Investigating Artificial Intelligence Algorithms to Predict College Students' Academic Performance: A Systematic Mapping Study

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Abstract. *The aim of this study is to analyse Artificial Intelligence (AI) algorithms in order to predict and identify Higher Education Institutions' (HEI) students' academic performance. A systematic mapping study (SMS) was carried out to investigate the limitations that researchers face when using AI algorithms to predict student academic performance and to determine which combinations of variables-algorithm yield the best results. A set of 43 studies was selected to be analysed. We found that the most commonly used variables to predict students' academic performance can be grouped into socioeconomic (gender, age, and professional position), previous academic performance (grades, GPA, frequency, and scores at entrance exams), internet activity (use of LMS systems, e.g., Moodle or Google Classroom, and use of social media), and psychological and health (quality of sleep, eating habits, social life, academic or professional workload). The results show that the most common algorithm with the best evaluations to predict academic performance is the Random Forest at the time of publishing this study, the most common limitation faced by researchers is related to few available data, and the most common data used in these algorithms is related to previous academic performance.*

1. Introduction

Higher Education Institutions (HEIs) aim for student success to foster economic and social progress. Student dropout is an international problem, representing a waste of academic and economic resources [Stelnicki et al. 2015, Bonaldo and Pereira 2016, Biasi et al. 2018, Silva et al. 2022, Morelli et al. 2023]. Increasing student retention in HEIs poses a challenge. The 2023 Higher Education Census from Brazil indicates a cumulative dropout rate of 44% of students that were admitted in 2019 across federal institutions [Silva et al. 2022, Brasil 2023]. In the USA, 55.5% of the part-time freshmen in colleges from 2021 to 2022 dropped out their studies [Hanson 2024]. Research has shown that student dropout is often linked to academic performance [Pinheiro et al. 2023, Rodrigues. et al. 2024]. Therefore, predicting student performance can help prevent dropouts by facilitating early interventions. Moreover, identifying important factors affecting performance can assist in improving education quality and keeping students engaged in classrooms. Performance prediction can also help in identifying students with limitations and their learning barriers [Proaño and Párraga 2018, Silva et al. 2020].

AI (Artificial Intelligence) algorithms offer a solution to predict student performance and identify students at risk of dropping out. Previous studies have shown their efficacy in tackling these problems [Hellas et al. 2018, Silva et al. 2020, Abdul Bujang et al. 2022, Iddrisu et al. 2023, Silveira et al. 2023]. However, Hellas et al. (2018) highlight the importance of reporting unfavourable outcomes and limitations in this field. Most systematic literature reviews and mapping studies report numerous used data types, algorithms, and metrics without specifying which combinations yield the best results, reported as a research gap to be explored [Hellas et al. 2018, Silva et al. 2020, Iddrisu et al. 2023]. As such, a systematic mapping study (SMS) was carried out to investigate the limitations researchers face when using AI algorithms to predict student performance. It also analyses the combination of algorithms and features used in the studies.

The remainder of this paper is structured as follows: Section 2 details previous systematic literature reviews and mapping studies on the topic; Section 3 presents the planning and execution of this SMS; Section 4 details the results; Section 5 discusses the findings; and Section 6 presents final remarks and future work.

2. Related Work

Over the past years, many systematic literature reviews and mapping studies were performed in this area. Student performance prediction is a highly distributed community where studies are done in a single course or institution and not replicated in a second population [Hellas et al. 2018]. As a consequence, systematic literature reviews and mapping studies have to be updated to keep up with this diverse scenario. Table 1 compare and summarize such SMS and Systematic Literature Reviews (SLR) we found on an ad hoc search in Google Scholar searching for “AI algorithms to predict academic performance in high education”. We analysed and summarized them, considering nine aspects:

1. Is the paper a systematic literature review or a systematic mapping study?
2. Which years does it cover?
3. How many databases were queried?
4. How many studies were reviewed?
5. Which were the most used variables found in their selected studies?
6. Which were the most used algorithms found in their selected studies?
7. Which were other relevant findings?
8. Does the study discuss limitations in implementing AI methods to predict student performance?
9. Does the study present the most effective algorithms and variables to predict student performance?

Table 1. SMS and SLR Characteristics and Findings

Reference	Type	Years	# of Databases	# of Studies	Most Used Variables	Other Relevant Findings
Hellas et al. (2018)	SLR	2010 - 2018	3	357	Socioeconomic and previous academic performance	Few studies related how the issue of bias is approached.
Silva et al. (2020)	SMS	2010 - 2019	1	35	Previous academic performance, demographic, environmental and internet behaviour characteristics	Studies aim to present results using visualization tools, but these methods do not concretely establish a cause-and-effect relationship necessary for diagnosing problems at HEIs.
Silveira et al. (2023)	SMS	1998 - 2022	2	85	Learning Management System (LMS) activity	Confusion Matrix is the most common metric to evaluate the models.
Iddrisu et al. (2023)	SLR	2016 - 2022	4	84	Sociodemographic and previous academic performance	The least analysed relate to psychological, family background, and school environment.
Abdul et al. (2024)	SLR	2015 - 2021	5	41	Not mentioned	The application of hybrid and feature selection methods supporting the generalization of the predictive model to boost student grade prediction performance is generally lacking.

Regarding limitations in implementing AI for predicting student performance, Hellas et al. (2018) discuss challenges encountered during their review but do not specify limitations within the studies themselves, impacting replicability. In terms of effective algorithms and variables, Iddrisu et al. (2023) identify effective algorithms but do not link them to variable types; Silveira et al. (2023) lists common algorithms without confirming if they consistently yield the best results; and Silva et al. (2020) focus on approaches without relating them to variable types. Only Hellas et al. (2018) connects algorithms, variables, and outcomes (e.g., GPA, dropout) but lacks variable-algorithm specificity, which is the unique focus of this paper.

We reviewed existing literature on student performance prediction to identify contributions. However, our study addresses the gap in discussing the limitations researchers face in this field and in exploring which variable-algorithm combinations yield the best results.

3. Research Method

The goal of this study is to conduct a global analysis of AI algorithms, methods, tools, models, and techniques for predicting and identifying HEI students at risk of poor academic performance. To achieve this, we followed an SMS protocol based on the secondary study guidelines by Kitchenham and Charters (2023) and Petersen et al. (2015), which include three main phases: (i) defining the research scope, (ii) searching and selecting studies, and (iii) extracting and analyzing data. The analysis was performed using Parsifal[1], an online SMS tool. Originally designed for Software Engineering research, this protocol was adapted for Educational Data Mining (EDM) [Baker et al. 2011].

3.1. Search Strategy and Data Sources

The research question that expresses the goal of this study was formulated following the criteria specified at the PIO (Population, Intervention and Outcome) strategy, an adaptation of PICO strategy, also with Comparison, which is not in the scope of an SMS, as explained by Santos et al. (2007) . The adopted PIO strategy is shown in Table 2.

Table 2. PIO Aspects to Formulate the Research Question.

PIO	
Population	Higher Education Academic Performance
Intervention	Artificial Intelligence Algorithms
Outcome	Algorithms, Limitations, Accuracies and Features

Therefore, the formulated research question (RQ) is: *How are artificial intelligence algorithms used to predict academic performance of higher education students?*

The desirable outcome of the research is to understand which AI algorithms are the most commonly used, which variables are used by these algorithms, which variables are used with each algorithm, how well these algorithms can predict students' academic performance in terms of accuracy, and the most common limitations on the implementation of such algorithms. The sources of the studies were: ACM Digital Library, IEEE Xplore and Scopus. In order to expand the comprehension of the research question, the following sub-questions were formulated:

[1]https://parsif.al/

(Sub-Q1): What are the limitations in using AI to predict academic performance?

(Sub-Q2): How do AI algorithms use features to predict academic performance in universities?

3.2. Search String

A generic search string was created from keywords and their synonyms. Keywords were connected using the AND logical operator, while variations and synonyms were connected using the OR operator. The terms of the search string were selected with the aim of a broader search, i.e., a large coverage of studies. We tested different configurations of the search string in Scopus. After calibrating the search string, the final string was:

("academic performance" OR "academic success" OR "grade") AND
("higher education" OR "college" OR "graduation" OR "university") AND
("predict*") AND
("artificial intelligence" OR "AI" OR "data science" OR "deep learning" OR "machine learning")

3.3. Selection Criteria

To properly address the research question and its subquestions, it is essential to establish selection criteria to include studies relevant to the topic and exclude those that are not.

The selection criteria consist of inclusion and exclusion requirements for studies on AI techniques predicting academic performance in higher education. The inclusion criterion (IC1) specifies that eligible studies must describe an AI technique for predicting academic performance in a higher education context. Exclusion criteria include studies focused on predicting performance in elementary, high school, MOOC, or graduate programs (EC1), as well as duplicate studies (EC2), those unavailable for reading or data collection (EC3), and non-peer-reviewed studies (EC4). Additionally, secondary studies (EC5), studies not in English (EC6), and those not relevant to AI techniques for academic performance prediction (EC7) are excluded. No criteria were set for the publication date, and studies from any country were considered acceptable

3.4. Study Selection Process

After retrieving studies from the sources, the following filters were used to select the studies: I) title, abstract, and keywords screening, II) introduction and conclusion screening, and III) complete screening.

3.5. Data Extraction

It was extracted the following data for each of the selected studies: study ID complete reference, algorithm used, variables used, accuracy of the best reported algorithm, and limitations of the study. The data extracted was saved in a spreadsheet form and later used to support the discussion of the SMS results.

4. Results

From the search for the chosen sources, 482 studies were retrieved. From the set of 482 studies retrieved by the search string query, 15 were retrieved by IEEE Xplore, 155 were retrieved by ACM Digital Library and 312 were retrieved by Scopus. After retrieving these studies, the duplicated ones were identified and excluded. In addition, the filtering process using the inclusion and exclusion criteria has been applied. In the end, 43 studies were accepted. The process of retrieving and filtering studies is described in Figure 1, which used the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) methodology [Moher et al. 2010]. The quantity of selected studies per year is described at Figure 2.

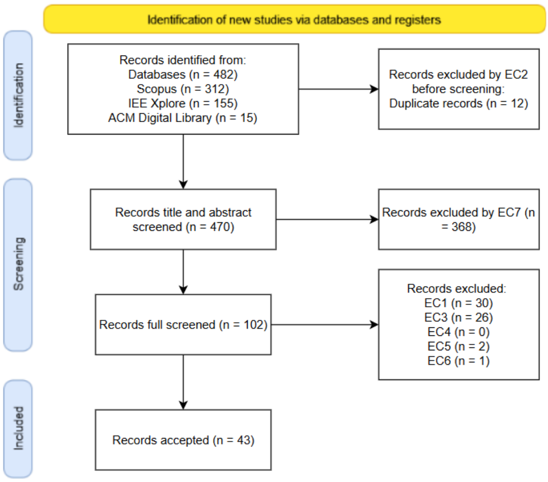

Figure 1. Process of retrieving, filtering and selecting studies using PRISMA

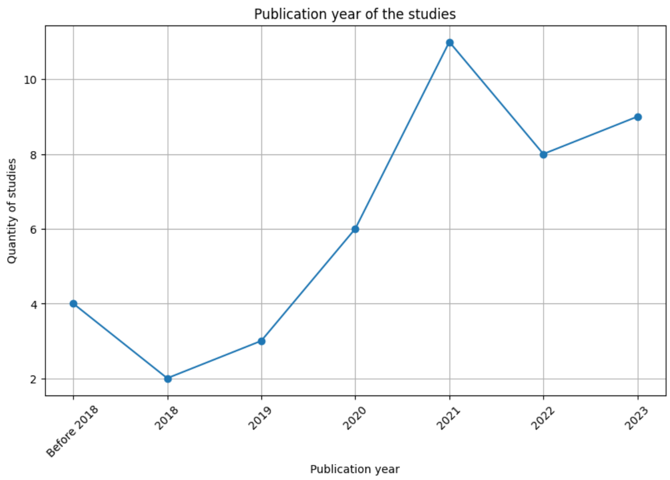

Figure 2. Publication year of the studies

Table 3 shows the studies classified by the main type of feature used in the algorithms. The reported variables will be further discussed in Section 4.5. Not all the variables used by the studies are shown in the table. When multiple algorithms were used in a study, the one with the highest accuracy was selected. A complete table detailing each study is available at https://zenodo.org/records/14617757.

4.1. Studied Undergraduate Programs of the Selected Studies

Figure 3 represents the undergraduate programs the researchers studied on the selected studies studied. It can be observed that Computer Science is the most researched under-

Table 3. Main types of features of the studies.

Previous academic performance	S1: [Newsted 1975], S2: [Butcher and Muth 1985], S3: [Rafique et al. 2021], S4: [Chen et al. 2023], S5: [Asthana et al. 2023], S6: [Alhazmi and Sheneamer 2023], S7: [Mengash 2020], S8: [Bujang et al. 2021], S9: [Sweeney et al. 2015], S10: [Barik et al. 2020], S11: [Crivei et al. 2019], S12: [Bydzovská and Brandejs 2014], S13: [Gkontzis et al. 2018], S14: [Nabil et al. 2021], S15: [Yakubu and Abubakar 2021], S16: [Falat and Piscová 2022], S17: [Prabowo et al. 2021], S18: [Yanta et al. 2021], S19: [Suleiman and Anane 2022], S20: [Zhang et al. 2021], S21: [Saluja et al. 2023], S22: [Kaensar and Wongnin 2023], S23: [Yagci 2022], S24: [Samsudin et al. 2022], S25: [Iqbal et al. 2019], S26: [Ghashout et al. 2023]
Socioeconomic	S27: [Jiang and Pardos 2021], S28: [Gardner and Brooks 2018], S29: [Hashim et al. 2020], S30: [Khan et al. 2021]
Psychological and health	S31: [Hassan et al. 2022]
Internet and LMS activities	S32: [Deo et al. 2020], S33: [Yu and Jo 2014], S34: [Khan et al. 2023], S35: [Popescu and Leon 2018], S36: [Zhao et al. 2021], S37: [Guerrero-Higueras et al. 2019], S38: [Gaftandzhieva et al. 2022]
Discipline assessments, quizzes and questionnaires	S39: [Williams et al. 2021], S40: [Zulfiker et al. 2020], S41: [Borhani and Wong 2023], S42: [Arun et al. 2021]
Not mentioned	S43: [Feng et al. 2022]

graduate program. It can possibly be explained because most researchers who research AI algorithms to predict academic performance also belong to Computer Science departments, which is a factor that facilitates access to the students' data. Finally, it can be concluded it would be beneficial to academic managers from other undergraduate programs to collaborate with Computer Science researchers so this kind of research benefits more students from other programs.

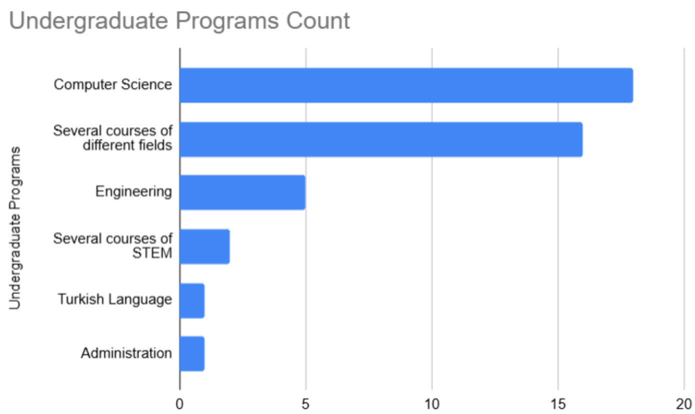

Figure 3. Undergraduate Programs of the studies

4.2. Country of Origin of the Selected Studies

The selected studies analysed the behaviour of academic performance in HEIs from different countries. It was identified one study each from Australia, Bangladesh, Bulgaria, Czech Republic, Greece, Indonesia, Iraq, Libya, Singapore, Slovakia, South Korea, Spain, Turkey, and Vietnam. It was identified two studies each from Egypt, India, Nigeria, Romania, Saudi Arabia, and Thailand. It was identified three studies from Malaysia. Four studies were identified from China and Pakistan. Finally, five studies were identified from the United States of America, the country with the most studies identified in this SMS. This multitude of countries reinforces the international scope of the performance prediction issue. Figure 4 represents the countries of the studies.

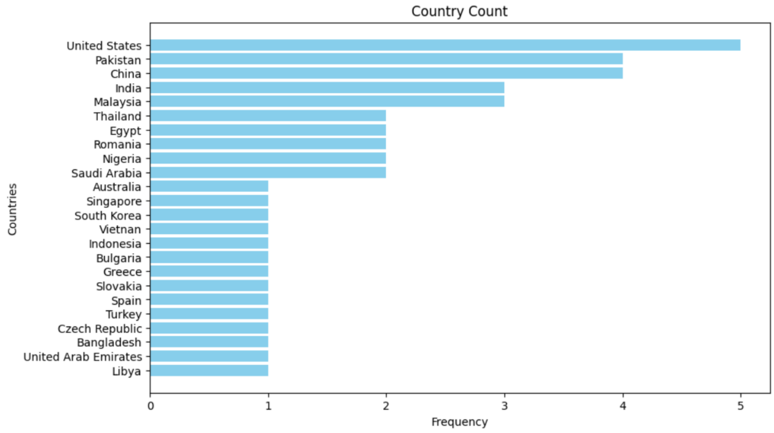

Figure 4. Countries of origin of the studies

4.3. Algorithms of the Selected Studies

The percentage of each algorithm found in the studies is described in Figure 5. To understand which feature-algorithm combinations yield the best results, in the case of studies that compared a set of algorithms, we only considered the algorithm with the highest accuracy. Therefore, it does not represent the total percentage of each algorithm used in the studies, but it represents the best performer algorithm (the one that presented the best evaluation metric) from each selected study. The algorithm reported most frequently as the best performer is Random Forest[2].

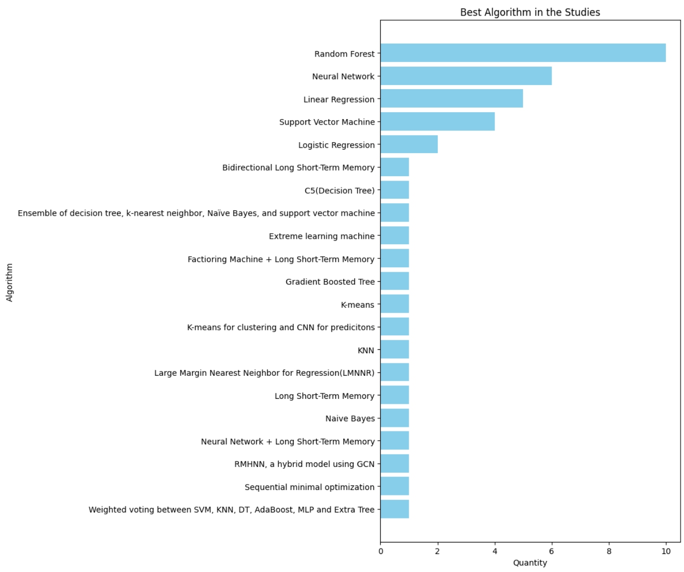

Figure 5. Algorithms reported in the studies

4.4. (Sub-Q1): What are the limitations in using AI to predict academic performance?

A notable 34.88% of studies (S6, S7, S8, S9, S13, S17, S21, S22, S25, S28, S29, S32, S37, S39, S42) did not mention limitations faced by researchers or HEIs. Among those

[2]Random Forest is an AI algorithm introduced by [Breiman 2001] that classifies and predicts a target feature based on the majority of votes of several decision trees, which are built with samples of features.

that did, the most commonly reported limitation was limited data availability, typically relying on institutional data from the authors' own HEIs, noted by 39.53% of studies (S1, S3, S5, S11, S15, S16, S18, S19, S20, S23, S28, S30, S33, S35, S36, S38, S41). This data limitation can introduce bias into analyses. Study S20 suggested that primary studies could share datasets with other researchers, while S27 found that oversampling didn't improve model metrics. S12 showed that not all friends influence a student's academic performance, and S43 observed that student behaviour was affected by COVID-19 and conflicts in Libya. Increased collaboration among institutions and researchers could foster knowledge and resource sharing, enabling the development of more robust and unbiased predictive models.

4.5. (Sub-Q2): How do AI algorithms use features to predict academic performance in universities?

Key variables for predicting HEI student academic performance include socioeconomic factors (e.g., gender, age, professional status), prior academic performance (e.g., GPA, entrance exam scores), internet activity (e.g., LMS usage), and psychological/health factors (e.g., sleep quality, social life). Table 3 presents feature types by study.

Some studies, such S37 and S8, included discipline assessments, while S39 considered study habits and mental health. Although the studies in this SMS did not explore the influence of social groups (e.g., gender, ethnicity), this does not imply no differences exist. Figure 6 shows that Random Forest with prior academic performance features was often the best combination, reflecting each category's popularity.

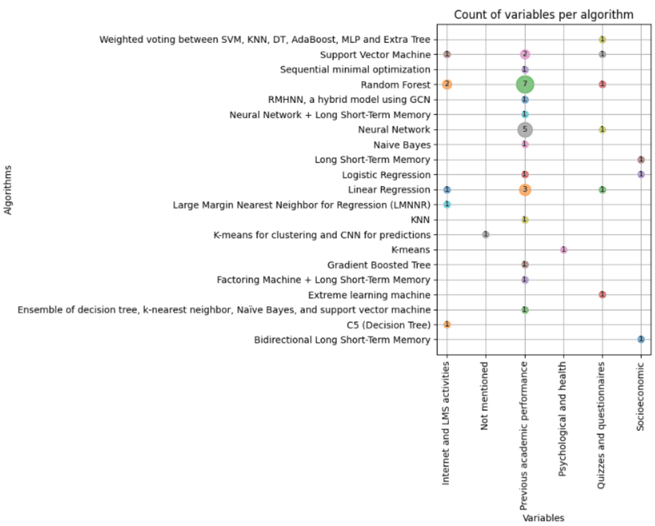

Figure 6. Algorithms per features

5. Discussion

Numerous researchers worldwide are exploring AI algorithms such Random Forest, Cat Boost, Logistic Regression, and others to predict student academic performance. When multiple algorithms were tested, this study only reports the best-performing one. A common limitation is limited data availability, as most studies rely on data from authors' affiliated HEIs.

For more reliable predictions, larger anonymized datasets from multiple HEIs are needed. However, this is challenging due to variations in data formats (e.g., grading scales) and privacy regulations, such as GDPR and LGPD. This study corroborates findings by Hellas et al. (2018), Silva et al. (2020), Issah et al. (2023), and Silveira et al. (2023), which emphasize prior academic performance, socio-economic, and LMS data as key predictors. However, unlike previous studies, we found Random Forest to be the most used algorithm, potentially because our analysis focused on the highest-performing algorithms, rather than all employed.

Regarding factors impacting academic performance, studies generally emphasize academic and socioeconomic elements. Only S12 considers social influences (e.g., peers' grades), and S28 focuses on psychological and health factors (e.g., sleep, exercise, diet).

Collaboration among HEIs, researchers, and regulatory bodies is essential to address these challenges. Data-sharing agreements that respect privacy laws, along with standardized data formats such as SPLICE[3] and transparent data practices, can promote a cohesive research environment for the prediction of academic performance.

Further research could explore temporal trends in grades to help prevent dropout, and applying machine learning interpretability methods may clarify how specific features contribute to predictions, enhancing insight into AI-driven academic performance predictions.

6. Conclusion

From these results, it can be concluded that the most common algorithm with the best evaluations to predict academic performance in HEIs is the Random Forest (at the time of the publication of this study). The recommended variables are related to previous academic performance, such as previous grades in the course, high school grades, and entrance exam scores. Random Forest and previous academic performance is the most common combination of algorithm and type of features. The most common limitations in implementing these AI algorithms are related to the unavailability of a large quantity of data to be used and the diversity of realities in which different HEIs and graduation courses are inserted.

The main limitations to this SMS are related to the strategies adopted to make the search string to retrieve primary studies and extract data from these primary studies. The completeness of this SMS may have been affected due to the missing of relevant primary studies because some of them may not be retrieved by the search string or because some of them were excluded by EC3 due to unavailable access to them. As a future work, we plan to train an algorithm to predict academic performance using employment data and to investigate how employment and company ownership influence academic performance

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[3]https://cssplice.org/

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