# Leveraging Machine Learning to Predict Academic Success: A Literature Review and Bibliometric Trend Analysis

### Abstract

### This study examines the application of machine learning (ML) for predicting academic success through a literature review and bibliometric trend analysis. Using the Web of Science (WOS) database and the PRISMA framework, 212 articles were analyzed to identify key research themes, publication trends, and methodological advancements. Results reveal a growing focus on ML’s potential to improve educational outcomes, with an emphasis on predictive analytics and performance modeling. Despite these advances, challenges such as inconsistent metadata, limited database coverage, and overuse of ML-related terminology persist.

### Keywords

data mining; machine learning; academic success; educational analysis; systematic literature review; bibliographical analysis

## Introduction

In today’s complex world, predicting academic success has become a key focus in education research (Guanin-Fajardo et al., 2024). As the demand for skilled professionals grows, understanding what helps students succeed is more important than ever. This has led to a surge in studies aiming to predict academic outcomes, such as graduation rates and the likelihood of student dropouts, or grade point average itself.

Student success is a key indicator of educational quality, and York et al., (2015) define academic success as a sum of six core components: academic achievement, satisfaction, skill acquisition, persistence, learning objectives, and career success, though it is often reduced to grade point average alone (Alyahyan & Düştegör, 2020). This overlaps with what students perceive as academic success, i.e. a combination of outcomes including grades and more holistic outcomes of personal development and achievements (Lynam et al., 2024). Academic success varies significantly among individuals (Schillereff et al., 2023), and is shaped by a combination of personal factors (Acosta-Gonzaga, 2023) such as self-regulation, motivation, and self-esteem; environmental factors (Edgerton & McKechnie, 2023) like socioeconomic status, school environment, and peer support; and lifestyle factors (Kassaw & Demareva, 2023) including dietary habits, sleep, and stress management.

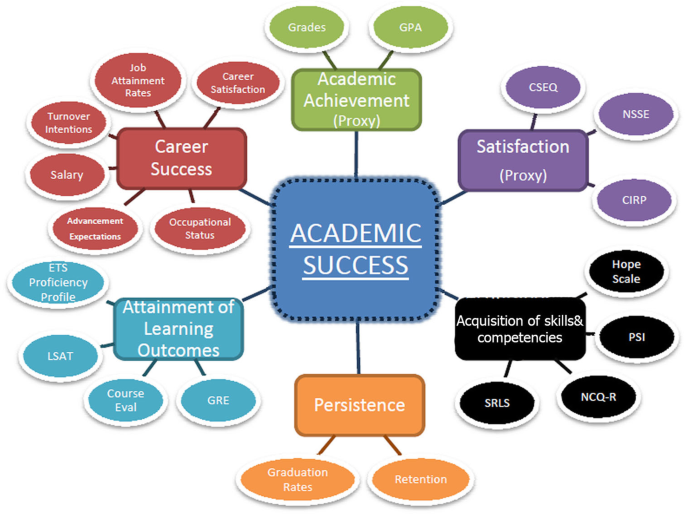


Figure 1: Definition of academic success (York et al., 2015).

Performance prediction has been studied as both a classification and regression problem, each with its own advantages and disadvantages. A wide variety of statistical algorithms have been employed in the literature (Zhao et al., 2021). However, comparing the performance of these algorithms is challenging due to the multisourced nature of the data (Zhao et al., 2021).

One of the most promising tools in this area of prediction is machine learning (ML; Balaji et al., 2021; Jin, 2023). ML allows researchers to analyze large amounts of data to find patterns and make predictions, and in contrast to traditional statistical models, ML reduces bias, offers flexibility, and provides more robust models (Bregant et al., 2025; Hilbert et al., 2021) . This technology can help identify students who might struggle, giving educators the chance to offer support early on. By using data like academic history and student behavior (Figure 2) and, more recently, even online learning behaviours where open-access data is increasingly available (Liang et al., 2023), ML models can provide insights that help improve student outcomes.

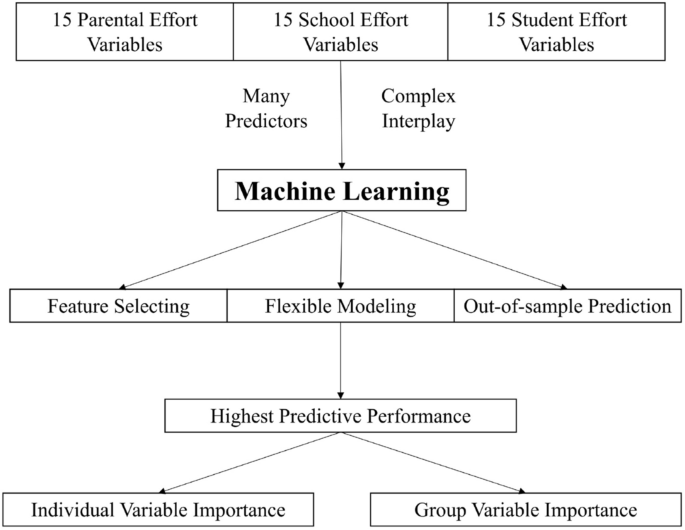


Figure 2: Example of machine learning modeling for student performance prediction by Jin (2023).

As we have seen, many studies (see Alyahyan & Düştegör (2020) section *Influential factors in predicting academic success*) have explored different factors that contribute to academic success, such as personal effort, family support, and the learning environment. These factors are crucial and have been widely researched, helping schools and educators develop strategies to support students. However, there is a noticeable gap in bibliometric analyses within this field. Understanding the research trends, publication patterns, and thematic developments through a bibliometric approach can provide valuable insights.

Bibliometric analysis is a quantitative method used in systematic literature reviews to assess research productivity and impact (Lim & Kumar, 2024). Many seminal guides on this topic have been published, e.g., by Donthu et al., (2021); Lim & Kumar, (2024), focusing on performance metrics such as publication counts, citation analysis, authorship trends, keyword clustering, nomological networking, knowledge gaps, coverage of research, and so on. This technique leverages big data and software tools (e.g., *Gephi*, V*OSviewer*, or other already established statistics library tools such as *bibliometrics* package in *R*) to provide an objective overview of a research domain .

The present review study is focused on research about ML methods for predicting academic success and therefore opens the following research questions:

RQ1: What are the primary research themes and trends in the domain of academic success prediction using machine learning, based on the analysis of abstracts and keyword co-occurrence?

RQ2: How do publication patterns and cited reference counts vary ~~across different publishers and~~ over time in the research on academic success prediction?

## Methods

The study was conducted in the academic year 2025 within the subject of *Raziskovalni seminar* on PhD program *Edukacijske vede* at the *Faculty of Education* within *University of Primorska*. To establish a rigorous, transparent, reproducible and adaptable review study, the search process was conducted based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol.

A preliminary analysis was conducted across *SCOPUS, Web of Science (WOS), Taylor & Francis* databases, and register *Digitalni portal Univerze na Primorskem*. A comparison between the databases and registries yielded a high degree of overlap in studies related to the prediction of academic success using machine learning techniques. Despite WOS having the fewest search results, it was chosen for the final bibliometric study due to its inclusion of the Science Citation Index, which aligns with one of the research questions. Articles from all selected databases and registries were accounted for in the review based on their relevance.

For the final report presented in this article, the final search in the WOS core collection was conducted in January 2025. The search string applied was *("machine learning" OR "ML") AND ("academic success" OR "academic performance" OR "student success") AND ("educational sciences" OR "education") AND prediction*. As the PRISMA flowchart in Figure 3 indicates, the search results in 307 matches, 96 of which were excluded from the bibliometric study.

The final selection of 212 articles was analysed using *Python* programming language to construct and visualize the bibliometric network. Despite *Python* already having a library *pyBibX* designated for bibliometric and scientometric analysis we chose to develop our own solution, which is openly available (Bregant, 2025), and can help future studies.

Records identified from\*:

Databases:

WOS (*n* = 307)

TAYLOR FRANCIS (*n*=1158)  
SCOPUS (*n* = 504)

Registers (*n* = 785) (digitalni portal Univerze na Primorskem)

Records removed *before screening*:

Records not in English (*n* = 3)

Records not articles (*n* = 86)

Records not in WOS (*n* =2447) – containing duplicates from other databases

Records published elsewhere than journals (*n* = 0).

**Identification**

Records screened based on title, abstract and key words

(*n* = 212)

Records excluded\*\*

Duplicate records (*n* = 1)

Records not deemed suitable (*n*=0)

**Screening**

Articles included in bibliographical analysis

(*n* = 211)

**Included**

Figure 3: PRISMA diagram. PORAVNAVA!

## Results

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Figure : Publishers... to bi izpustili verjetno, ni pomembno pa še nekaj zadetkov je čudnih…

For word cloud analysis, the *CountVectorizer* module was used in collaboration with *Latent Dirichlet Allocation* (LDA) to extract the most frequently used words from keywords and abstracts. Common English stopwords (e.g., “the”, “and”, “is”) were removed to minimize noise, along with words appearing in more than 95% of the documents and those appearing in fewer than two documents.

As depicted in Figure 4, the word clouds for each year reveal key themes and shifts in research focus over time. In 2017, terms such as "prediction," "classification," and "attrition" were prominent, reflecting an early emphasis on predictive analytics and student outcomes. By 2018, there was a noticeable focus on "machine learning" and "performance," indicating a growing interest in applying machine learning techniques to educational data. This trend continued through subsequent years, with "student," "learning," and "data mining" consistently appearing as central topics. By 2024, terms such as "educational," "prediction," and "performance" highlight ongoing research into predictive models for student success and academic performance. Overall, the progression of themes suggests a sustained and evolving interest in leveraging data analytics and machine learning to enhance educational outcomes. The years 2015 and 2025 were omitted from the analysis for specific reasons: The results from 2015 were not included as the thematic focus during that year was still fairly new and in the early stages of progression, making the data less relevant for current trends. Interestingly, 2018 yielded no significant results, which may indicate a gap in research publications or data availability for that year. Additionally, 2025 was excluded as the data from that year is still new and scarce, limiting its impact on the overall analysis.

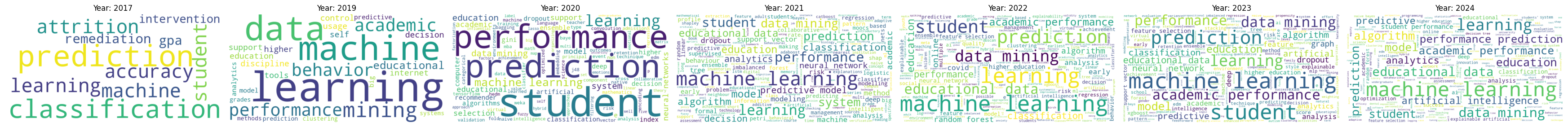


Figure : Word cloud analysis through the years.

As we can observe in Figure 5, the distribution of cited reference counts among the articles presents a notable variation, illustrating a substantial spread within the interquartile range. The majority of articles receive a moderate number of citations, but several outliers represent publications with significantly higher citation counts. This indicates that a few studies attract disproportionate scholarly attention. The observations corroborate the methodology used in WoS Citation Reports (*Web of Science Core Collection: Finding the Average Number of Citations per Article in a Journal*, 2022), where the average citations per item provide an essential measure of scholarly impact.

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Figure : Cited reference counts.

As illustrated in Figure 6, the number of publications in this field has been steadily increasing over the years, reflecting growing interest within the academic community. However, it is important to note that not all publications explicitly use "machine learning" as a keyword. This discrepancy suggests that a significant portion of the research may be related to machine learning concepts without directly referencing the term, which highlights the diverse terminology used in the field and the broad scope of research topics that intersect with machine learning methodologies.

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Figure : Number of publications by year.

A graph of a number of publications

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Figure : Number of publications per year with highlighted publications using “machine learning” as a keyword.

The growing popularity of the subject is also reflected in the increasing total number of citations over the years, indicating a rising impact and recognition within the academic community. As more research is conducted and published in this field, the cumulative citation count continues to climb. Interestingly, while the total number of citations has seen significant growth, the average number of citations per year has remained relatively consistent, as pictured on Figure 9. This suggests that while the volume of research output is expanding, the influence and reach of individual publications are maintaining a steady rate of scholarly engagement and reference over time.

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Figure : Total citations.

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Figure : Average citations per year.

## Discussion and conclusion

This study highlights the increasing role of ML in predicting academic success, as reflected in the growing volume of research and citations in recent years. The bibliometric trend analysis reveals a sustained interest in this field, with a noticeable shift toward more sophisticated data-driven approaches to educational analysis. The findings underscore the potential of ML models to provide actionable insights for improving student outcomes, identifying at-risk students, and enhancing the overall quality of education.

One of the key observations is the diversification of research themes over time. Early studies predominantly focused on basic predictive analytics and classification techniques. However, recent work has expanded to incorporate more complex models and interdisciplinary approaches, integrating insights from psychology (Burman et al., 2021), sociology (Davies et al., 2021), and others. This trend suggests a maturing field that is increasingly leveraging the power of ML to address multifaceted challenges in education. This reflects a growing consensus on the importance of predictive models in understanding and enhancing academic performance. Additionally, the rising number of publications and citations indicates a broader acceptance and recognition of ML's value in educational research. However, it is crucial to recognize that the terms "ML" and "AI; Artificial intelligence" are increasingly overused and misused (Chen & Lin, 2024), often serving as buzzwords which can lead to misconceptions about the capabilities and limitations of these technologies. With rapid technological advancements, AI will undoubtedly play a crucial role in educational sciences (Istenič Starčič, 2019).

Despite these positive trends, the study also reveals certain discrepancies and challenges, particularly regarding the overuse and misuse of terminology like “ML” and “AI.” These terms are increasingly being applied loosely to a wide range of studies that may not strictly utilize or focus on ML or AI methodologies. This overuse dilutes the precision of academic discourse, creating difficulties in categorizing and synthesizing relevant research effectively. Many studies claiming to employ ML or AI techniques often fail to provide a clear, rigorous application of these methods, instead using the terms to attract attention or align with popular trends. Conversely, some significant works in the field may not explicitly reference ML or AI, despite employing related concepts, due to varying terminologies or frameworks. These inconsistencies hamper the discoverability of relevant research and creates barriers to effective literature synthesis (Zhao et al., 2023). The proliferation of these buzzwords risks overshadowing genuinely innovative and methodologically sound studies. As a result, there is a growing need for more standardized and precise terminology in academic publications.

Furthermore, the choice of databases significantly influences the scope and comprehensiveness of bibliometric analyses. Different databases, such as SCOPUS, WOS, and specialized educational repositories, offer varying levels of coverage, indexing, and citation data (Mongeon & Paul-Hus, 2016), which can affect the identification of key studies and trends (Delgado‐Quirós et al., 2024). The discrepancies between databases highlight the importance of selecting appropriate sources to ensure a balanced and accurate representation of the research landscape.

In conclusion, this review underscores the significant impact of machine learning in predicting academic success and its growing prominence in educational research.

## Limitations and future directions

While this study provides valuable insights into the application of ML for predicting academic success, several limitations must be acknowledged. Firstly, the reliance on bibliometric data from the WOS database may introduce selection bias, as WOS might not capture the entirety of relevant publications, especially those published in regional or non-indexed journals. Similarly, the focus on specific keywords in the search strategy could have excluded studies employing alternative terminologies, thereby limiting the comprehensiveness of the analysis.

Another limitation pertains to the variability in the quality and consistency of metadata across different publications. Inconsistencies in keyword usage, authorship details, and citation practices can affect the reliability of bibliometric indicators. Furthermore, the dynamic nature of the field means that recent publications, particularly from 2025, may not yet have accumulated sufficient citations to accurately reflect their impact, leading to potential underestimation of their significance.

Future research should address these gaps by incorporating broader databases and more inclusive search strategies. Advanced text-mining techniques could uncover latent trends and themes, while longitudinal studies could track the evolution of ML applications in education over time.

Integrating bibliometric analysis with qualitative assessments would provide deeper insights into the relevance of key studies. Collaboration between researchers, educators, and policymakers is essential to ensure ML models are effectively applied to enhance educational outcomes and support student success.

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