Advancing Engineering and Computing Education through the Lens of Learning Analytics

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***Abstract*—This research category full paper explores the application of learning analytics in engineering and computing education over the past decade. Although these fields have gained increasing attention in nowadays technologically advanced environment, research about how learning analytics has been utilized within these disciplines remains limited. To address this issue, we conducted a bibliometric analysis with topic modeling on 903 articles published from 2011 to 2023 at the Learning Analytics and Knowledge conference. Specifically, our analysis identified prevalent research topics, methodological innovations, and pedagogical practices of the use of learning analytics within engineering and computing education. The study provides significant insights into how learning analytics has advanced engineering and computing education and highlight future research directions.**

Keywords—Learning Analytics, Bibliometric Analysis, Topic Modelling, Engineering and Computing Education

I. Introduction

Learning analytics (LA) is considered as the third wave in educational technology given the unique opportunities it presents [1]. Over the past decade, the field of LA has emerged as a pivotal component in understanding and enhancing the educational experience [2], leveraging data to inform decision-making and pedagogical strategies [3], and personalizing learning paths [4]. As we delve deeper into the capabilities of LA in educational contexts, it becomes critical to examine its role and alignment with overarching goals of promoting inclusivity and ethical standards in education. At its core, LA is about using insights gleaned from data to provide effective, adaptive, and equitable experiences for all learners [5], and to ensure that education is advanced not only in its methods but also rooted in principles of fairness and ethical practice [6].

As we continue to navigate the complexities of integrating technology in education, the role of LA becomes increasingly vital. However, there are significant gaps in our understanding of the specific impacts and outcomes associated with the use of LA. To bridge these gaps, this research aims to systematically review the existing literature from the Conference of Learning Analytics Knowledge (LAK) conference in the past decade and identify key trends, contributions, and areas of focus that have shaped the field. The LAK conference was chosen due to its prominence and coverage of learning analytics research, providing a robust dataset for analysis. Additionally, limiting the search to the last decade ensures the relevance of findings, reflecting the most current trends and technologies in the field. This analysis is guided by the following research questions (RQs).

RQ1. What is the landscape of academic performance of the selected papers in LAK?

A. *What is the trend of publications and citations within LAK by year?*

B. *Which countries, institutions, and authors emerge as the primary contributors to LAK?*

C. *What patterns of scientific collaboration exist among the major contributors to LAK?*

RQ2. What are the popular topics within LAK and how do they change over time?

RQ3. How has engineering and computing education been studied in LAK?

II. Literature Review

Within the fields of engineering and computing education, educational approaches have continuously evolved to adopt emerging technologies to enhance teaching practices and learning experiences [7]. Among these, LA has emerged as a pivotal tool that primarily focuses on improving student engagement [8] and predicting academic performance [9]. For instance, the effectiveness of LA used in an interactive learning dashboard significantly enhanced students' engagement in challenging courses such as programming [10]. By analyzing data from the learning management systems (e.g., Blackboard) and providing different types of feedback, students in the experiment group tended to more motivated to access the course and engage in discussions. Another notable example is using LA to identify problematic exercises at-risk students in a computing course[11]. This research highlighted the importance of analyzed performance data to serve a broad range of stakeholder.

Furthermore, the application of learning analytics to curriculum and instructional design has helped transform the instructional strategy for improved educational efficacy [12]. Data collected from LA can facilitate the identification of curriculum components that either enhance or impede students' learning, enabling educators to optimize learning content to better suit students' needs [13]. For instance, analysis of student interaction with the course materials can pinpoint specific topics or concepts students find challenging. Additionally, LA supports the iterative development of the curriculum by providing evidence-based feedback. Several of LA was used to analyze curricula and students' academic records to assist the curriculum committee in reflecting the design of the curriculum, faculty teaching, and student learning [14].

III. Method

This study is grounded in bibliometric analysis, which provides a comprehensive overview of the field of LA by quantitatively evaluating certain features of the research in a particular field [15], [16], and [17]. Topic modeling has been widely used to model topics, a probability distribution over a set of words, in textural documents. It is usually used to pinpoint the trends of research interests, with a specific journal or a research field [18] and [19]. Given the research gap identified above, in our study, Latent Dirichlet Allocation (LDA) was used to model the topics of the articles published in LAK and to identify the prevalent research topics regarding the employment of learning analytics in computing and engineering education.

A. *Data Collection*

A total of 903 articles published at the Conference of LAK between 2011 and 2023 were retrieved. The results were restricted to original research articles . Metadata including title, publication year, authors, affiliated countries and institutions, keywords, abstract, and references were extracted and saved in an Excel worksheet for further analysis as they are widely considered to represent the essential components of research articles.

B. *Data Analysis*

Firstly, we utilized descriptive analysis to reveal publication patterns, counting the frequency and citations of each study within LAK in order to measure the productivity and impact. We also engaged in network analysis, specifically, social network analysis, to investigate collaboration patterns among the authors, including connections among scholars, their institutions, and their countries. Social network analysis is a widely used approach in social science to explore the relationship among different entities [7]. This analysis used Gephi, a sophisticated tool for network visualization [20]. Topic modeling was performed through Latent Dirichlet Allocation (LDA) to uncover prevailing research themes by analyzing the titles, keywords, and abstracts of publications retrieved from the LAK database. These elements are pivotal as they contain the core objectives, issues, and outcomes of the research, providing a comprehensive overview of thematic trends [21], [22]. Our data processing included tokenization, which breaks down texts into smaller units; normalization, which converts text to lowercase; and removal of punctuations, symbols, as well as stop words. Pre-processed data were then lemmatized to ensure a clean corpus for effective LDA implementation.

The findings from LDA offered insights into the dominant topics and their distribution across the corpus, highlighting the evolution of themes over time and their representation in significant publications [23], [24]. The integration of these three analysis methods—descriptive analysis, network analysis, and topic modeling—provides a robust framework for understanding the dynamics of learning analytics in our specified educational contexts, therefore effectively addressing the proposed research questions.

We conducted a performance analysis to measure the productivity and impact of studies by identifying the count of publications and citations of each study within LAK. Social network analysis is a commonly used approach in social science to explore the relationship among different entities [7]. In this context, we conducted the social network analysis for co-authorship analysis to explore the intellectual collaborations among the active scholars within the LAK as well as their affiliated institutions and countries. We used Gephi to visualize the collaborations between prolific authors and their affiliated countries and institutions [20].

We employed LDA, a commonly used technique in natural language processing, to perform topic modeling on the corpus. We utilized the title, keywords, and abstract as data for topic analysis as they could uncover the key insights of articles [21], [22]. Abstracts summarize the research objectives, issues in a research field, and major findings, and therefore can be used as supplementary to keywords and titles for further uncovering key information about articles [23], [24]. Pre-processing was performed to enhance the analysis [14]. We conducted the tokenization to transform the texts into simple words, converted all the words to lowercase, and eliminated symbols, punctuations, and stop words (a, an, is, of, for, the, etc.). Then, we performed the lemmatization to obtain the stem of the words and produce the preprocessed corpus that was ready for LDA analysis. Finally, the representative terms of the identified topics, the proportion of their distribution within the corpus, their yearly trend, and representative works were visualized and discussed in detail.

IV. Results

A. *Analysis of trends of the yearly publication and accumulated citation counts*

The yearly trends of publication and accumulated citation counts are depicted in Fig. 1. There is a steady increase in the number of publications within LAK from 2011 to 2017, peaking at 127 before a sharp decrease to 60 in 2018. From 2018 onwards, the yearly publication counts showed a stable increasing trend with a slight decline between 2020 and 2022. Overall, the results indicate a growing interest in LA research within LAK over time.

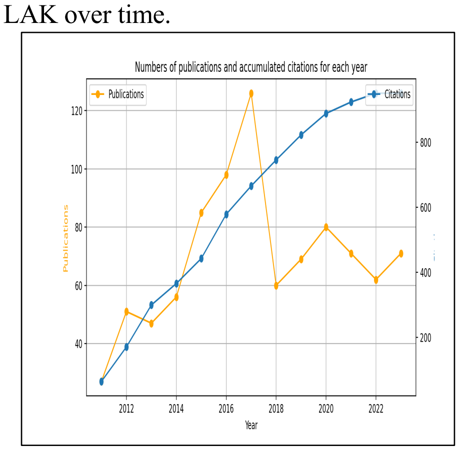

Fig. 1. Yearly publications and accumulated citation counts

	Country/Region	TP	TC(R)
1	USA	459	409
2	Australia	214	357
3	UK	109	184
4	Germany	80	88
5	Canada	70	53
6	Netherlands	57	49
7	China	50	22
8	Spain	38	26
9	Switzerland	25	30
10	Belgium	24	51
11	Japan	23	10
12	Norway	21	26
13	Brazil	19	19
14	France	19	8
15	Serbia	17	33

Fig. 2. Top 15 countries ranked by the publication counts (abbreviations TP: publication counts, TC: citation counts)

	Institution	Country/Region	TP	TC(R)
1	Monash University	USA, Australia	110	183
2	University of Technology Sydney	Australia	61	95
3	University of South Australia	UK, Australia	61	124
4	University of Michigan	USA	60	54
5	The Open University	UK, South Africa	55	122
6	Carnegie Mellon University	USA, Taiwan	43	40
7	University of Pennsylvania	USA	37	38
8	New York University	USA	30	18
9	The University of Adelaide	Australia	28	41
10	Vanderbilt University	USA	26	43
11	Arizona State University	USA	23	18
12	KU Leuven	Belgium	23	50
13	University of Colorado	USA	22	18
14	Leibniz Institute for Research and Information in Education	Germany	22	36
15	University of Florida	USA	21	14

Fig. 3. Top 15 institutions ranked by the publication counts (abbreviations TP: publication counts, TC: citation counts)

In terms of citations, the annually accumulated citations of the 903 articles exhibited a steadily increasing trend, suggesting that the field of LA has been gaining impact and recognition within the LAK community. From this, it is reasonable to predict a continuous increase in the number of its yearly citations in the future.

B. *Analysis of prolific countries/regions and institutions*

A total of 70 countries/regions contributed to the 903 articles comprising the LAK corpus. The top 15 countries accounted for more than 80% of the corpus (Fig. 2). The top five prolific countries in LA research are the USA (459), Australia (214), the UK (109), Germany (80), and Canada (70), suggesting these countries significant presence and contribution to the field of LA. It is worth noting that the articles from Australia and the UK received more citations compared with their publication counts, suggesting the high impact of the articles published by the academics associated with these two countries.

A total of 666 institutions contributed to the LAK corpus. The top 15 prolific institutions are shown in Fig. 3. Among them, 8 are based in the USA and 4 are from Australia. Notably, Australian institutions such as the Monash University, the University of Technology Sydney, and the University of South Australia emerged as the top 3 in both publication and citation counts. This underlines the considerable academic influence of Australian institutions within the LAK community.

C. *Analysis of scientific collaborations among prolific entities (countries, institutions, and authors)*

There are 765 collaborations in total between countries. The scientific collaborations among the top 15 prolific countries were visualized through social network analysis using Gephi (Fig. 4). In this visualization, countries were denoted by nodes. The size of the node stands for the publication counts of each country. The nodes were color-coded to reflect continental affiliations. The thickness of the edge represents the frequency of their scientific collaborations. This collaborative network including 81 links reveals that the USA, Australia, Germany, the UK, and Canada collaborated with the most prolific countries, with 12, 7, 7, 4, and 4 respectively. The USA and Australia had the highest number of collaborative publications (15), followed by the USA and Germany (11), the USA and the UK (5). Equally significant is the collaboration between Australia and the UK, which yielded an impressive total of 12 publications.

There are 2,588 collaborations in total between institutions. Fig. 5 shows the collaborative network among the top 15 prolific institutions with 46 links. From the figure, the top 3 collaborative institutions are the University of South Australia, Monash University, and the University of Technology Sydney. Monash University and the University of South Australia produced the highest number of co-authored publications (28). This is followed by the University of Technology Sydney and the Open University with 16 joint articles, and the University of Technology Sydney with Monash University with 10 collaborative works.

In terms of the scientific collaborations among authors, 6,657 collaborations were conducted among 1,485 scholars within the retrieved articles. Fig. 6 displays the collaboration patterns between the top 15 prolific authors including 27 nodes and 40 links. From the figure, we can see that the scholars with the most collaborative publications are Gašević, D (38), Shum, S.B (33), Dawson, S (31), and Pardo, A (31). Gašević, D appears to be the most active scholar with 81 publications and 38 collaborative works. Most of the scholar's collaborations were conducted with Dawson, S. (18) and Joksimović, S. (14). Notably, compared with productive scholars like Shum, S.B and Dawson, S, Pardo, A. has more collaborative works (31) with other scholars.

To answer RQ2, this section presents results regarding the distribution proportions and yearly trends of the commonly researched topics. We first presented the most prevalent 11 topics studied within LAK. Then, we showed the most representative terms for each topic. The yearly trend of the representative topics and the most representative terms underpinning each topic were visualized.

D. Analysis of the commonly studied topics

Our LDA analysis shows 11 topics to be optimal based on average topic weights across 903 publications. Fig. 7 displays these 11 topics along with their representative terms and their distribution proportions within the entire corpus. The topic "Research and Tools in Learning Analytics" has been commonly researched, accounting for 20.09% of the corpus, followed by "Interdisciplinary Team-Based Learning" (13.98%), "Student Performance and Learning Systems Analysis"(12.54%), and "Learning Visualization and Assessment Techniques"(12.19%).

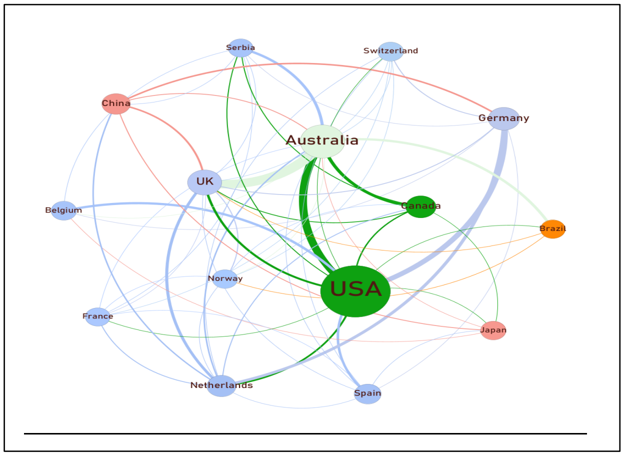

Fig. 4. Collaborations among the top 15 prolific countries/regions

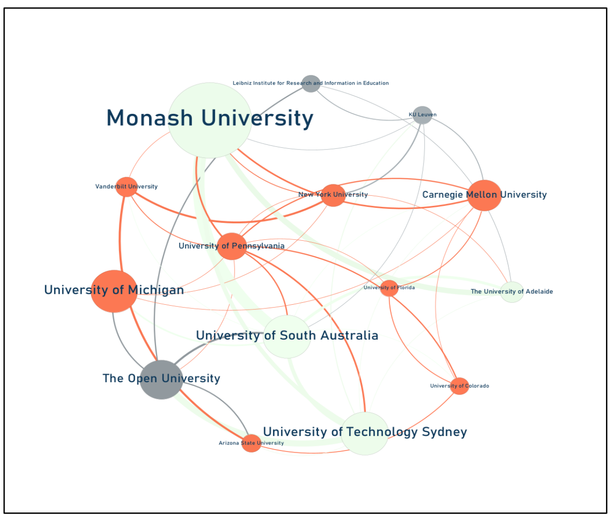

Fig. 5. Collaborations among the top 15 prolific institutions

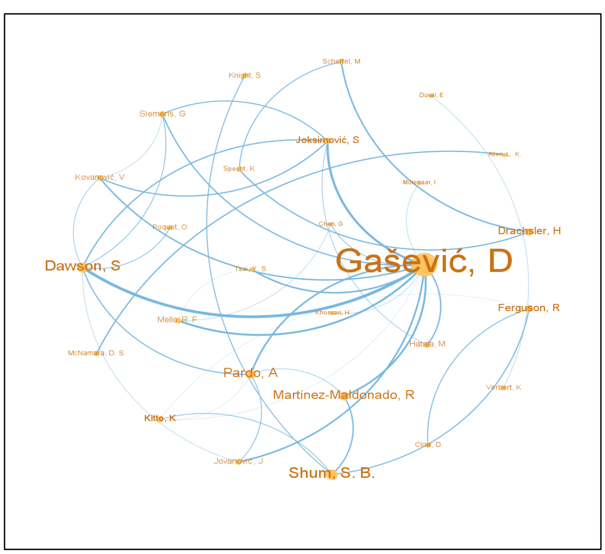

Fig. 6. Collaborations among the top 15 prolific authors

E. Analysis of the representative terms of each topic

Fig. 8 illustrates the representative terms underlying each topic and provides insights about how each topic was studied. The size of each term corresponds to how frequently it is mentioned within the topic, and the density shows the count of terms that are associated with the topics. The higher density suggests the more related terms in this topic. These representative terms could also uncover the potential relationship among the identified topics.

For example, the terms related to discourse like "discussion", "writing", "feedback", "thread", and "forum" were mentioned in several topics like "Language Skill Evaluation", "Collaborative Learning Models and Analytics", and "Educational Recommender Systems", indicating that these topics are interrelated to each other in some way. For instance, the topic "Language Skill Evaluation" could employ learner discourse analysis and classification of features to analyze and evaluate students' writing skills in discussion within a collaborative learning environment. Similarly, the topic "Collaborative Learning Models and Analytics" could use the threads of online discussion forums in MOOCs to investigate students' online learning behaviors. The studies covering the topic "Educational Recommender Systems" could explore learning assessment by analyzing writing feedback among peers through a dashboard system.

Notably, terms like "model", "dashboard", and "analysis" were commonly discussed across topics, suggesting their significance in diverse research contexts including "Learning Environment Design", "Interdisciplinary Team-Based Learning", "Predictive Models for Academic Success", and "Learning Visualization and Assessment Techniques". For instance, the topic "Student Performance and Learning Systems Analysis" could use students' learning behavior data to analyze their learning engagement with a course. The topic "Predictive Models for Academic Success "could focus on utilizing learning data for predictive modeling and provide data-driven results to assist the teaching process. Similarly, the topic "Learning Visualization and Assessment Techniques" could employ visualization tools to better present learning performance metrics to assist students' learning process.

F. Analysis of the annual trend of each topic

Fig. 9 illustrates the evolving trajectories of the 11 topics, based on how frequently each topic was discussed annually. From the figure, we can see that nearly all the topics present an increasing trend during the relevant period. The topics such as "Learning Environment Design and Student Strategies" and "Predictive Models for Academic Success" displayed a similar increase, suggesting their concurrent relevance, particularly from 2017 onwards. The topic 'Learning Environment Design and Student Strategies ' showed a steady increase within a range of 2 to 14, indicating its consistent research interest from the LAK over the past decade. Topics such as "Learning Visualization and Assessment Techniques" "Student Performance and Learning Systems Analysis", "Feedback Mechanisms and Learning Analytics", and "Predictive Models for Academic Success" are likely to continue increasing in their relevance and study within the field. Overall, these top 11 topics were actively researched throughout the period, despite some showing minor fluctuations.

To answer RQ3, according to 33 articles identified within the LAK corpus, LA has been extensively applied to engineering and computing education to enhance learning performance, facilitate personalized learning experiences, and improve learning outcomes. By using data mining and machine learning methods, the relevant studies within the LAK analyzed students' learning behaviors from diverse dimensions. These include the trajectory of learning engagement with course materials, online help-seeking behaviors, exam strategies, instructors' feedback, and collaborative patterns in a discussion session. Popular techniques and methods including learner profiling, multivariate linear model, layered Markov chain probabilistic model, Natural Language Processing (NLP), voice activity detection (VAD) algorithms, and Early Warning System (EWS) were deployed to support learning and teaching practices like improving assessment quality, identifying at-risk students, increasing student retention, and boosting learning engagement.

For example, in the field of computing education, to resolve issues like high attribution rates of computing degree programs, [25] leveraged undergraduate students' learning and social data to develop a Learning Management System (LMS) that presents the analysis of these data interactively. The system not only identifies students' struggles to deliver automated learning interventions but also encourages students to reflect on their programming assignments by providing visualized data results. Similarly, the learning intervention technique was utilized as a course design diagnostic tool by [26] to pinpoint the modules and assignments that most students have struggled with or any inconsistencies between the learning objectives and assessment metric. To better understand the relationship between online help-seeking behaviors and academic performance in an undergraduate introductory programming course, [27] investigated the impacts of such behaviors across multiple online resources, particularly the computer-mediated conversations such as Q&A forum and online office hours (OHQ) on students' grades. They found that the use of the recourse varies between low-performing and high-performing students. The results help them design online resources to support students in the introductory programming course at scale.

In terms of engineering education, by integrating the temporality and change to profile students' learning engagement with a blended undergraduate engineering course, [28] investigated how the changes in students' profiles relate to their learning performances based on their weekly entropy values and they used these to cluster students into distinct groups. To improve the first-year students' retention in the Mechanical Engineering course and support at-risk students' study at scale, [29] collected students' learning data and used a layered Markov chain probabilistic model to explore the exam strategies adopted by successful students. Similarly, [30] developed an Early Warning System (EWS) to support academic mentors in identifying at-risk students for timely intervention and enhance the effectiveness of academic mentoring in an undergraduate engineering course. [31] investigated the characteristics of instructors' feedback that could contribute to the improvement of students' grades in online higher education engineering classrooms using Natural Language Processing (NLP) techniques and a multivariate linear model. The finding helped instructors form feedback content from observed student behavior to improve students' grades in their engineering courses. [32] used voice activity detection (VAD) algorithms to model students' collaborative patterns in activities like turn-taking and talk duration in class discussions to investigate students' discussion patterns and overall learning performances in undergraduate engineering discussion sections.

V. Discussion

A. *Insights from bibliometric analysis*

The growing trend in the number of annual publications and accumulated citations of the 903 publications within the LAK corpus highlights the research potential of LA. According to the analysis of collaboration patterns among the top 15 prolific countries, the USA and Australia lead with the most collaborative publications (15), followed by the USA and Germany (11), and the USA and the UK (5). Among institutions, Monash University and the University of South Australia top the list with 28 co-authored publications, followed by the University of Technology Sydney and the Open University following (16), and the University of Technology Sydney and Monash University (10). The most collaborative scholars are Gašević, D (38), Shum, S. B (33), Dawson, S (31), and Pardo, A (31).

B. *Insights from topic modeling analysis*

The commonly investigated topics within the corpus are "Research and Tools in Learning Analytics" (20.09%), "Interdisciplinary Team-Based Learning" (13.98%), "Student Performance and Learning Systems Analysis" (12.54%), and "Learning Visualization and Assessment Techniques" (12.19%).

To gain a deeper understanding of the identified 11 topics and the interconnection between them, we analyzed the most representative research works for each topic and found that techniques such as social interaction analysis and learning visualization were employed across different educational settings. These techniques were deployed to facilitate interdisciplinary team-based learning and enhance the assessment of linguistic skills and learning performance in computing and engineering education. Various types of learning data were utilized to model key learning constructs, such as engagement levels with the relevant learning contexts. Predictive learning analytics was extensively explored in various contexts, and its implementation informs the design of learning systems and feedback mechanisms, providing a personalized learning experience tailored to the individual learner profiles.

Studies that examined the topics regarding “Learning Environment Design”, “Research Tools in LA,” and “Student Performance and Learning Systems” generally focused on integrating various instructional design methods and learning theories to enhance learning system efficacy and exploring different learning models across diverse educational settings. For example, [33] explored various scaffolding strategies to promote self-regulated learning (SRL) within educational technologies and emphasized the need for careful consideration of how these tools are implemented to effectively support learning.

“Feedback Mechanism” was studied in conjunction with topics like “Educational Recommender Systems”, “Predictive Models for Academic Success”, and “Learning Visualization and Assessment Techniques”. It focused on providing feedback tailored to individual students’ needs to enhance learning outcomes by using machine learning models and relevant key learning theories and principles. For example, [34] found that specific features of feedback affect the changes in students’ performances, suggesting that feedback can be designed effectively based on certain metrics to enhance students’ learning performances. By using machine learning models and combining automated feedback design principles and self-regulated learning theories, this system effectively analyzed students’ mechanistic reasoning in their written assignments and provided actionable recommendations for better learning outcomes. It is worth noting that [26] employed the learning visualization technique to identify and highlight learning challenges students encountered to provide insights for instructors with better course design and timely intervention in a first-year undergraduate engineering course.

Various learning modes emerged from the identified topics. For example, under the topic “Collaborative Learning Models”. [32] examined the combination of two modeling strategies to improve the customization and effectiveness of second language acquisition (SLA) tutoring systems and specifically looked at how models can optimize the timing and retrieval practices of language contents to boost language retention. [33] modeled students’ learning behavior to measure their engagement with robot-mediated collaborative interactions. [34] explored the effects of different models of network construction on the accuracy and relevance of learner positioning to facilitate the discourse quality and academic performance in online discussion post forums.

The topic “Predictive Models for Academic Success” has received increasing attention within the field. The relevant studies mostly aimed to improve learning performances by using descriptive and predictive learning data to model certain learning constructs relevant to learning outcomes. For example, [28] quantified and analyzed the changes in student study behaviors in a blended undergraduate engineering course using learning analytics and complex dynamical systems theory. By modeling students’ learning behaviors using clickstream data, the study categorized three patterns of students’ weekly learning performances to better understand the relationship between students’ learning behavior profiles, academic learning outcomes, and effects of different methods for profiling learning, and to provide actionable recommendations for their future learning. Similarly, [30] investigated the effectiveness of a learning system in identifying at-risk students for timely intervention and desirable learning outcomes in an undergraduate engineering course. The system was designed with the actionable insights derived from LMS learning data such as their submission of assignments and participation of discussions that underly their academic performances and engagement levels.

Most importantly, research within the LAK community offers profound insights into both research methodologies and pedagogical practices for computing and engineering education. By utilizing machine learning techniques like multivariate linear models, Natural Language Processing (NLP), voice activity detection (VAD) algorithms, and Early Warning Systems (EWS), these studies addressed critical issues like high attrition rates in undergraduate computing programs and inefficiencies in online help-seeking, while also facilitating timely learning interventions. Additionally, they enhanced pedagogical practices by identifying the characteristics of feedback content, discussion organization, and course design that effectively improve learning engagement and performance on a large scale within engineering and computing education.

VI. Conclusion

The present research is the first in-depth study that quantitively analyzed the academic performances and commonly researched topics within the LAK conference from 2011 to 2023. The bibliometric analysis identified the major contributors to the LAK and visualized the scientific collaborations among them. The topic modeling analysis of title, keywords, and abstract of the 903 articles contributed to the field by providing a comprehensive overview of its community. It uncovered the popular research topics and their annual trend as well as the most representative terms underpinning each topic. It also answered questions like how the prevalent topics, as well as engineering and computing education, were studied by discussing the representative key articles of each topic.

The study makes significant contributions to the field of computing and engineering education in two primary ways. Firstly, it provides important pedagogical implications for instructors on the use of learning analytics (LA) in computing and engineering education. This includes leveraging Visual Analytics Dashboards (VAD) and Early Warning Systems (EWS) to address high attrition rates and students' inefficiencies in online help-seeking for complex subject knowledge by providing timely learning interventions. Secondly, it offers insights for researchers on prevalent research topics and models in LA within computing and engineering education. This encompasses the exploration of collaborative learning models and predictive models to enhance student engagement and motivation in learning technical hands-on skills.

VII. Limitations and future directions

Future research could expand the dataset to explore how engineering and computing education is researched beyond the scope of the LAK conference by examining other databases such as the Journal of Learning Analytics. Additionally, inter-topic relationships could be investigated from different approaches, such as using keyword co-occurrence to explore keyword clustering and the Mann-Kendall test to identify significant research trends, focusing on the most prevalent learning analytics research topics in the field of engineering and computing education.

Representative Terms	%	Topics
course, moocs, online, student, model, data, analysis, assessment, study, success, recommendation	0.200887	Research and Tools in Learning Analytics
analytics, data, curriculum, technology, challenge, mmla, repository, toolkit, research, order, workshop, portal	0.139816	Interdisciplinary Team-Based Learning
model ,student, data, feature, performance, science, prediction, result, learning, machine, analysis, problem	0.125372	Student Performance and Learning Systems Analysis
student, system, model, knowledge, assessment, learning, question, approach, data ,problem, performance, feedback	0.121944	Learning Visualization and Assessment Techniques
discussion, video, presence, analytics, study-issue, forum, classification, analysis, approach, dialogue, paper	0.086528	Predictive Models for Academic Success
data, learning, learner, analytics, student, analysis, process, study, srl ,environment, activity, paper	0.072655	Learning Environment Design and Student Strategies
analytics, learning learner, collaboration ,framework, tool, education language quality task paper	0.069821	Educational Recommender Systems
network, analysis, learning, analytics, interaction, group, forum, community, study, learner, visualization, environment	0.05967	Language Skill Evaluation
student, course, learning study analytics feedback strategy data performance education system result	0.0461	Online Learning Networks and Interaction Analysis
policy, data ,language, privacy, processing, student, essay, analysis, system, score, classroom ,comprehension	0.042673	Feedback Mechanisms
analytics, learning ,design, teacher, research, dashboard, data, paper, classroom, tool, practice	0.034532	Collaborative Learning Models

Fig. 7. Representative terms of the 11 topics and their proportions in the corpus

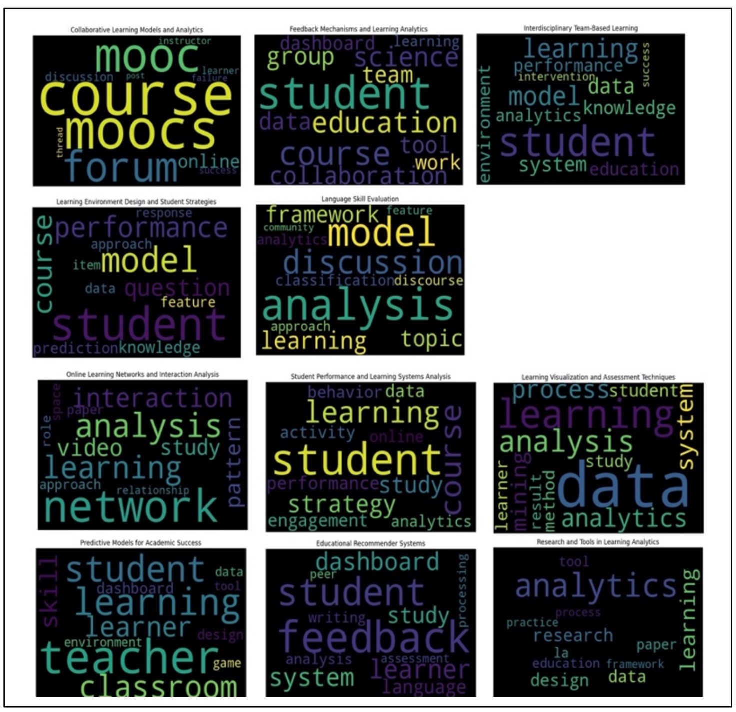

Fig. 8. Representative terms of the identified topics

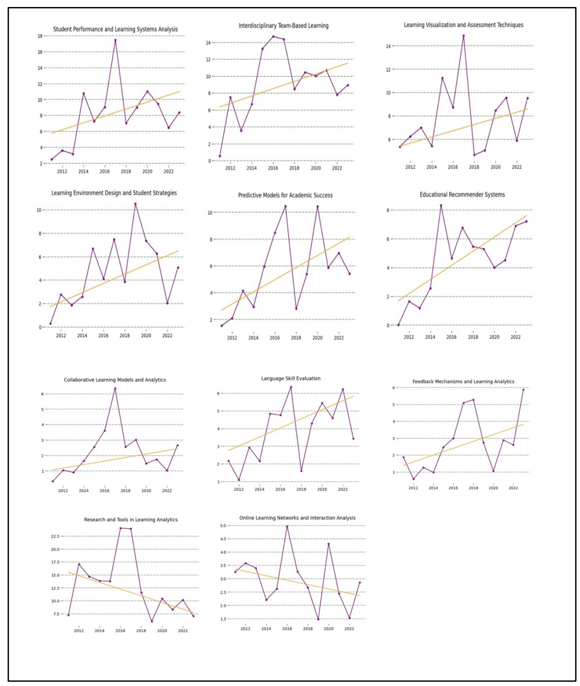

Fig. 9. Annual trend of the identified topics

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