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Bibliometrics Analysis on Using Machine Learning Algorithms in Teacher Education Researches

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Abstract: Machine learning (ML) techniques hold promise for innovating teacher preparation and development programs. However, the current state of research leveraging artificial intelligence in teacher-focused contexts remains unclear. This study undertook a systematic bibliometric analysis to characterize the emerging domain investigating ML applications for enhancing teacher effectiveness. Using the bibliographic R tool Bibliometrix, metadata of 740 English-language articles published during 2019-2023 extracted from Web of Science educational databases were examined to determine performance metrics, science mapping, citation networks, and research trends situating at the intersection of ML and teacher education. Document growth averaged 39.57% annually, with collaborations involving 87% of publications and 21.62% engaging international co-authorships. The USA led productivity metrics, though opportunities exist to expand geographical diversity. Analyses revealed research activity presently concentrates around employing ML for student analytics, assessment frameworks, and online learning environments. Highly cited works dealt with ML systems for evaluation and competency modeling of teachers rather than directly supporting pedagogical practice. Significant gaps persist exploring intelligent recommendation engines and affective computing chatbots tailored to teachers' dynamic training needs and emotional responses. This bibliometric review synthesizes the contours and trends in investigating ML applications for augmenting teachers' capabilities. Findings inform stakeholders to mobilize efforts strategically advancing this domain for enriching classrooms.

Keywords: bibliometric analysis, teacher education, research trends, knowledge mapping

INTRODUCTION

Teacher education plays a vital role in shaping positive educational outcomes for students. As Darling-Hammond (2017) notes, "student achievement is more influenced by teacher quality than any other in-school factor". Thus, improving teacher preparation and ongoing development should be a key priority. With the proliferation of new technologies, there are growing opportunities to innovate and enhance teacher education programs.

One area with particular potential is machine learning (ML) – a subset of artificial intelligence (AI) focused on algorithms that can learn from data and make predictions or decisions without being explicitly programmed to do so (Alpaydin, 2020). ML has demonstrated success in fields like computer vision, speech recognition, and predictive analytics. As Akgun and Greenhow (2022) and Murphy (2019) argue, ML also holds promise for enhancing educational processes and outcomes. For example, ML could help provide personalized learning for teacher candidates, assess teacher competency skills, or give real-time coaching and feedback to teachers.

However, teacher education has been slow to adopt ML techniques (Inyega & Inyega, 2020). This paper aims to analyze the current research activity focused specifically on using ML in teacher education contexts. Using bibliometric analysis, an established methodology for quantitatively assessing scholarly publications, it will identify knowledge clusters, influential authors and studies, trends over time, and gaps to inform future work. The findings can help direct research and development of ML for enhancing teacher learning and development – ultimately leading to better support for K-12 student success.

The scholarly discourse is increasingly recognizing the transformative potential of machine learning (ML) methodologies in the domain of teacher education (Hilbert et al., 2021). With the advent of sophisticated algorithms across various sectors such as natural language processing, computer vision, and affective computing, there is an emerging interest among academicians to investigate the application of these advanced technologies within the realm of teacher training and support (Blikstein & Worsley, 2016; Garcia-Garcia et al., 2018; Hellas et al., 2018). Specifically, ML has the capability to engender customized and adaptive pedagogical frameworks, offer instantaneous mentorship within virtual settings, evaluate pedagogical competencies, prognosticate the likelihood of teacher attrition, and catalyze numerous other pedagogical innovations.

However, the current literature focused specifically on using machine learning in teacher education is diffuse and has yet to be comprehensively analyzed (Hilbert et al., 2021). A rigorous mapping of this emerging field can help identify where research activity is clustered, pinpoint gaps and opportunities, and showcase models of promising work to emulate. Bibliometric analysis (Donthu et al., 2021), involving statistical analysis of published scholarly literature, provides an established methodology to reveal patterns and trends in research foci over time. By examining details of publications, citations, author networks, and other quantitative indicators, we can better understand the contours of current work at the intersection of machine learning and teacher education.

The rationale is clear for undertaking a bibliometric analysis of this domain at this formative stage. Synthesizing the current landscape of ML applications in teacher preparation and development will provide an important foundation to guide future projects. The analytical insights derived can help researchers shape impactful research agendas leveraging AI, direct funding and resources appropriately, and inspire new innovations for enhancing teacher effectiveness – ultimately benefiting K-12 student learning. This study will expand our conceptual understanding of the potentials of machine learning in teacher education thus far and chart strategic directions for research and practice moving forward.

This study aims to carry out a systematic bibliometric analysis around existing literature focused on machine learning applications in teacher education. Mapping out this emerging domain will help reveal meaningful patterns in how scholarship in this area has developed so far and where future directions may lie. The first core objective is to identity the parameters of current literature at the intersection of machine learning and teacher training/development. By surveying leading research databases using relevant search criteria, we will compile a corpus of documents published to date with a focus on ML in teacher education contexts. Analyzing publication volumes over time and across channels will highlight general trends. A second objective is to pinpoint the most prominent and impactful studies, researchers, and publication outlets that form the foundation of work in this domain so far. By aggregating citation data and other metrics, we can spotlight the current seminal texts and thought leaders directing scholarly conversations. Clustering analysis will also uncover thematic concentrations that show where research has primarily focused on applying machine learning techniques.

Finally, through a holistic perspective of the evolving literature, the review aims to reveal significant gaps where opportunities exist to expand ML applications in teacher education. Identifying understudied areas by subfield, methodology, geographical spread, and so on can provide researchers valuable direction for shaping high-potential projects to meaningfully move this niche domain forward. Overall, systematically assessing patterns and trends will generate crucial insights to accelerate progress at the intersection of machine learning, teacher effectiveness and ultimately student success.

Research Questions

1. What are the main themes and trends in the literature on ML in teacher education?
2. Which ML algorithms are most commonly applied in teacher education research?
3. What are the potential gaps and future directions in this field?

LITERATURE REVIEW

Machine learning (ML) refers to algorithms that have the ability to learn from data without being explicitly programmed (Alpaydin, 2020). ML algorithms can be grouped into three main categories – supervised learning, unsupervised learning, and reinforcement learning.

Supervised learning is a major category of ML algorithms, where the goal is to map input data to known output values (Sen et al., 2020). In supervised learning, the training data fed into the algorithm includes the desired solutions, called labels or targets. Some common supervised learning algorithms include linear regression, logistic regression, neural networks, decision trees, random forests, and support vector machines (Osisanwo et al., 2017). These algorithms analyze the training data and find patterns that allow them to predict the output values for new unseen data. In supervised learning, the algorithm is trained on input data that is labeled with the desired outputs, so that it can learn a function that maps inputs to outputs (Sarker, 2021). For example, in an education setting, a supervised learning model could be used to predict student performance (Namoun & Alshanqiti, 2021; Yakubu & Abubakar, 2022). The training data would consist of historical student records showing attributes like attendance, class test scores, time spent on coursework, etc. as the input variables along with the final class grade (the target variable). By learning from this labeled historical training dataset, the supervised model would determine which student attributes are correlated and predictive of better grades. It can then be used on records of new incoming students to predict what grade they will achieve based on their input attributes.

One major advantage of supervised learning is that labeled training data allows the models to achieve very high accuracy for prediction tasks (Alpaydin, 2020). However, a key challenge is that preparing large training datasets can be expensive and time-consuming in some cases because it requires humans to manually label each input to provide the desired solutions (Sajjadi et al., 2016). But in education, historical student data with grades already assigned provides ideal training data for supervised learning. Overall, supervised learning powers many important real-world applications like medical diagnosis, speech recognition, credit risk assessment and more – all situations where historical data with known outcomes exists (Shetty et al., 2022). In the education vertical it helps optimize student recruitment approaches, identify at-risk students needing intervention, improve personalized education and more.

Unsupervised learning is a class of ML techniques that analyze data without labeled responses in order to discover hidden patterns and groupings (Kotsiantis et al., 2006). Instead of mapping inputs to known outputs as in supervised learning, the key goal in unsupervised learning is to model the underlying structure and relationships in the data (Nawaz et al., 2022). Clustering is one of the most common unsupervised learning methods whereby the algorithm groups data points that are similar to each other into distinct clusters (Alpaydin, 2020).

For example, in an educational setting, student data like test scores, background, demographics, school attendance rates, and extracurricular activities could be analyzed via unsupervised clustering. The clustering algorithm would group students that are similar across the various attributes into student segments or personas without requiring predefined labels (Purnama Sari & Hanif Batubara, 2021). This allows educators to personalize interventions and supports for groups of similar students. The algorithm could identify one cluster of very engaged and high achieving students as well as underperforming student clusters that frequently miss class and require additional support. Additional common unsupervised techniques like anomaly detection and dimensionality reduction can also be impactfully applied in education.

Overall, while supervised techniques make predictions using labeled training data, unsupervised methods have the advantage of working with unlabeled data and exposing intrinsic data relationships. This allows discovery of new insights and improved decision-making in education and other fields (He et al., 2022). A key challenge remains interpretation of unsupervised model outputs which do not have predefined accuracy measures (Alpaydin, 2020).

Reinforcement learning is an area of ML inspired by behavioral psychology concepts of reward and punishment (Sutton & Barto, 2018). In reinforcement learning, the algorithm learns to optimize behaviors in an environment in order to maximize a cumulative reward signal through continuous trial-and-error interactions (Mousavi et al., 2018). Unlike supervised learning which provides correct input-output pairs, reinforcement learning algorithms choose actions and discover the optimal behavior based solely on feedback in the form of reward or penalty from interactions (Garnelo et al., 2018).

For example, reinforcement learning could be used to create an adaptive digital learning platform that tailors course content sequence and difficulty level personalized for each student to optimize engagement and minimize dropouts. The platform would continually recommend study resources, assess student fatigue, and tune recommendations. Student engagement metrics like time spent, content completion rates, or self-reported satisfaction surveys would provide the "reward" feedback signal. Over many such recommendation cycles and feedback instances, the platform learns an optimal policy for sequencing materials for each student profile. This emergent data-driven and learner-centric strategy is a key benefit of applying reinforcement techniques in education (Fu, 2022).

Overall, by learning through self-driven interactions akin to human/animal learning processes, reinforcement learning can enable technologies to automatically develop expertise, decision-making skills and optimized behaviors for complex real-world education environments (Mousavi et al., 2018). However, challenges like sample efficiency, stability, and interpretability remain active research areas (Sutton & Barto, 2018).

ML has seen growing use in education (Hilbert et al., 2021). For example, it has shown promise in providing adaptive and personalized learning experiences (Taylor et al., 2021). ML techniques have also been leveraged for assessment, including automatic essay scoring (Dong & Zhang, 2016). Predictive analytics utilizes student data to help identify those at risk of adverse outcomes (Namoun & Alshanqiti, 2021). And applications in intelligent tutoring systems aim to provide customized feedback, hints, and practice to support student success (Nye, 2015). However, the application of ML specifically in teacher education contexts remains relatively nascent.

While ML has seen growing adoption in areas like adaptive learning and assessment, its application in teacher education has been more limited. However, promising work has started to emerge at the intersection of ML and preparing or developing teachers.

In one line of inquiry, researchers have developed ML models to assess teacher performance or readiness. For instance, Bartram et al. (2021) utilized ML to reliably rate teacher portfolios. Other work has examined using AI to provide scoring agreements with human raters in evaluating teacher candidate responses (Gardner et al., 2021). Such applications could enhance consistency in high-stakes teacher competency evaluations.

Another active focus involves preparing teachers to integrate ML in their own classrooms. Efforts have included designing courses on AI concepts for teachers (Touretzky et al., 2019) and developing pedagogical agents powered by ML to teach data literacy skills (Amershi et al., 2019). Equipping teachers to utilize ML tools tailored for education can ultimately support enhanced student outcomes.

In terms of direct teacher training, some emerging work has explored using ML for personalized learning. ML recommendation model for suggesting customized content based on teacher needs and interests (Díaz Redondo et al., 2021; Fidan, 2023). Similarly, a reinforcement learning-based approach for teacher development that considers dynamic factors like emotions (Chaipidech et al., 2022; Tammets & Ley, 2023). These initiatives aim to increase engagement and effectiveness through individualized ML-powered experiences.

Bibliometric analysis refers to the quantitative statistical analysis of academic literature to uncover historical patterns in publication and citation data (Ellegaard & Wallin, 2015). It provides both descriptive and evaluative information to map the contours of research fields and trends over time. Common bibliometric indicators include publication volume, author productivity counts, journal impact factors, and citation frequencies. Through statistical modeling and visualization of networks, clusters, and changes across the scholarly record, we gain a birds-eye view of the evolution of topics (Caputo & Kargina, 2022).

Bibliometric techniques have been increasingly used to assess scholarship in diverse education domains. For example, Waheed et al. (2018) recently conducted a bibliometric analysis of learning analytics research over the past decades. By constructing citation networks, they revealed the most influential studies, countries, and authors leading work in this niche area involving using data analytics to understand learning processes. In another case, Jing et al. (2023) aims to bridge the knowledge gap by conducting a systematic review of articles on bibliometric mapping in educational technology research. According to the results of the study, bibliometric mapping is mainly used for quantitative analysis in five research topics: specific journals, emerging technologies, learning environments, online and distance learning, and subject concepts.

Overall, bibliometric analyses enable holistic assessment of academic corpora to inform research planning and resource allocation (Baraibar-Diez et al., 2020). In emerging interdisciplinary areas especially, bibliometric reviews help characterize the current state and trajectory of literature at a macro level. Mapping publication and citation patterns sheds light on the productivity, diffusion, and authority of scholarly contributions on a given topic over time (Ellegaard & Wallin, 2015). More studies adopting bibliometric methodologies can thus provide crucial perspective on developing fields connecting education and leading-edge technology, like ML.

In conclusion, ML is a promising field with diverse applications in education, though teacher training contexts remain an underexplored area of focus. The current research at the intersection of ML and teacher effectiveness covers several directions, including ML for assessment, developing AI readiness in teachers, and experimenting with adaptive ML systems for personalized professional learning. However, these emerging efforts remain disjointed and a systematic perspective of the state of work focused on enhancing teacher outcomes with ML is lacking. This underscores the rationale for the present bibliometric study aimed at synthesizing the existing activity in this domain. Mapping scholarly output through quantitative analysis can reveal meaningful patterns and opportunities to further develop the niche area of ML applications in teacher preparation and development. More research attention here would ultimately serve the shared goal of leveraging education technology innovations to augment teacher quality and K-12 student achievement.

METHODS

This bibliometric investigation employs a structured quantitative methodology to extensively evaluate the global research dynamics and intellectual frameworks within the burgeoning domain of ML applications in teacher education. Employing bibliometric methodologies, this study leverages statistical methods and visualization tools to discern trends and patterns in scholarly works pertinent to the subject (Donthu et al., 2021). The adopted approach is characterized by rigorously outlined stages for data acquisition, preprocessing, analytical scrutiny, and interpretive synthesis.

For the scope of this analysis, specific database platforms were selected to amass metadata on scholarly articles focusing on the intersection of ML and teacher education over the designated five-year span. Web of Science (WoS) databases were pinpointed due to their comprehensive inclusion of educational research literature. The retrieval of publication metadata was executed through targeted keyword searches and stringent selection criteria to guarantee the pertinence of the data. This data was then amalgamated into a cohesive dataset primed for thorough examination.

To facilitate this bibliometric inquiry, the Bibliometrix R-tool was engaged for its advanced capabilities in bibliometric analysis, including the evaluation of scientometric metrics, the generation of visual maps depicting knowledge domains, and the assessment of conceptual interconnections (Aria & Cuccurullo, 2017). The analysis was methodically arranged to illuminate insights on research output trends, diversity in document types, patterns of authorship, prominent publication venues, the impact of citations, collaborative endeavors, and the identification of novel research trajectories and thematic clusters through co-occurrence mapping.

Data Section Process

In this study, we employed a rigorous data collection process to assemble a dataset of journal articles at the intersection of ML and teacher education, spanning from 2019 to 2023. Utilizing the WoS database, known for its comprehensive coverage of educational science literature, we conducted a targeted search using the keywords "Machine Learning" AND "Teacher* Education", with the asterisk allowing for variations on "Teacher". This search was confined to articles published in English to ensure uniformity and accessibility of the data. Our focus was narrowed to scholarly journal articles to maintain the academic integrity of our dataset. We specifically extracted these articles from the "Educational Science" subject collection within WoS, ensuring the relevance of our data to the field of education research. The selected articles were downloaded in the BibTeX (.bib) format, facilitating ease of use with bibliometric analysis tools such as the Bibliometrix R-tool. This meticulous process ultimately yielded a final dataset comprising 740 articles, carefully curated to reflect the most pertinent and impactful research at the nexus of ML and teacher education over the specified four-year period.

Table 1. Descriptive information on datasets

Variable	Value
Main information about data	
Timespan	2019:2023
Sources (journals, books, etc.)	172
Documents	740
Annual growth rate (%)	39.57
Document average age	2.39
Average citations per document	7.804
References	31,171
Document contents	
Keywords plus (ID)	920
Author's keywords (DE)	2,422
Authors	
Authors	2,121
Authors of single-authored documents	76
Authors collaboration	
Single-authored documents	87
Co-authors per document	3.33
International co-authorships (%)	21.62
Document types	
Article	740

Data Analysis

The data analysis leveraged the Bibliometrix R-tool for conducting a bibliometric review of publications on using ML algorithms in teacher education, as indexed within the source database over 2019-2023. Metadata for the 740 documents was processed using Bibliometrix to determine performance metrics and map intellectual connections. The dataset showed rapid output growth at 39.57% annually, with articles constituting the entire corpus. Bibliometrix analyses of citations, h-index, and other indices highlighted influential works examining student performance, analytical frameworks, and learning environments. A total of 2121 authors contributed, with prolific publishers identified by h-index calculations in Bibliometrix. Co-occurrence matrices exposed relationships between keywords like "students," "performance," "analytics," and "education." Collaboration analytics revealed a collaborative culture, with 87% co-authored documents and 21.62% international partnerships. Results ranked the University of Michigan as the top institutional contributor. In summary, Bibliometrix enabled a multi-faceted bibliometric analysis, granting enhanced visualization of research activity, impact, interconnectedness, and cooperation advancing ML applications in teacher education. The findings provide insights to inform pedagogical innovation and policy in this rapidly evolving interdisciplinary domain.

RESULTS

The bibliometric analysis for the study spans a five-year period from 2019 to 2023. This period reflects the current trends and developments in the field. A total of 172 sources, including journals and books among others, have been consulted, indicating a comprehensive collection of research materials. The study encompasses 740 documents, suggesting a substantial volume of research activity on the application of ML in teacher education. A notable annual growth rate of 39.57% points to a rapidly expanding interest in the domain, a figure which is significantly higher than many academic fields, highlighting the dynamism and increasing relevance of this interdisciplinary area of study. The documents are quite recent, with an average age of 2.39 years, assuring the timeliness of the research considered. On average, each document is cited nearly 8 times, which indicates that the work is generating meaningful discussion within the academic community. The extensive number of references, amounting to 31,171, underscores the depth and breadth of the research undertaken in these studies. **Table 1** shows descriptive information on datasets.

Table 2. Trends machine learning in teacher education research

Year	n	MeanTCperArt	MeanTCperYear
2019	68	21.49	3.58
2020	89	18.92	3.78
2021	161	8.04	2.01
2022	164	4.74	1.58
2023	258	2.16	1.08

When it comes to the content of the documents, the use of 920 'Keywords Plus' indicates that the research covers a wide array of subtopics and themes, providing a rich, indexed tapestry of the field. The 2,422 author-supplied keywords further amplify this diversity, suggesting that authors are exploring a broad spectrum of theories, methodologies, and contexts within the niche of ML in teacher education.

The authorship data reveals that 2,121 researchers have contributed to this body of work, demonstrating a robust and varied academic community. Among these, 76 authors have presented their work independently through single-authored documents, indicating that there remains space for individual contribution and expertise within this collaborative field. With 87 documents authored by a single researcher, it suggests that a portion of the field values the depth of individual scholarly inquiry. Collaboration is a significant aspect of this research area, as evidenced by an average of 3.33 co-authors per document. This collaborative spirit is further emphasized by the fact that 21.62% of the papers include international co-authorships, reflecting a global interest in the subject and underscoring the importance of cross-border academic cooperation.

Importantly, all 740 documents are categorized as articles, pointing towards a focus on peer-reviewed journals, which are typically held in high regard in academia. This reliance on peer-reviewed articles ensures that the study draws from credible and high-quality sources, thus enhancing the reliability of the bibliometric analysis. In summary, the bibliometric data portrays the field of ML in teacher education research as an active, rapidly growing, and internationally collaborative discipline, characterized by recent, influential, and extensively cited work.

Trend in Publication

Table 2 appears to display data over a five-year span, from 2019 to 2023. 'Mean total citations per article,' which shows a declining trend from 21.49 citations per article in 2019 to just 2.16 in 2023. This suggests that, on average, articles are being cited less as time progresses. The number of articles published each year, which inversely increases from 68 in 2019 to 258 in 2023. This increase in publication volume might contribute to the dilution of citations per article as more literature becomes available for citation. 'Mean total citations per year,' which also shows a downward trend from 3.58 to 1.08 over the same period. This metric may suggest that the average number of citations that articles receive per year is decreasing, which could be due to a variety of factors such as the novelty of research waning over time or a saturation of the topic area. Overall, while the number of published articles is increasing each year, the average number of citations per article and per year is decreasing. This could indicate that while the field is becoming more prolific in terms of published work, individual articles may be having less impact or are less frequently cited in subsequent research. This might reflect a rapid expansion of the literature where new publications quickly supersede older ones, or it might point to a larger proportion of publications that fail to gain significant attention in the academic community.

Table 3 presents bibliometric indicators for the top 10 sources within using ML in teacher education research, likely educational technology, based on various metrics such as the h-index, g-index, m-index, total citations (TC), and the number of papers (NP).

Education and Information Technologies stands out with the highest h-index of 13, suggesting that its articles are frequently cited and it's a leading publication in the field. With 581 total citations across 100 papers, this source provides a rich citation pool and could be recommended for researchers looking to publish impactful work.

Computers & Education has a notable g-index of 25, indicating it has numerous highly cited papers, making it a top-tier journal for researchers aiming for wide dissemination and citation of their work. Despite having fewer papers (25), its high citation count (780) implies a significant impact per article.

Table 3. Top source of journal in using machine learning in teacher education research

Journal	h_index	g_index	m_index	TC	NP
Education and Information Technologies	13	20	2.167	581	100
Computers & Education	12	25	2.000	780	25
Interactive Learning Environments	12	21	2.000	484	35
IEEE Transactions on Learning Technologies	11	16	1.833	296	33
Journal of Science Education and Technology	11	14	1.833	205	15
British Journal of Educational Technology	10	18	1.667	326	19
Education Sciences	8	12	1.333	173	27
International Journal of Emerging Technologies in Learning	8	14	1.333	285	40
Educational Technology & Society	6	8	1.500	81	13
Frontiers in Education	5	7	0.833	72	23

Interactive Learning Environments and *IEEE Transactions on Learning Technologies* both have an h-index of 12 and 11, respectively, with substantial total citations, indicating they are well-regarded in the field and would be recommended for researchers looking for journals with a strong citation record. *Journal of Science Education and Technology* shows a strong m-index, which suggests sustained citation performance over time, making it a consistent choice for researchers looking to engage with enduring scholarly conversation.

British Journal of Educational Technology and *Education Sciences* are also prominent, with balanced h-index and g-index scores, indicating a solid citation history and a reputable standing in the field. For those interested in emerging trends, International Journal of Emerging Technologies in Learning offers a substantial number of papers (40) with a good citation rate, indicating it is a growing source for cutting-edge research. *Educational Technology & Society* has a lower h-index and g-index but offers a higher m-index relative to its h-index, which may appeal to researchers whose work aligns with more niche or emerging areas of the field.

Frontiers in Education despite having the lowest h-index, still presents a decent number of papers (23) and may be a suitable venue for new researchers looking to enter the academic discourse or for studies with a more innovative or interdisciplinary approach. In summary, these suggestions aim to guide researchers toward journals that not only align with their research interests but also offer the best potential for their work to be recognized and cited within the academic community.

Table 4 lists what appears to be the most effective authors in a particular field of study, assessed by bibliometric indices such as the h-index, g-index, m-index, total citations (TC), number of papers (NP), and the year they started publishing (PY_start).

Zhai, X. tops the list with the highest h-index of 8, indicating a significant impact within the scholarly community, with 147 total citations across 9 papers since 2020. This author stands out not just for productivity but also for the influence of the published work. *Xing, W.*, with an h-index of 5 and the highest g-index of 10 on the list, has amassed an impressive 216 citations across 10 papers since 2019. The high g-index suggests that *Xing, W.* has several highly cited papers, signifying a major contribution to the field.

Yang, S. J. H. and *Hu, J.* both have an h-index of 5, indicating their work is well-cited. *Yang, S. J. H.*'s work, starting from 2020, has already garnered 100 citations from 6 papers, suggesting rapid recognition in the field. *Hu, J.*, with a more recent start in 2021, also demonstrates significant impact with 91 citations from the same number of papers. *Salas-Rueda, R. A.* has an h-index of 4 with 49 citations from 13 papers since 2019. Despite a lower citation count, the higher number of papers suggests a consistent contribution to the literature.

Wu, J. Y., *Doleck, T.*, and *Haudek, K. C.* have h-indexes of 4 but vary in their m-index, which indicates the consistency of citations over time. *Doleck, T.* shows a slightly higher m-index, indicating a stable citation rate since starting in 2020. Several authors, including *Wulff, P.*, *Von Wangenheim, C. G.*, *Huang, A. Y. Q.*, and *Urban-Lurain, M.*, have an h-index of 3 with similar g-indexes, but their m-indexes and total citations reflect varying levels of influence. *Wulff, P.*'s higher m-index, starting in 2021, suggests a growing recognition over a short period. The remaining authors, including *Zhang, W.*, *Lemay, D. J.*, *Hauck, J. C. R.*, *Lu, O. H. T.*, and others, maintain an h-index of 3, indicating their research is acknowledged in the academic community. The consistency of their citation rates, as reflected by their m-indexes, suggests they are established contributors to their fields.

Table 4. Top author in using machine learning in teacher education research

Author	h_index	g_index	m_index	TC	NP	PY_start
Zhai, X.	8	9	1.6000	147	9	2020
Xing, W.	5	10	0.8333	216	10	2019
Yang, S. J. H.	5	6	1.0000	100	6	2020
Hu, J.	4	6	1.0000	91	6	2021
Salas-Rueda, R. A.	4	6	0.6670	49	13	2019
Wu, J. Y.	4	5	0.8000	86	5	2020
Doleck, T.	4	4	0.8000	93	4	2020
Haudek, K. C.	3	5	0.6000	34	5	2020
Wulff, P.	3	5	0.7500	25	5	2021
Von Wangenheim, C. G.	3	4	0.6000	71	4	2020
Huang, A. Y. Q.	3	4	0.6000	67	4	2020
Urban-Lurain, M.	3	4	0.6000	60	4	2020
Nowak, A.	3	4	0.7500	25	4	2021
Zhang, W.	3	3	0.6000	84	3	2020
Lemay, D. J.	3	3	0.6000	81	3	2020
Hauck, J. C. R.	3	3	0.6000	73	3	2020
Lu, O. H. T.	3	3	0.6000	66	3	2020
Yang, J.	3	3	0.5000	59	3	2019
Khaldi, M.	3	3	0.6000	46	3	2020
Cui, Y.	3	3	0.6000	45	3	2020

Table 5. Most influential studies in using machine learning in teacher education research

Document	DOI	Year	LC	GC	Ratio	NLC	NGC
Tomasevic, N., 2020	10.1016/j.compedu.2019.103676	2020	16	133	12.030	15.822	7.029
Hew, K. F., 2020	10.1016/j.compedu.2019.103724	2020	13	142	9.155	12.856	7.505
Jescovitch, L. N., 2021	10.1007/s10956-020-09858-0	2021	12	27	44.444	19.918	3.360
Gray, C. C., 2019	10.1016/j.compedu.2018.12.006	2019	11	78	14.102	12.467	3.630
Beaulac, C., 2019	10.1007/s11162-019-09546-y	2019	10	46	21.740	11.333	2.140
Marques, L. S., 2020	10.15388/infedu.2020.14	2020	8	43	18.604	7.911	2.272
Maestrales, S., 2021	10.1007/s10956-020-09895-9	2021	8	18	44.444	13.278	2.240
Iatrellis, O., 2021	10.1007/s10639-020-10260-x	2021	8	26	30.770	13.278	3.235
Musso, M. F., 2020	10.1007/s10734-020-00520-7	2020	7	31	22.581	6.922	1.638
Adekitan, A. I., 2019	10.1007/s10639-018-9839-7	2019	6	41	14.634	6.800	1.908

Note. LC: Local citation; GC: Global citation; NLC: Normalized local citation; & NGC: Normalized global citation

In conclusion, these authors are recognized for their effective contributions to their academic domain. Their work is not only prolific but also impactful, with a range of citation metrics suggesting both influence and steady scholarly activity. For researchers in the field, these authors' works would likely be key readings, and for new researchers, their trajectories could serve as a model for scholarly impact and presence.

Table 5 provides a comparative analysis of the impact of various studies within the educational field, based on their citation metrics both locally and globally from their year of publication to the present.

Tomasevic, N.'s 2020 study published in *Computers & Education* leads with the highest local citations of 16 and a considerable number of global citations at 133. Its citation ratio of approximately 12 suggests that for every local citation, there are roughly 12 global citations, indicating its broad international impact. This is further supported by its high normalized local and global citations scores, which could account for differences in citation practices across fields or over time, suggesting this study's findings are widely recognized and utilized. *Hew, K. F.*'s 2020 publication in the same journal also shows significant impact with 13 local citations and a higher global citation count of 142. Despite a lower citation ratio than *Tomasevic, N.*'s study, its normalized citation scores are still substantial, indicating its strong influence in the academic community. *Jescovitch, L. N.*'s 2021 article in *Journal of*

Table 6. Contribution of countries in using machine learning in teacher education research

Country	TC	Article
USA	1,364	626
China	851	320
United Kingdom	468	113
Australia	252	102
Germany	186	131
Canada	170	60
Spain	150	57
Morocco	149	71
Serbia	145	11
Greece	127	29
Turkey	118	51
Brazil	115	45
Japan	100	35
Portugal	94	15

Science Education and Technology has fewer total citations but an exceptionally high ratio, especially in local citations, indicating it may have rapidly become foundational in local or specialized settings after its publication.

Gray, C. C.'s 2019 paper in *Computers & Education* and *Beaulac, C.*'s 2019 study in *Research in Higher Education* both maintain double-digit local citations with relatively high global citations, reflecting their sustained relevance and impact. *Marques, L. S.*'s 2020 work in *Informatics in Education*, *Maestrales, S.*'s 2021 study in *Journal of Science Education and Technology*, and *Iatrellis, O.*'s 2021 article in *Education and Information Technologies* all have lower local and global citations but maintain high ratios, especially in normalized local citations. This indicates that while their total citation numbers may be lower, their influence per citation is significant.

Musso, M. F.'s 2020 study in *Higher Education* and *Adekitan, A. I.*'s 2019 paper in *Education and Information Technologies* round out the list with the lowest local citations but still maintain respectable global citations. Despite lower ratios, their normalized citation scores suggest that these studies have had a measurable impact relative to their publication years.

In summary, **Table 5** suggests that while some studies quickly establish a strong citation record both locally and globally, others may gain influence more gradually. The citation metrics provide insight into the reach and impact of academic work, with normalized values offering a more equitable comparison across different contexts and years. These studies present a blend of both immediate and growing impacts in educational research, reflecting a diverse array of influential work in the field.

Which Countries and Institutions Have Contributed to Research

Table 6 provides a straightforward comparison of research output from various countries, quantified by total number of citations (TC) and the number of articles produced (Article).

The United States leads both in terms of total citations with 1,364 and the number of articles with 626, indicating a robust research output with a significant global impact. *China* follows, with a total of 851 citations from 320 articles, suggesting that Chinese research is also highly impactful and prolific. *The United Kingdom*, although having a smaller number of articles at 113, has accrued a substantial number of citations (468), which points towards a high impact per article and a strong international influence in research. *Australia*'s figures show a healthy research output with 252 citations across 102 articles, denoting a solid presence in the academic field relative to the number of articles published.

Germany's data presents a similar picture to Australia in terms of citation impact with 186 citations from 131 articles, indicating a steady contribution to the global research landscape. *Canada* and *Spain* have similar numbers of articles published, but *Canada*'s study is slightly more cited, with 170 citations compared to *Spain*'s 150, indicating a marginally higher impact of Canadian research on the global stage.

Table 7. Contribution of institutions in using machine learning in teacher education research

Institution	Article
Michigan State University	47
National Autonomous University of Mexico	26
University of Florida	25
University of Georgia	22
Monash University	21
University of Oslo	18
Nanyang Technological University	17
Purdue University	16
University of Hong Kong	16
Zhejiang University	16
University of South Australia	15
East China Normal University	14
National Central University	14
University of Illinois	14
Carnegie Mellon University	13

Morocco's research output, while not as voluminous as some of the leading countries, still shows significant reach with 149 citations from 71 articles. *Serbia* stands out due to its exceptionally high impact in proportion to the number of articles; with only 11 articles, it has accumulated 145 citations, suggesting that *Serbian* research is highly influential and perhaps pioneering within its niche. *Greece, Turkey, Brazil, Japan,* and *Portugal* show varying levels of research output and citation impact, with Greece and Turkey having over 100 citations each, which is indicative of their active research communities. *Brazil, Japan,* and *Portugal* have the lowest numbers of articles and citations among the listed countries, but even so, their contributions are noteworthy, as they have reached a century mark in total citations, suggesting their research is recognized and cited in the academic world.

In summary, **Table 6** reflects the diverse scientific contributions of different countries, with the *USA* and *China* leading in quantity, while other countries like *Serbia* demonstrate significant influence despite smaller research volumes. The data underscores the global nature of research, where both quantity and quality play crucial roles in a country's academic reputation and the dissemination of knowledge.

Table 7 lists various universities and corresponding numerical values that likely represent a measure of academic output or impact, such as the number of publications, citations, or another form of academic contribution.

Michigan State University is at the top of the list with a value of 47, which suggests that it may be the leading institution in terms of the measured academic metric. This high number indicates a significant contribution to the field, whether that is through influential research, publication volume, or another valued academic activity. *The Universidad Nacional Autónoma de México* comes second with a value of 26, which is almost half of Michigan State's figure, yet it still signifies a strong academic presence. This could reflect the university's strong research capabilities or its faculty and students' active engagement in academic pursuits. *The University of Florida* and the *University of Georgia* follow closely, with values of 25 and 22, respectively, implying that these institutions are also major contributors in their academic fields. Their positions suggest a robust output that could enhance their visibility and prestige in the global academic community.

Monash University and *the University of Oslo* show significant contributions with values of 21 and 18. Their figures suggest a strong academic influence, likely due to quality research output or other scholarly activities. *Nanyang Technological University, Purdue University, the University of Hong Kong,* and *Zhejiang University* all have values ranging from 16 to 17. These institutions are evidently active in the academic domain, contributing valuable research and knowledge to their respective fields. *The University of South Australia, East China Normal University, National Central University,* and *the University of Illinois* are represented with values from 14 to 15, indicating a solid academic performance. *Carnegie Mellon University*, with a value of 13, rounds out the list. Despite being the last on this list, a value of 13 still reflects a noteworthy level of academic engagement.

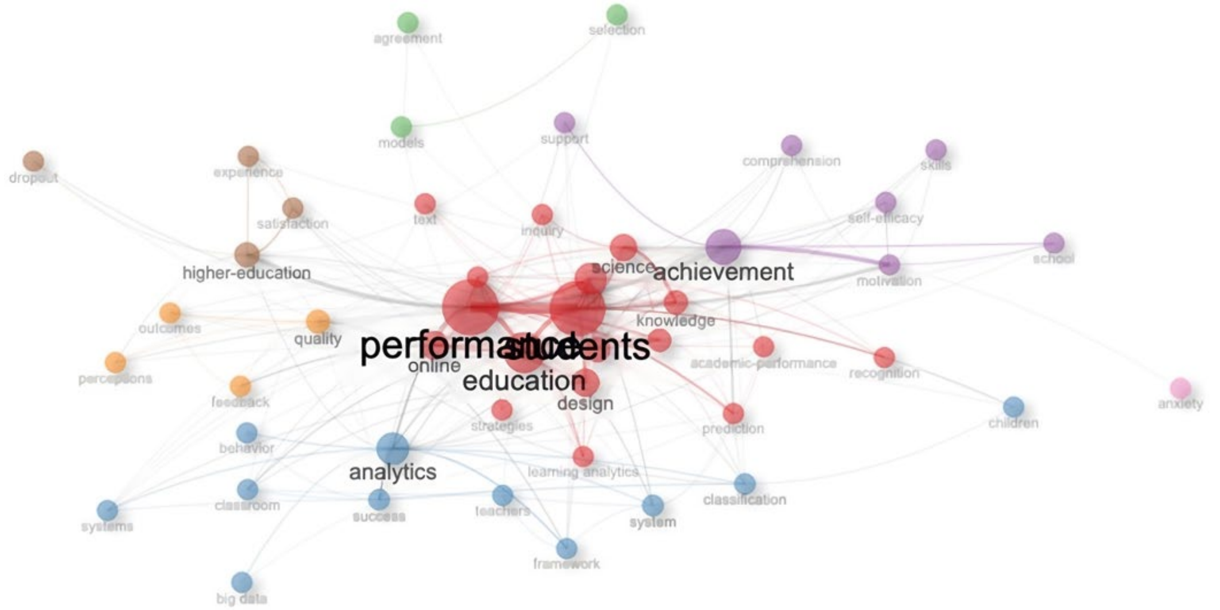

Figure 1. Co-keywords used in the studies

Overall, **Table 7** paints a picture of the academic landscape across various renowned institutions worldwide, each contributing to the advancement of knowledge and research in their unique ways. The values likely point to the impact and productivity of these universities in a global academic context.

Figure 1 likely represents a co-word analysis, which is a bibliometric tool used to assess the strength and centrality of terms within a body of literature. In the context of the study titled "Bibliometrics analysis on using machine learning algorithms in teacher education research," the terms listed (nodes) are probably keywords or key terms frequently associated with each other in the literature on this topic.

"*Performance*" seems to be a central term, with a high betweenness centrality, suggesting it plays a significant role in bridging various concepts within the literature on ML in teacher education. Its high PageRank indicates that it's a pivotal term within the network of keywords, possibly denoting the performance of ML algorithms or the performance outcomes in teacher education research. "*Students*" with even higher betweenness centrality and the highest PageRank, underscores its importance, suggesting that a lot of the research in this area focuses on the impact or application of ML on students within the educational context.

"*Education*" with a substantial betweenness centrality and a moderate PageRank, may indicate it's a broad term that encompasses various aspects of the research but may not be as central as "*performance*" or "*students*" in connecting different topics within ML and teacher education literature. The term "*model*" has lower betweenness centrality and PageRank, which might suggest that while models are essential within ML research, they may represent more specialized or technical aspects that are less frequently connected to other terms in the field. Terms such as "*online*" "*science*" "*design*" and "*knowledge*" have varying levels of centrality and PageRank scores, likely reflecting their relevance to the application of ML in online learning environments, scientific research in education, instructional design, and knowledge acquisition or dissemination.

In the second cluster, "*analytics*" stands out, possibly representing the focus on learning analytics within the context of ML in education. Its high betweenness centrality and PageRank might reflect the growing interest in how analytics can inform and enhance teacher education. Other terms like "*classification*," "*system*," "*framework*," and "*success*" in the subsequent clusters might represent specific aspects of ML applications in teacher education, such as classification algorithms, educational systems, theoretical frameworks, and measures of success in educational interventions.

The nodes in clusters with lower betweenness and PageRank, such as "*text*," "*academic-performance*," "*inquiry*," and "*recognition*," could indicate more niche areas of research that are emerging or less central in the current corpus of literature.

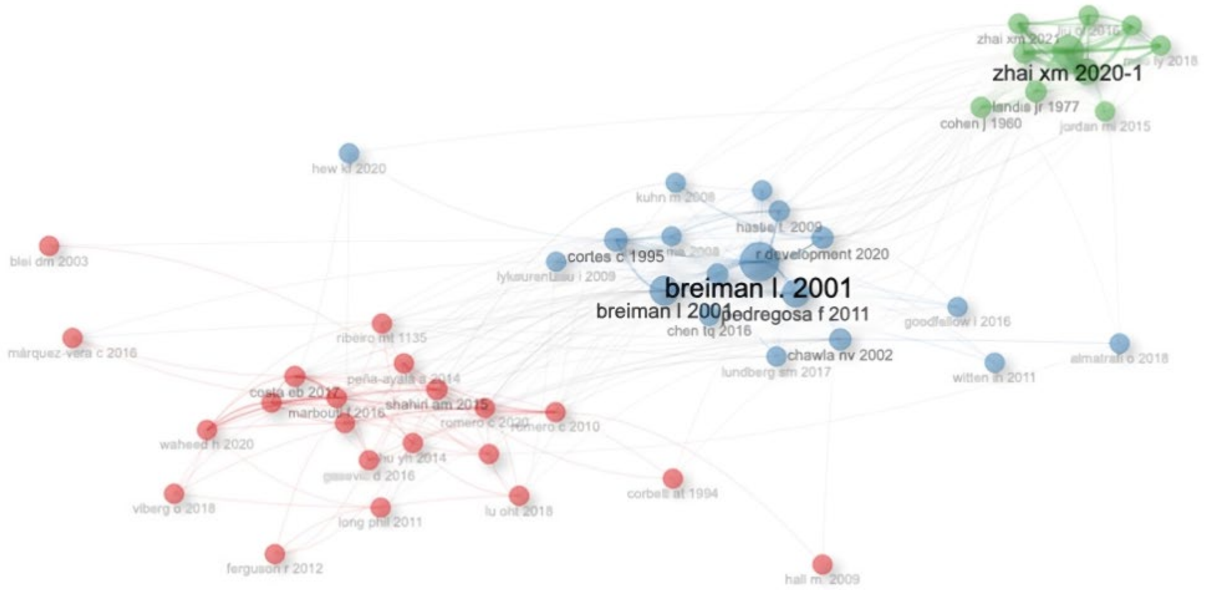

Figure 2. Co-references used in the studies

In summary, **Figure 1** provides insight into the interrelatedness and importance of various terms in the research on ML in teacher education. It identifies which concepts are central to the discourse and how they might interconnect to form the research landscape within this field.

Figure 2 appears to outline a co-references analysis, a bibliometric method that examines how often certain articles are cited together within a body of literature – in this case, the literature pertaining to the use of ML algorithms in teacher education research.

The "*Betweenness*" centrality indicates a node's role as a bridge within the network of references. For example, "*Costa Eb 2017*" and "*Romero C 2010*" have high betweenness centrality scores, suggesting that they are frequently cited by articles that do not directly cite each other, thus acting as a connecting bridge in the literature. "*Closeness*" is a measure of how close a node is to all other nodes in the network. A higher closeness score, like that of "*Romero C 2010*," implies that the work is central to the field and can quickly connect to other nodes (i.e., it is frequently co-cited with many other articles). In the context of bibliometrics, a higher PageRank – such as the score for "S*hahiri A.M 2015*" or "M*arbouti F 2016*" – indicates that an article is frequently cited by other highly-cited papers, signifying its importance and influence in the field.

Several nodes authored by "*Romero C*" appear in cluster 1 with varying scores, implying that this author's work is prominent and central to this cluster's theme. The multiple entries for "*Romero C*" suggest that their work is a staple in the conversation over time and through various publications.

In cluster 2, "B*reiman l. 2001*" and "*Hastie t. 2009*" have high betweenness centrality, indicating their significant role in connecting the literature within that cluster, possibly relating to ML methodologies. Cluster 3 features "C*ohen J 1960*" with a notably high betweenness centrality, suggesting that this particular work is foundational and connects a wide range of articles in the discourse on ML in teacher education. The clusters may represent different thematic focuses within the field. For example, cluster 1 might revolve around foundational theories and practices in ML and teacher education, cluster 2 could be focused on specific ML methods or statistical models, and cluster 3 might relate to assessment and evaluation using ML tools.

In the first cluster, "*Zhai, X.*" stands out with the highest betweenness centrality, suggesting that this work acts as a significant bridge within the network, linking various other research nodes. This indicates that "*Zhai, X.*" is a crucial intermediary in the spread and exchange of information within this cluster. Despite some nodes having a closeness centrality of 0.1667, which is lower than "*Zhai, X.*", they still have a relatively high PageRank, like "*Krajcik, J.*", indicating their importance in the network despite not being central connectors.

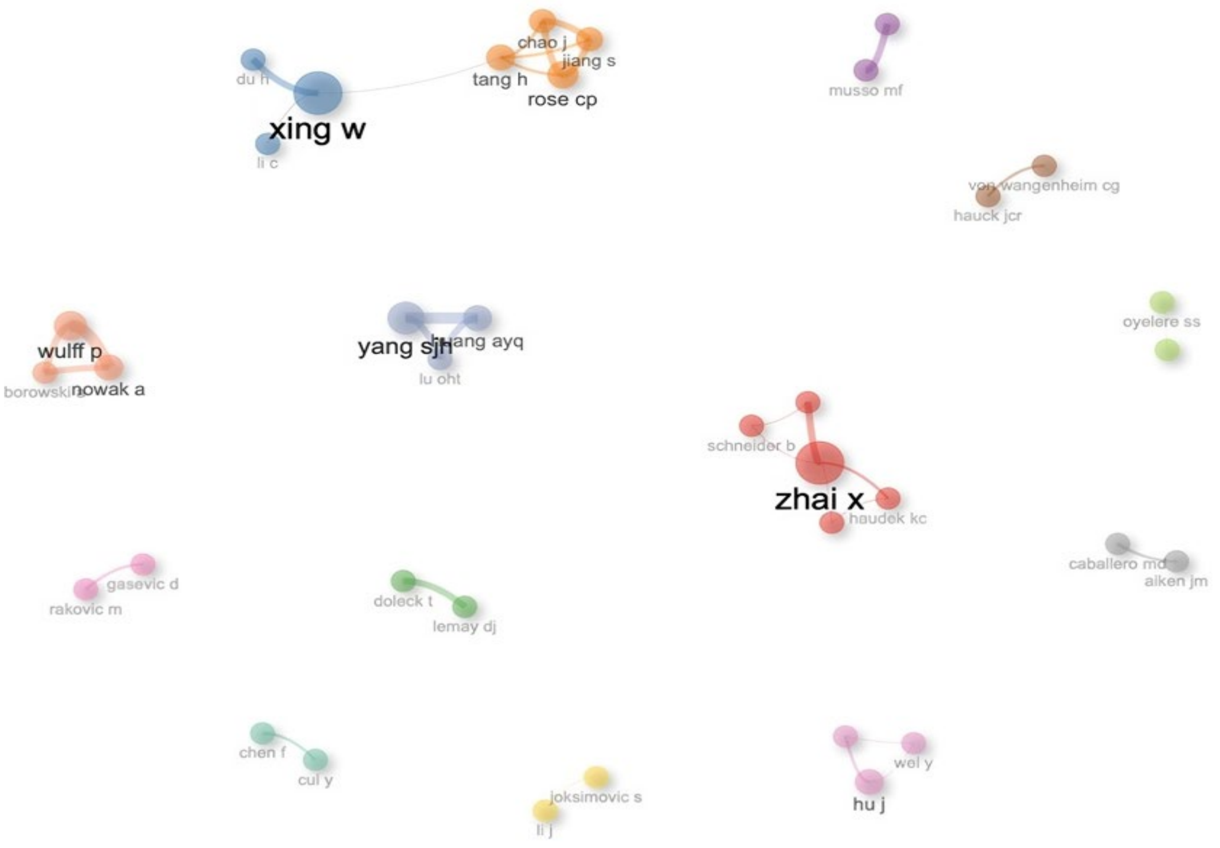

Figure 3. Co-work analysis

The second cluster includes nodes like "*Xing, W.*", which has a notable betweenness centrality and a higher closeness centrality compared to other nodes in the same cluster. This suggests "*Xing, W.*" is a prominent node within the cluster, likely cited alongside various other works and acting as a junction for the flow of information.

Clusters with nodes having a closeness centrality of 1, like "*Doleck, T.*", "*Lemay, D. J.*", and "*Musso, M. F.*", may indicate that these works are isolated or peripheral in the literature network. They are likely self-contained and not as interconnected with other works, which could mean they are highly specialized within their research niche.

In clusters such as 5, I see "*Tang, H.*" with a non-zero betweenness centrality and a higher closeness centrality, suggesting that it may have a unique role in connecting disparate nodes or facilitating the flow of research ideas within its cluster. For other nodes with a closeness centrality of 0.5 and a PageRank score that indicates a moderate level of influence, like "*Wulff, P.*" and "*Nowak, A.*", it can be inferred that these works are somewhat central within their own clusters and have a certain degree of importance in the network (**Figure 3**).

DISCUSSION

The bibliometric analysis revealed several insightful patterns and trends regarding the emerging interdisciplinary domain of ML applications in teacher education. Overall, the quantitative indicators point to a nascent but rapidly expanding field, with research output growing at an average annual rate of 39.57% over the 5-years analyzed. As Hilbert et al. (2021) predicted, scholarly activity at this intersection does appear to be gaining momentum. However, there remain significant opportunities to further develop this niche area, as teacher preparation contexts still seem to be lagging other educational applications of ML focused directly on students.

The results exposed a strongly collaborative culture, with 87% of documents involving co-authorships and 21.62% engaging international partners. This aligns with findings from bibliometric studies in similar education sub-fields like learning analytics, which uncovered high international collaboration levels (Waheed et al., 2018). The geographic and institutional productivity analysis further highlighted the dominance of the USA, China, and select

European countries in leading research. A diversity of journals are supporting publications in this domain, both from the educational technology field along with more interdisciplinary ML and computer science venues. Still, opportunities exist to expand visibility of this research line across the teacher training and development communities.

In examining the conceptual linkages between prevalent author keywords, notable clusters formed around the themes of student performance analytics, ML frameworks and models, and online learning environments. This points to these topics representing the current foci energizing research at the intersection of data-driven algorithms and preparing teachers. The co-citation analysis reinforced the influence of foundational texts on educational applications of ML, as well as statistical learning techniques. However, references dealing explicitly with teacher professional development were more peripheral.

The citation analysis spotlighted the visibility and influence attained by pioneering empirical works experimenting with ML in contexts like automated teacher competency assessments (Hew et al., 2020; Tomasevic et al., 2020) and AI platforms to build data literacy in teachers (Jescovitch et al., 2021). However, fewer highly cited studies dealt directly with ML systems for adaptive teacher training. This presents a significant research gap, considering the opportunities to boost personalized and emotionally intelligent learning experiences by leveraging recommendation engines, reinforcement learning chatbots, and affective computing (Chaipidech et al., 2022).

Overall, the findings from this bibliometric review validate the promise of ML within teacher education, while exposing underdeveloped areas regarding intelligent technologies for personalized and enhanced professional development. The quantitative performance and science mapping analysis provides researchers valuable insights regarding high-potential research directions that require greater attention. Building on the computational analytics and student success applications that dominate the current discourse, future work should increase focus explicitly on teacher-centric and adaptive ML systems to ultimately augment instructor pedagogical practices. With intelligent algorithms powering transformative gains in multiple spheres, directing research priorities towards improved teacher preparation and experiences can maximize benefits towards the shared objective of raising education outcomes.

CONCLUSION

This study undertook a comprehensive bibliometric analysis to chart the evolution of the emerging domain combining machine learning and teacher education over the past five years. The quantitative methodology provided crucial perspective on the scientific contours and dynamics that characterize this nascent interdisciplinary field. Calculated performance metrics exposed a proliferation of active researchers investigating diverse aspects of artificial intelligence in enhancing teacher effectiveness. However, mapping of conceptual linkages and influential citations revealed that the current discourse remains centered around ML applications enhancing student learning analytics, assessment frameworks, and online education environments. Though promising, experiments specifically leveraging AI's potentials to transform teacher training, adaptive competency development, and personalized recommendation systems are still fringe.

The findings from this systematic analysis of 740 multi-disciplinary articles offer data-driven insights regarding high-potential avenues to further advance this domain. The field displays tremendous possibilities at the intersection of leading ML technologies and the shared priority of strengthening teacher quality to bolster student success. Though countries like the USA and China currently lead research activity, ample prospects exist for scholarship from other nations to expand the scope through context-specific applications. Significant gaps also persist regarding intelligent teacher training platforms, emotionally responsive pedagogical agents, and other innovations elevating instructor capabilities by exploiting affective computing and reinforcement learning advancements. Ultimately, this bibliometric review synthesized the existing ecosystem of scientific contributions focused on uniting machine learning and teacher enhancement. The evidence-based perspective and identified opportunities should galvanize stakeholders to mobilize efforts expanding investigations in this domain to enrich classrooms worldwide with capable instructors and promising futures for students.

Recommendations

The bibliometric findings suggest several recommendations to advance the emerging domain of machine learning applications in teacher education:

1. Researchers across regions should undertake cross-institutional collaborations to expand the geographical diversity addressing context-specific teacher training needs with adaptive ML systems. Partnerships between developed and emerging economy universities hold particular promise.
2. With much current focus on student-centric analytics, assessment, and online applications, future interdisciplinary efforts should explicitly direct priority towards teacher-focused ML research – including experiments with intelligent tutors, voice agents for real-time support, and affective computing for personalized feedback.
3. The field requires engagement from a broader group of learning sciences and teacher training experts to complement the heavy computer science perspectives driving most existing projects on ML in education. Multidisciplinary input would allow for platforms better calibrated to teacher requirements.
4. Funding agencies and education philanthropies should establish targeted funding calls to explicitly catalyze innovative projects situated at the intersection of enhancing teacher effectiveness with ML – similar to those currently centered on improving student achievement.
5. Journals focusing explicitly on teacher development and pedagogical innovation should actively encourage submissions documenting applications of novel ML methods to prepare, assist, and augment instructors as beyond just analytical tools. This can expand awareness and provide greater visibility.

Limitation of the Study

While the study presented a broad bibliometric perspective, certain limitations provide context when interpreting the findings:

1. The dataset comprised only scholarly articles indexed in the chosen databases over the 5-year analytical period. Relevant scholarly outputs like books, conference papers, and non-English reports may offer additional insights.
2. Citation analysis fairly quickly after publication may underestimate the influence for promising recent articles with accumulation of citations over years. Findings mostly captured initial impact.
3. The visual knowledge mapping relies considerably on author-supplied keywords, which can vary in specificity; analysis using indexed keywords could reveal different topical clusters.
4. Journal quality indicators can disproportionately favor publications from developed economies versus equally innovative research from the emerging world.
5. Temporal analyses could indicate shifts in focus, but 5 years may be an inadequate duration for accurately detecting paradigm changes.

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