w_3 \times Prior\ Education \\ & + w_4 \times Age + w_5 \times Gender + w_6 \times Disability\ Status \end{aligned}$$

This approach is grounded in recent research indicating that these characteristics significantly influence educational opportunities and resources, thereby impacting academic performance [48]. 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.

$$Score_{global} = w_1 x Score_{cognitive} + w_2 x Score_{social} + w_3 x Score_{emotional} + w_4 x Score_{demographic}$$

To enrich our model, we supplement learning traces with learners' demographic data. We collect information on their academic background, interactions, emotional states, submitted activities, successes/failures, as well as other specific factors such as the resources consulted, connection duration, and learning preferences. Our online academic performance prediction model is grounded in this systemic approach that integrates the cognitive, social, emotional, and demographic indicators. In terms of the social dimension, Bonafini *et al.* [49] demonstrated that engagement in discussion forums was associated with higher scores and greater retention in massive open online courses (MOOCs). Additionally, the data analyzed in research [50] 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 [50] 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. 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.

4. CONCLUSION

Education is undergoing a profound transformation with the rise of digital learning, particularly online education. This paper introduces the 4I-CBT conceptual model, designed to predict and enhance learners' academic performance in online environments. The model leverages artificial intelligence, utilizing techniques such as multiple regression, artificial neural networks, and random forests, while integrating cognitive, social, emotional, and demographic indicators. Unlike previous studies that often focused on one to three dimensions to predict academic performance, neglecting the complexity of factors influencing learner outcomes, our multimodal model integrates four dimensions and 17 distinct characteristics, offering a more comprehensive and accurate evaluation. This model is designed to enrich the online learning experience by considering these diverse dimensions. It also provides a foundation for understanding competency-based online learning processes, offering numerous research opportunities to validate or refute its propositions. In the future, we plan to enhance our model by exploring new deep learning techniques and refining the criteria for evaluating predictive performance. We also envision expanding our model to support personalized online learning, providing tailored pedagogical recommendations based on predicted academic performance.

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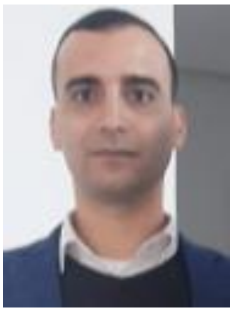
BIOGRAPHIES OF AUTHORS

Jamal Eddine Rafiq is a pedagogical inspector in computer science Marrakech, Morocco, and a current Ph.D. student, Laboratory of Artificial Intelligence and Complex Systems Engineering, Hassan II University. His research interests focus on human computer interaction, artificial intelligence, and digital learning traces. He can be contacted at email: jamal.rafiq-etu@etu.univh2c.ma.

Zakrani Abdelali holds a Ph.D. in computer sciences at Mohammed V University, Rabat, Morocco, in 2012. He is currently professor (Higher Degree Research (HDR)) at ENSAM, Hassan II University, Casablanca, Morocco. His current research interests' artificial neural network, data mining, and software engineering. He can be contacted at email: abdelali.zakrani@univh2c.ma.



Mohammed Amraouy holds a Ph.D. in computer sciences at National Institute of Posts and Telecommunications, Rabat, Morocco in 2023. He is currently a pedagogical inspector in computer science and part-time trainer at Regional Center for Education and Training Profession Oujda, Morocco. His research interests focus on human computer interaction, artificial intelligence, and online learning assessment. He can be contacted at email: amraouy.mohamed1@gmail.com.

Said Nouh holds a Ph.D. in computer sciences at National School of Computer Science and Systems Analysis (ENSIAS), Rabat, Morocco in 2014. He is currently professor (Higher Degree Research (HDR)) at Faculty of Sciences Ben M'Sick, Hassan II University, Casablanca, Morocco. His current research interests are artificial intelligence, machine learning, deep learning, telecommunications, information, and coding theory. He can be contacted at email: said.nouh@univh2m.ma.

Abdellah Bennane is a professor at the Training Center of Teaching Inspectors, and member of International Center of Academics Pedagogy and Management (Faculty of Education Sciences, University Mohamed V Souissi), Rabat, Morocco. He is professional in applied informatics in education sciences. His recent research is e-learning, development of the teaching software and use of machine learning techniques. He can be contacted at email: abdellah.bennane@gmail.com.