The Impact of Artificial Intelligence on the Academic Performance of Undergraduate Engineering Students: A Bibliometric Review

Félix Díaz[1]; Nhell Cerna[2]; Rafael Liza[3]
[1]Universidad Autónoma del Perú, Lima 150142, Perú, *felix.diaz@autonoma.pe*
[2]Universidad Tecnológica del Perú, Perú, *e14167@utp.edu.pe*
[3]Universidad Científica del Sur, Perú, *rliza@cientifica.edu.pe*

Abstract*– This review examines the impact of Artificial Intelligence and Natural Language Processing on the academic performance of undergraduate engineering students. Data were collected from Scopus and Web of Science, analyzed following PRISMA guidelines, and processed using the Bibliometrix package. The review encompasses 100 peer-reviewed articles published between 2000 and 2024. The findings reveal a marked surge in publications after 2020, underscoring the growing integration of AI tools such as machine learning models and ChatGPT into engineering education. Key contributors and influential journals were identified, with significant research outputs originating from China, the United States, Spain and Peru. The thematic analysis indicates a clear shift from traditional educational methods toward data-driven learning strategies, positioning AI, machine learning, and engineering education as central themes in current research. This study offers valuable insights into the evolving role of AI in education, providing an important foundation for future research aimed at enhancing academic performance through technological innovations.

Keywords*-- *Artificial Intelligence, Natural Language Processing, Academic Performance, Engineering Education, AI, NLP.

I. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) and Natural Language Processing (NLP) has significantly transformed multiple sectors, with engineering education standing out as a field poised to benefit from these innovations [1-3]. AI-driven tools like machine learning algorithms and language models like ChatGPT are increasingly integrated into educational practices to enhance academic performance, personalize learning experiences, and optimize assessment methodologies. These technologies offer new opportunities for engineering students, fostering more interactive, data-driven, and effective learning environments [4-11].

Recent studies underscore the growing impact of AI in educational contexts. The work [12] developed an AI-enabled model to predict academic performance in online engineering courses, demonstrating how machine learning can be leveraged to enhance student outcomes. Similarly, the study [3] conducted a systematic review and meta-analysis, highlighting the transformative role of AI and computational sciences in improving student performance, particularly within STEM disciplines. These findings point to the increasing relevance of AI in engineering education, yet they also reveal the need for a comprehensive mapping of the broader research landscape.

In order to address this gap, this study conducts a bibliometric analysis focusing on the influence of AI and NLP on the academic performance of undergraduate engineering students. Using a structured Boolean search strategy, data were collected from Scopus and Web of Science, two of the most comprehensive academic databases [13-18]. The selection and screening processes adhered to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, ensuring transparency and replicability [19-23]. This review included 100 peer-reviewed articles published between 2000 and 2024.

The Bibliometrix package in R was utilized for data analysis to examine publication trends, key contributors, co-authorship networks, and thematic developments [24-30]. This approach provides insights into the evolution of research in this field, highlighting prevailing themes, emerging technologies, and global patterns of collaboration. By offering a comprehensive overview of the literature, this review aims to guide researchers, educators, and policymakers in harnessing AI potential to enhance engineering education and academic performance.

II. METHODOLOGY

A. Data Sources and Search Strategy

The present review examines the influence of AI and NLP on the academic performance of undergraduate engineering students. Data were systematically retrieved from two leading academic databases: Scopus and Web of Science. The search was conducted ensuring the inclusion of the most recent and relevant literature available.

In order to achieve comprehensive coverage, the following Boolean search equation was applied across both databases: ("artificial intelligence" OR "AI" OR "machine learning" OR "natural language processing" OR "NLP" OR "ChatGPT" OR "GPT models" OR "language models") AND ("academic performance" OR "learning outcomes" OR "educational success" OR "academic achievement" OR "student success") AND ("engineering students" OR "engineering education").

The initial search yielded 451 records, with 417 from Scopus and 34 from Web of Science. With the purpose of refining the dataset, only peer-reviewed journal articles published in English between 2000 and 2024 were included. Duplicate records, publications in other languages, articles outside the specified date range, and non-article documents—such as conference papers, reviews, books, retracted publications, early access articles, and datasets—were excluded. This process narrowed the dataset to the most relevant and high-quality studies for the bibliometric analysis

B. Screening and Selection Process

The screening process adhered to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency and replicability. The selection process is illustrated in Figure 1.

A total of 451 records were identified, with 30 duplicates removed. After screening 421 records, 4 were excluded due to date restrictions, and 1 non-English publication was eliminated, leaving 416 records for eligibility assessment. From these, 316 were excluded based on document type, including conference papers, reviews, books, retracted publications, early access articles, and datasets. Ultimately, 100 articles were included in the final review.

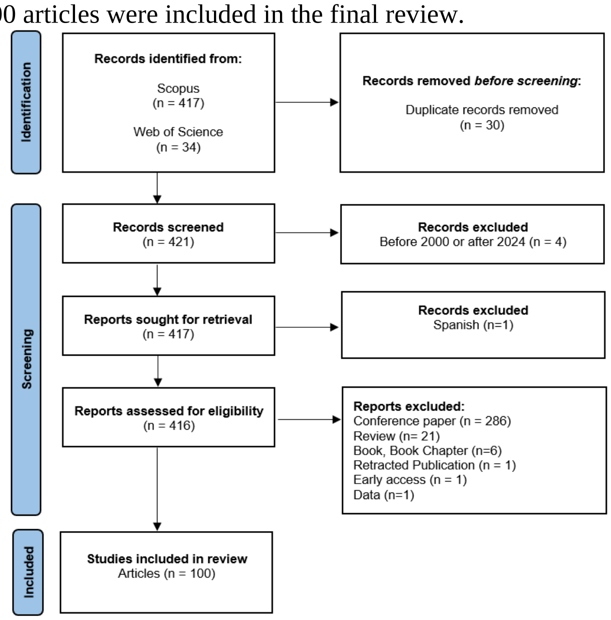

Figure 1: PRISMA Flowchart

The articles were analyzed using *Bibliometrix* in R, focusing on key bibliometric indicators. These included publication trends, citation counts, co-authorship networks, and thematic evolution, all contributing to a comprehensive understanding of the research landscape.

III. RESULTS

The results of this bibliometric review are structured into distinct subsections to offer a comprehensive overview of the research landscape. Initially, publication trends over time are analyzed to illustrate the growth trajectory of studies on AI and NLP in engineering education. The latter is followed by evaluating the most influential journals and articles, highlighting key contributors to the field. Subsequently, authorship patterns and collaboration networks are examined to reveal relationships among researchers and institutions. The geographical distribution of research is also presented, emphasizing regional contributions and disparities. Furthermore, keyword co-occurrence and thematic evolution analyses are conducted to identify emerging trends and focal areas within the field. Lastly, citation analysis is performed to evaluate the impact and dissemination of the reviewed articles, offering insights into the scholarly influence of the research.

A. Publication Trends Over Time

The analysis of publication trends reveals a marked increase in research activity over time. As illustrated in Figure 2, the first relevant publication emerged in 2007 with a single article. However, no publications were recorded between 2008 and 2013, highlighting a slow initial adoption of AI and NLP within engineering education.

Growth began to gain momentum in 2014 with two publications, followed by a gradual rise that peaked at seven articles in 2020. Although there was a slight decline in 2021, with four articles published, a sharp increase occurred in subsequent years: 14 articles in 2022, 20 in 2023, and a peak of 32 articles in 2024.

The cumulative growth curve demonstrates a consistent acceleration, particularly from 2020 onwards, reflecting the increasing interest in and integration of AI tools—such as ChatGPT and machine learning models—into engineering education. This trend underscores the growing recognition of AI's potential to enhance academic performance, establishing it as a central focus of research in recent years.

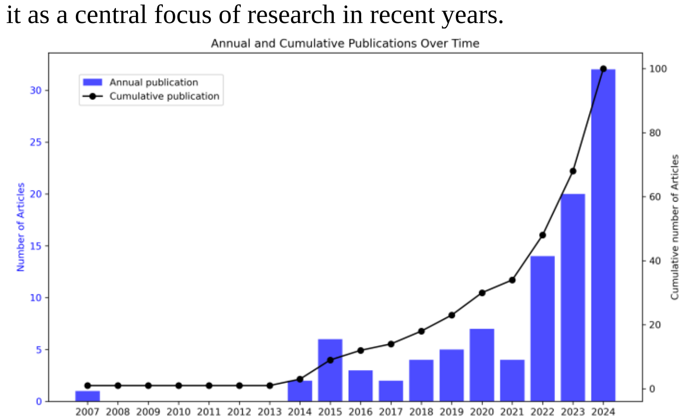

Figure 2: Annual and cumulative number of publications.

B. Most Influential Journals

The distribution of publications across journals highlights the primary platforms for disseminating research on AI and NLP in engineering education. As shown in Figure 3, the *International Journal of Engineering Education* leads with nine publications, followed by *Computer Applications in Engineering Education* and *IEEE Access*, each contributing five articles. Other significant journals include the *International Journal of Emerging Technologies in Learning*, with 4 articles, and the *European Journal of Engineering Education*, with 3.

Further contributions come from journals such as *IEEE Transactions on Education*, the *International Journal of Advanced Computer Science and Applications*, and *Computers and Education*, each publishing between 2 and 3 articles. This distribution reflects a multidisciplinary interest, with journals focusing on engineering education and technological innovations playing a pivotal role in advancing the discourse.

Moreover, a broad range of journals contributed single publications, underscoring the wide-reaching interest and diverse perspectives on the role of AI and NLP in academic performance.

Figure 3: Distribution of publications across journals.

Considering the quartile rankings of these journals, it is evident that many leading sources are positioned in Q1 and Q2 categories according to Scopus and Web of Science. Notably, journals such as *IEEE Access* and *Computers and Education* are ranked in Q1, underscoring the high quality and impact of the published research. The presence of Q1 and Q2 journals reinforces the credibility and relevance of the studies included in this review, suggesting that the intersection of AI and academic performance in engineering education is gaining prominence in prestigious academic outlets.

C. Authorship and Collaboration Networks

Analyzing authorship patterns reveals a diverse and distributed landscape with several key contributors. As illustrated in Figure 4, authors such as Bosman L, Chen Y, Li Z, Lin Y, Onia J, Pasic M, and Raja S R each contributed two publications, demonstrating sustained engagement in the field. In contrast, most other authors contributed a single article, reflecting a wide array of researchers investigating AI and NLP applications in engineering education.

This distribution indicates that, while a few authors are consistently active, the field primarily comprises a broad and dynamic base of contributors from varied academic and geographic backgrounds.

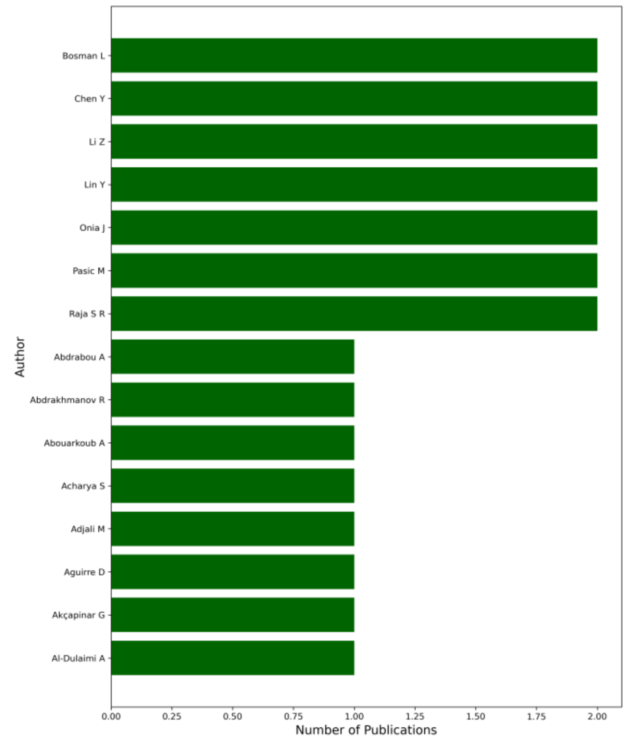

Figure 4: Relevant Authors

The co-authorship network analysis, depicted in Figure 5, reveals distinct collaboration clusters among researchers. The largest and most interconnected cluster includes authors such as Alfaisal A, Alfaisal R, Alhumaid K, and Aljanada R, reflecting a strong and consistent partnership within this group. Other significant clusters feature collaborations between Anton-de L S M, Anton-de L S J, and Alejandro A, as well as the Assaf R, Alsurakji I, and Assad M team.

While some clusters exhibit tightly knit collaborations, indicating established research teams with frequent joint publications, others, such as the partnerships between Bosman I. and Bartholomew S. or Aguirre D. with Alyuz N. and Aslan S, suggest emerging or more isolated collaborations. This variation in network structures underscores the presence of both well-established research groups and the potential for expanding interdisciplinary and international collaborations. The observed patterns highlight opportunities for fostering broader partnerships that could enhance the diversity and impact of future research in AI and NLP applications within engineering education.

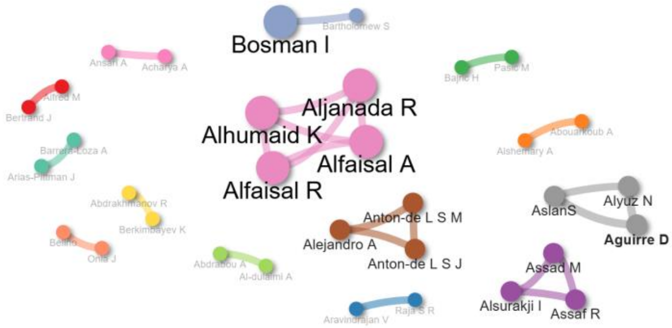

Figure 5: Collaboration Network

D. *Geographical Distribution of Research*

The geographical analysis of publications highlights a widespread global interest in applying AI and NLP within engineering education. As shown in Figure 6, China leads with 35 articles, followed by the United States with 28 publications. Spain is third with 19 articles, underscoring a strong European presence in this research domain.

Other countries with significant contributions include Greece and Peru, each with 8 publications, and Bolivia with 7, reflecting notable research activity in both Europe and South America. Additionally, countries such as the Philippines (5 articles), along with Canada, Chile, India, and Portugal (each contributing four publications), demonstrate active engagement in this field.

While leading nations account for the majority of publications, the broad range of contributing countries—from Asia, Europe, and the Americas to Oceania—emphasizes the global relevance of AI and NLP in engineering education.

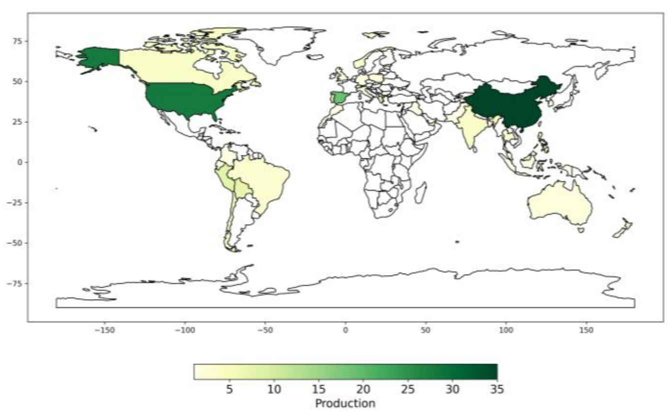

Figure 6: Country Production

As illustrated in Figure 7, the analysis of the corresponding authors' countries reveals distinct patterns of collaboration. China and the United States lead with the highest number of single-country publications (SCP), demonstrating strong domestic research output. However, China also exhibits a smaller yet significant proportion of multiple-country publications (MCP), indicating active engagement in international collaborations. In contrast, Spain and Peru predominantly contribute through single-country studies, focusing on national research efforts. Meanwhile, countries like Cyprus and Ecuador show more international collaborations than their total output, highlighting their integration into global research networks despite smaller publication volumes.

This distribution underscores the growing recognition of AI's transformative potential across diverse educational contexts. Leading and emerging countries shape the field through varied collaboration patterns.

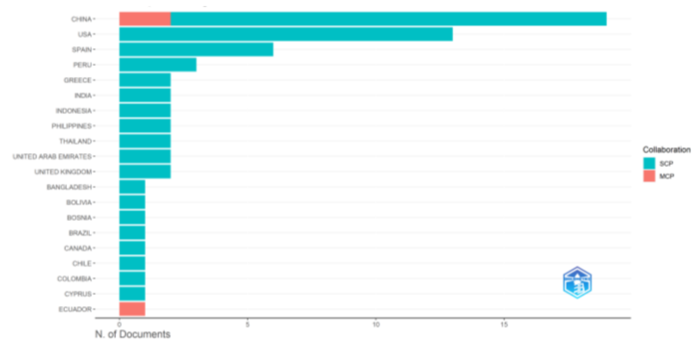

Figure 7: Corresponding Author's Countries

E. *Keyword Analysis and Thematic Evolution*

The analysis of author keywords offers valuable insights into the key themes and focal areas within the research landscape. As shown in Figure 8, the most frequently cited keywords include "active learning" (19 mentions), "machine learning" (18 mentions), "engineering education" (16 mentions), and "artificial intelligence" (10 mentions). These terms underscore the pivotal role of AI technologies in transforming educational methodologies and enhancing academic outcomes in engineering education.

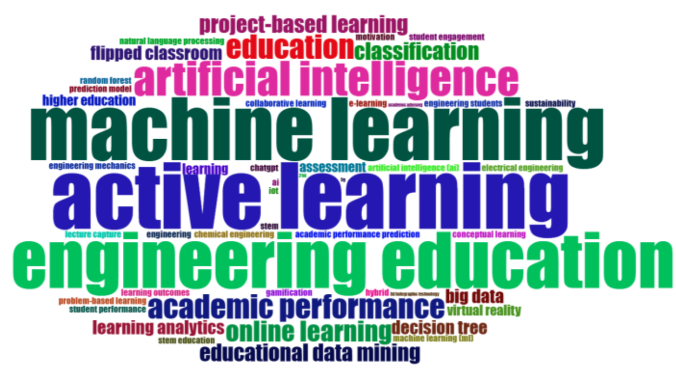

Figure 8: Word cloud -Author's keywords

Additional prominent keywords, such as "academic performance" and "online learning," reflect the increasing focus on how AI and digital platforms impact student success. The recurrence of terms like "project-based learning," "flipped classroom," and "gamification" indicates a strong interest in innovative, AI-facilitated teaching strategies designed to improve student engagement and learning outcomes.

Emerging topics such as "natural language processing," "ChatGPT," and "educational data mining" highlight the growing integration of advanced AI tools within educational contexts. Furthermore, the presence of keywords like "big data," "decision tree," and "random forest" points to the application of sophisticated data analysis techniques to better understand and optimize academic performance.

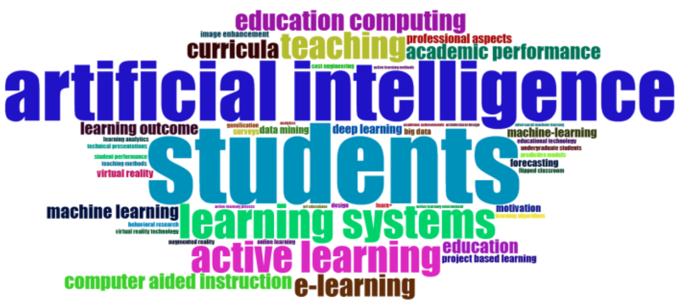

Figure 9: World cloud Keyword Plus

Thematic trends are further illuminated through the Keyword Plus analysis, as shown in Figure 9. The most recurrent terms—"students" (51 occurrences), "engineering education" (49 occurrences), and "artificial intelligence" (38 occurrences)—reinforce the centrality of these concepts within the research field. Additionally, terms such as "learning systems" (22 occurrences), "active learning" (20 occurrences), and "teaching" (17 occurrences) highlight the dual focus on technological tools and innovative pedagogical methodologies.

Keywords like "e-learning," "education computing," "curricula," and "academic performance" reflect the intersection of digital technologies with traditional educational structures, illustrating how AI is reshaping both content delivery and student assessment. Furthermore, emerging concepts such as "virtual reality," "augmented reality," "gamification," and "machine learning algorithms" point to the dynamic evolution of educational practices influenced by cutting-edge AI technologies.

A comparison between Author Keywords and Keyword Plus reveals both convergences and divergences in thematic focus. Shared terms such as "artificial intelligence," "engineering education," "active learning," and "academic performance" appear prominently in both sets, underscoring the centrality of AI technologies and their applications in educational contexts.

However, distinct patterns emerge in the emphasis of each keyword set. Author Keywords tend to highlight specific methodologies and tools, such as "machine learning," "natural language processing," and "ChatGPT," reflecting a more technical orientation aligned with the researchers' specialized interests. In contrast, Keyword Plus introduces broader educational concepts, including "students," "teaching," "curricula," and "learning systems," which reflect a more generalized categorization derived from indexing databases.

This distinction suggests that while Author Keywords focuses on the technological innovations and specific AI tools driving academic performance, Keyword Plus provides a wider lens, capturing the broader educational context. It encompasses pedagogical strategies, systemic approaches, and technology integration within traditional educational frameworks. Together, these perspectives offer a comprehensive view of the field, balancing the technical advancements of AI with their pedagogical implications.

Figure 10 depicts the thematic evolution of Author Keywords, which illustrates the dynamic progression of research topics over time. During the early period (2007–2018), the focus was primarily on "engineering education" and "active learning," reflecting an emphasis on foundational pedagogical methodologies aimed at improving student engagement and learning outcomes within engineering disciplines.

Between 2019 and 2022, the thematic scope broadened to include terms such as "academic performance," "online learning," "machine learning," and "education." This shift indicates a growing interest in integrating digital tools and performance metrics into educational practices, likely influenced by the increasing availability of technology and the rapid adoption of online learning platforms, particularly in response to global events like the COVID-19 pandemic.

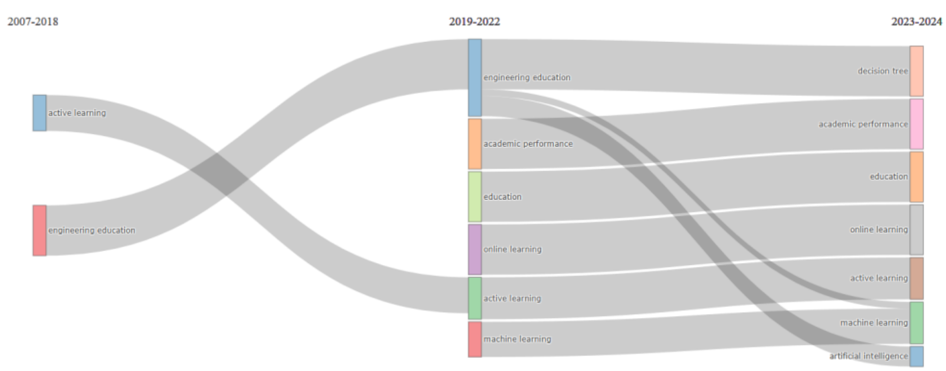

Figure 10: Thematic-map Evolution Author keywords

In the most recent period (2023–2024), emerging themes such as "decision tree," "artificial intelligence," and the sustained prominence of "machine learning" highlight a significant transition towards data-driven decision-making and the application of advanced AI technologies in engineering education. This evolution reflects a clear trajectory from traditional educational methods toward innovative, AI-enhanced learning environments, demonstrating the field's responsiveness to technological advancements and its commitment to optimizing academic outcomes through sophisticated analytical tools.

Figure 11 presents a thematic map that categorizes concepts related to engineering education and artificial intelligence along two dimensions: the degree of development (density) on the vertical axis and the degree of relevance (centrality) on the horizontal axis. The vertical axis reflects how mature or well-developed a topic is within the field, while the horizontal axis indicates the importance or connectedness of a topic to other themes in the domain. The map is divided into four quadrants, facilitating the interpretation of the current status and trajectory of different research themes.

In the upper left quadrant are niche themes, characterized by high specialization but limited integration with other topics in the field. Terms such as academic performance prediction, e-learning, hybrid, lecture capture, and natural language processing are positioned here. While these topics are well-developed and demonstrate significant depth, their broader impact within the field remains relatively confined, suggesting that they serve specific, targeted research interests.

The upper right quadrant contains motor themes, which are both highly developed and central to the discipline. This quadrant includes key concepts like engineering education, artificial intelligence, academic performance, education, online learning, project-based learning, big data, and assessment. The presence of these terms indicates their fundamental role in driving current research, reflecting their strong interconnectedness and influence across various studies.

In the lower left quadrant are emerging or declining themes, which are underdeveloped and exhibit low relevance within the broader research landscape. The appearance of the term engineering students in this quadrant suggests that this topic may either be experiencing a decline in scholarly attention or is in the nascent stages of academic exploration, with potential for future growth.

Finally, the lower right quadrant represents basic themes, which are essential and highly relevant to the field but may still require further development to reach full maturity. This quadrant includes concepts such as machine learning, classification, educational data mining, decision tree, learning analytics, random forest, and student performance. These topics, while foundational, are still evolving, indicating opportunities for deeper exploration and refinement in future research.

IV. Discussion and Conclusions

This bibliometric review provides a comprehensive overview of the research landscape concerning the impact of Artificial Intelligence and Natural Language Processing on the academic performance of undergraduate engineering students. The findings highlight significant growth, key contributors, geographical distribution, and evolving themes within this rapidly developing field.

The publication trends demonstrate a marked increase in research activity from 2014 onwards, with an exponential rise in recent years, particularly after 2020. This surge aligns with the broader adoption of AI tools in educational contexts, reflecting heightened interest in leveraging AI technologies like ChatGPT and machine learning models to enhance academic performance. The cumulative growth suggests that this study area has transitioned from an emerging field to a central focus in engineering education.

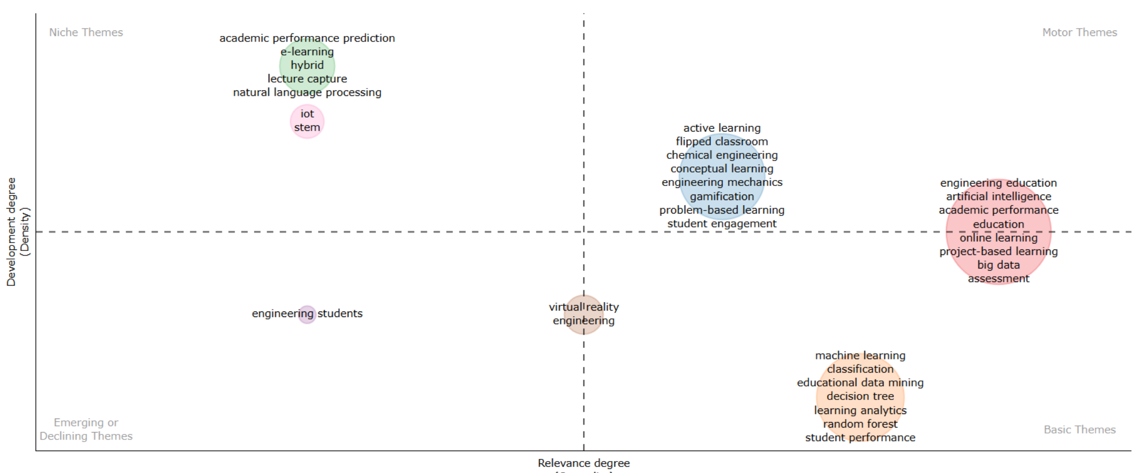

Figure 11: Thematic map

These findings reaffirm the main objective of this study, which was to map how AI and NLP influence academic performance among undergraduate engineering students. Beyond identifying publication trends, contributors, and thematic clusters, the review offers insights that can inform curriculum redesign. The increasing integration of intelligent technologies in education underscores the need to incorporate digital competencies, computational thinking, and data-informed pedagogy into engineering programs. Moreover, equipping educators with the skills to apply these tools effectively ensures their pedagogical value extends beyond technical novelty.

The prominence of high-impact journals, such as the International Journal of Engineering Education and IEEE Access, indicates that research in this domain is gaining recognition within reputable academic platforms. The presence of Q1 and Q2 journals further underscores the quality and credibility of the studies, suggesting that the topic is attracting rigorous scholarly attention. This trend highlights the increasing importance of AI in shaping educational practices and outcomes.

The authorship analysis reveals a diverse range of contributors, with established and emerging researchers engaging in this field. While some authors, like Bosman L and Chen Y, have shown consistent contributions, the overall landscape is characterized by a wide array of researchers, reflecting the interdisciplinary nature of this topic. The co-authorship networks indicate strong collaborations within specific clusters, such as the group involving Alfaisal A and Alhumaid K, while also revealing opportunities for expanding international and cross-disciplinary partnerships.

The geographical analysis highlights China and the United States as leading contributors, reflecting their dominant technological innovation and educational research roles. Spain, Greece, and Peru also demonstrate significant engagement, indicating a broader international interest in applying AI to improve academic performance in engineering education. Notably, emerging contributions from countries like Bolivia, the Philippines, and Portugal suggest a growing global diffusion of AI-related educational research. The varying levels of international collaboration, as seen in countries like China and Ecuador, reflect diverse approaches to integrating AI in education, with some regions emphasizing local research while others foster cross-border partnerships.

The thematic analysis reveals a shift from foundational educational methods towards more technologically driven approaches. Early research focused on traditional educational strategies like engineering education and active learning. However, recent studies have increasingly incorporated advanced AI methodologies, such as machine learning, decision trees, and natural language processing.

The thematic evolution indicates that artificial intelligence and machine learning have become central to the discourse, driving innovations in academic performance prediction and personalized learning systems. Additionally, the growing interest in online learning, flipped classrooms, and gamification reflects a broader shift toward digital and interactive learning environments.

Thematic mapping further categorizes these trends, with motor themes like AI, engineering education, and academic performance demonstrating high development and centrality in the field. In contrast, basic themes such as machine learning and educational data mining indicate foundational topics that are essential but still evolving. Niche themes like natural language processing and academic performance prediction suggest specialized areas with potential for targeted research. Meanwhile, emerging themes such as engineering students hint at new directions or underexplored aspects of the field.

In conclusion, integrating AI and NLP in engineering education is no longer a peripheral topic but a core area of research, with growing evidence of its potential to enhance academic performance. This review highlights the rapid growth of publications, the concentration of influential research in high-impact journals, and the global distribution of scholarly contributions. While there is substantial progress, several opportunities remain for future research. The evolution of machine learning and natural language processing in educational contexts suggests a need for more empirical studies to assess their long-term impact on student outcomes. Furthermore, expanding international collaborations can facilitate knowledge exchange and foster innovative applications across diverse educational systems.

Finally, the role of AI in engineering education is poised to expand further, offering transformative potential for teaching methodologies and student learning experiences. Future research should continue exploring these technologies' capabilities, ensuring they are harnessed effectively to improve academic performance and global educational equity.

V. Implications and Future Perspectives

The integration of AI in engineering education not only boosts academic performance but also transforms classroom dynamics and redefines the role of the teacher, who moves from being a transmitter of knowledge to a facilitator of personalized learning experiences. This transition, however, poses significant challenges related to teacher training, curricular adaptation, and the technological infrastructure necessary to implement these tools effectively.

Moreover, in light of these findings, several recommendations are proposed to enhance undergraduate engineering education. Institutions should consider the gradual integration of AI tools across core and transversal subjects alongside targeted faculty development programs focused on digital pedagogy. Designing active learning tasks supported by AI, such as automated formative assessments or intelligent tutoring systems, could further support student engagement and achievement. These strategies aim to complement traditional teaching methods, providing more personalized and scalable approaches to academic support.

Additionally, adopting AI in the educational field introduces crucial ethical considerations, especially regarding equity in access to these technologies. Institutions with limited resources may face difficulties in integrating these innovations, which could widen existing gaps in educational quality. Therefore, it is imperative to design strategies that ensure equitable access, guaranteeing that the benefits of technology reach all students.

Finally, future research should explore the impact of AI on academic performance and its influence on the development of transversal skills, such as critical thinking, collaboration, and complex problem-solving. It is also recommended that the analysis be expanded by including regional databases and conducting qualitative studies that complement the bibliometric findings, providing a more complete view of the integration of AI in engineering education.

REFERENCES

[1] F.-J. Hinojo-Lucena, I. Aznar-Díaz, M.-P. Cáceres-Reche, y J.-M. Romero-Rodríguez, "Artificial Intelligence in Higher Education: A Bibliometric Study on its Impact in the Scientific Literature," Education Sciences, vol. 9, no. 1, p. 51, 2019, doi: 10.3390/educsci9010051.

[2] C. Guan, J. Mou, and Z. Jiang, “Artificial intelligence innovation in education: A twenty-year data-driven historical analysis,” Sep. 29, 2020, Elsevier BV. doi: 10.1016/j.ijis.2020.09.001.

[3] I. García-Martínez, J. M. F. Batanero, J. F. Cerero, and S. P. León, “Analysing the Impact of Artificial Intelligence and Computational Sciences on Student Performance: Systematic Review and Meta-analysis,” Jan. 01, 2023, University of Alicante. doi: 10.7821/naer.2023.1.1240.

[4] S. Khosravi, S. G. Bailey, H. Parvizi, and R. Ghannam, “Wearable Sensors for Learning Enhancement in Higher Education,” Sensors, vol. 22, no. 19. Multidisciplinary Digital Publishing Institute, p. 7633, Oct. 08, 2022. doi: 10.3390/s22197633.

[5] M. Escueta, V. Quan, A. Nickow, and P. Oreopoulos, “Education Technology: An Evidence-Based Review,” Aug. 01, 2017. doi: 10.3386/w23744.

[6] A. A. Александров, Y. B. Tsvetkov, and M. Zhileykin, “Engineering Education: Key Features of the Digital Transformation,” Jan. 01, 2020, EDP Sciences. doi: 10.1051/itmconf/20203501001.

[7] V. González-Calatayud, P. Prendes-Espinosa y R. Roig-Vila, "Artificial Intelligence for Student Assessment: A Systematic Review," Applied Sciences, vol. 11, no. 12, p. 5467, 2021, doi: 10.3390/app11125467.

[8] S. Hajkowicz, C. Sanderson, S. Karimi, A. Bratanova y C. Naughtin, "Artificial intelligence adoption in the physical sciences, natural sciences, life sciences, social sciences and the arts and humanities: A bibliometric analysis of research publications from 1960-2021," Technology in Society, vol. 74, 2023, doi: 10.1016/j.techsoc.2023.102260.

[9] Y. Wanyan, X. Chen, and D. Olowokere, “Integration of artificial intelligence methodologies and algorithms into the civil engineering curriculum using knowledge-based expert systems: A case study,” Oct. 25, 2017, HBKU Press. doi: 10.5339/eel.2017.3.

[10] G. Agarwal, S. Gupta, and A. Agrawal, “Evaluation of Student Performance for Future Perspective in terms of Higher Studies using Fuzzy logic Approach,” Apr. 11, 2019. doi: 10.5120/ijca2019918640.

[11] B. A. Al-Sheeb, A. M. S. Hamouda, and G. M. Abdella, “Modeling of student academic achievement in engineering education using cognitive and non-cognitive factors,” Jan. 28, 2019, Babeș-Bolyai University. doi: 10.1108/jarhe-10-2017-0120.

[12] P. Jiao, F. Ouyang, Q. Zhang, y A. H. Alavi, "Artificial intelligence-enabled prediction model of student academic performance in online engineering education," Artificial Intelligence Review, vol. 55, pp. 6321-6344, 2022, doi: 10.1007/s10462-022-10155-y

[13] M. S. Lowe, B. Maxson, S. M. Stone, W. Miller, E. Snajdr, and K. Hanna, “The Boolean is Dead, Long Live the Boolean! Natural Language versus Boolean Searching in Introductory Undergraduate Instruction,” Jan. 01, 2018, Association of College and Research Libraries. doi: 10.5860/crl.79.4.517.

[14] M. S. Lowe, S. M. Stone, B. Maxson, E. Snajdr, and W. Miller, “Boolean redux: Performance of advanced versus simple boolean searches and implications for upper-level instruction,” Aug. 28, 2020, Elsevier BV. doi: 10.1016/j.acalib.2020.102234.

[15] N. J. van Eck and L. Waltman, “Accuracy of citation data in Web of Science and Scopus,” Jan. 01, 2019, Cornell University. doi: 10.48550/arxiv.1906.07011.

[16] C. W. Miller, M. D. Chabot, y T. C. Messina, "A student's guide to searching the literature using online databases," American Journal of Physics, vol. 77, no. 12, pp. 1112–1117, 2009, doi: 10.1119/1.3213525.

[17] B. S. Ballew, "Elsevier's Scopus® Database," Journal of Electronic Resources in Medical Libraries, vol. 6, no. 3, pp. 245–252, 2009, doi: 10.1080/15424060903167252.

[18] M. Khabsa y C. L. Giles, "The Number of Scholarly Documents on the Public Web," PLoS ONE, vol. 9, no. 5, p. e93949, 2014, doi: 10.1371/journal.pone.0093949.

[19] S. H. Asar, S. H. Jalalpour, F. Ayoubi, M. R. Rahmani, y M. Rezaeian, "PRISMA; preferred reporting items for systematic reviews and meta-analyses," Journal of Rafsanjan University of Medical Sciences, vol. 15, no. 1, pp. 68-80, 2016.

[20] D. Moher, A. Liberati, y D. G. Altman, "PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses," PLoS Med, vol. 6, no. 7, 2009.

[21] V. Mishra y M. P. Mishra, "PRISMA for Review of Management Literature–Method, Merits, and Limitations–An Academic Review," Advancing Methodologies of Conducting Literature Review in Management Domain, pp. 125-136, 2023.

[22] M. J. Page et al., "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," BMJ, vol. 372, p. n71, Mar. 29, 2021, doi: 10.1136/bmj.n71.

[23] M. J. Page et al., "PRISMA 2020 flow diagram," PRISMA Statement, 2020. [Online]. Available: https://www.prisma-statement.org/prisma-2020-flow-diagram. [Accessed: 07-Feb-2025].

[24] J. A. Moral-Muñoz, E. Herrera-Viedma, A. Santisteban-Espejo, y M. J. Cobo, "Software tools for conducting bibliometric analysis in science: An up-to-date review," El profesional de la información, vol. 29, no. 1, e290103, 2020, doi: 10.3145/epi.2020.ene.03

[25] M. K. Linnenluecke, M. Marrone, y A. K. Singh, "Conducting systematic literature reviews and bibliometric analyses," Australian Journal of Management, vol. 45, no. 2, pp. 175–194, 2020, doi: 10.1177/0312896219877678

[26] M. Aria y C. Cuccurullo, "Bibliometrix: An R-tool for comprehensive science mapping analysis," Journal of Informetrics, vol. 11, no. 4, pp. 959–975, 2017, doi: 10.1016/j.joi.2017.08.007.

[27] D. Diksha y R. Chakravarty, "Global trends in the research output on sustainable development goals: A bibliometric analysis using Bibliometrix R-Tool," Futuristic Trends for Sustainable Development and Sustainable Ecosystems, pp. 27-47, 2022.

[28] F. Tan, J. Yang, y C. Zhou, "Historical review and synthesis of global carbon neutrality research: A bibliometric analysis based on R-tool," Journal of Cleaner Production, p. 141574, 2024.

[29] R. Rodríguez-Soler, J. Uribe-Toril y J. De Pablo Valenciano, "Worldwide trends in the scientific production on rural depopulation, a bibliometric analysis using bibliometrix R-tool," Land Use Policy, vol. 97, p. 104787, 2020, doi: 10.1016/j.landusepol.2020.104787.

[30] F. Tan, J. Yang, y C. Zhou, "Historical review and synthesis of global carbon neutrality research: A bibliometric analysis based on R-tool," Journal of Cleaner Production, vol. 424, art. no. 141574, abr. 2024. DOI: 10.1016/j.jclepro.2024.141574.