JORIDS

Journal of Research in Didactical Sciences

www.jorids.net

Vol. 2, Issue 1

Journal of Research in Didactical Sciences

Publisher

JORIDS is published by Nuri Balta

906 Appalachian Dr, Wylie, TX 75098, USA

Content

Journal of Research in Didactical Sciences
ISSN: 2997-5905 (Online)
VOL. 2, ISSUE 1, 2023
Article No: 14202

RESEARCH ARTICLE

OPEN ACCESS

Bibliometrics Analysis on Using Machine Learning Algorithms in Teacher Education Researches

Servet Demir [1*]

[1] Free Researcher, Turkey
* Corresponding author: servetdemirtr27@gmail.com

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.

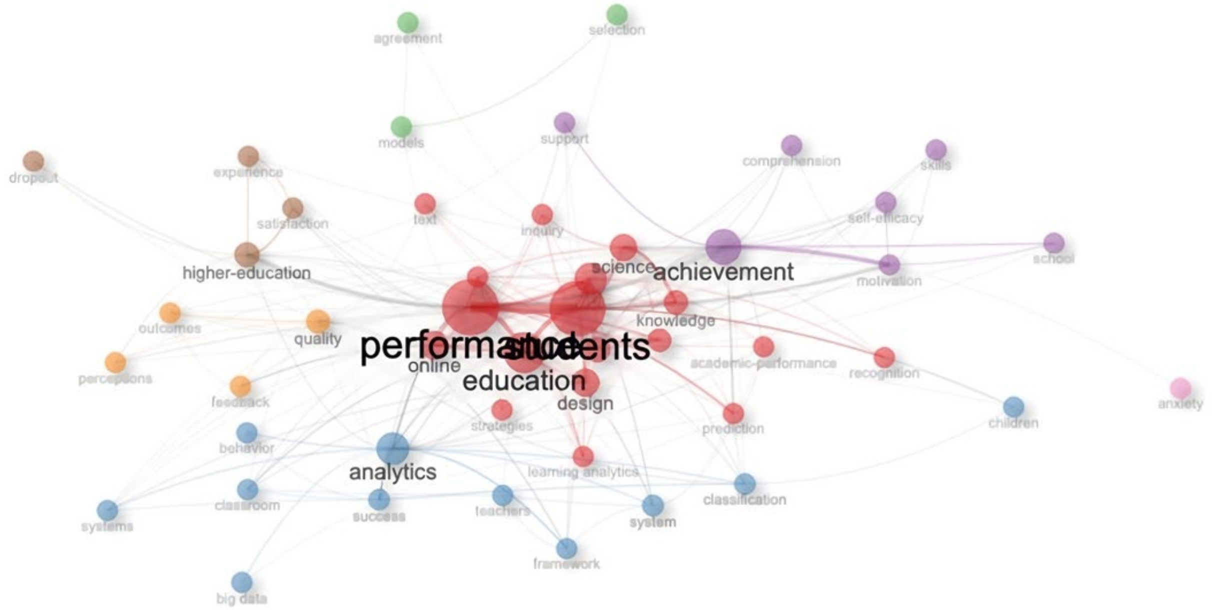

Figure 1. Co-keywords used in the studies

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.

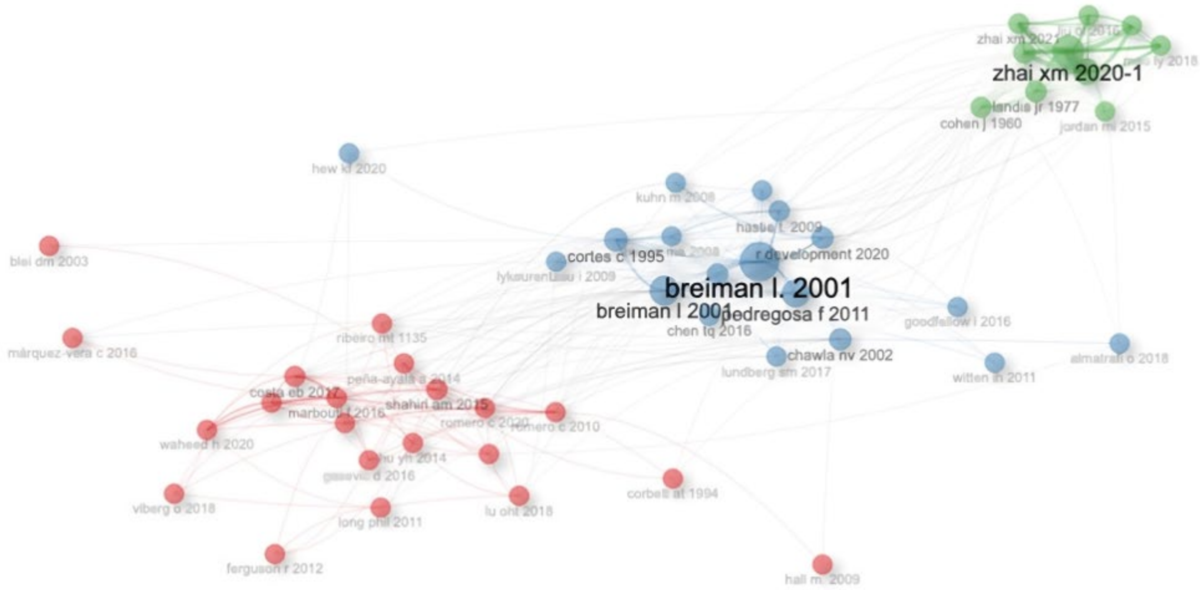

Figure 2. Co-references used in the studies

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.

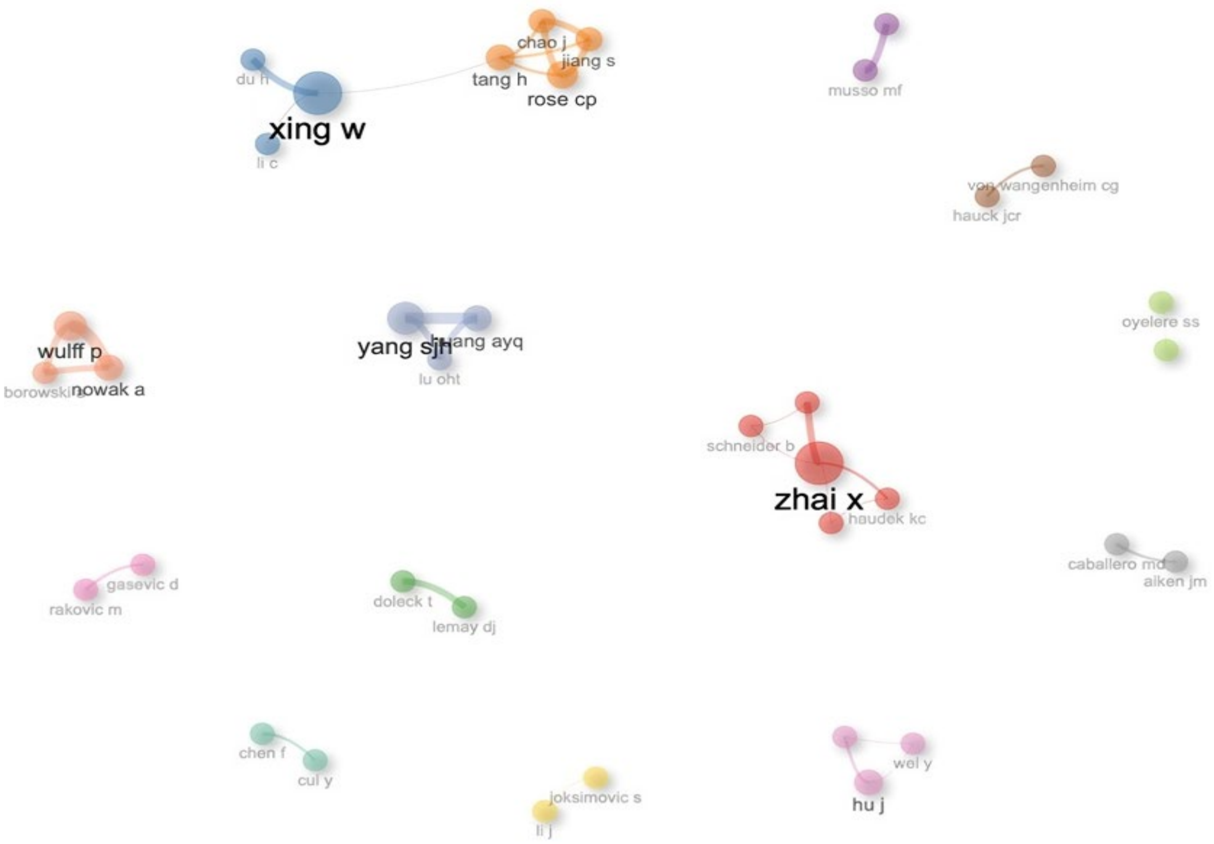

Figure 3. Co-work analysis

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.

REFERENCES

Akgun, S., & Greenhow, C. (2022). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. *AI and Ethics, 2*(3), 431-440. https://doi.org/10.1007/s43681-021-00096-7

Alpaydin, E. (2020). *Introduction to machine learning*. MIT Press.

Amershi, S., Begel, A., Bird, C., DeLine, R., Gall, H., Kamar, E., Nagappan, N., Nushi, B., & Zimmermann, T. (2019). Software engineering for machine learning: A case study. In *Proceedings of the 2019 IEEE/ACM 41st International Conference on Software Engineering: Software Engineering in Practice* (pp. 291-300). https://doi.org/10.1109/ICSE-SEIP.2019.00042

Baraibar-Diez, E., Luna, M., Odriozola, M. D., & Llorente, I. (2020). Mapping social impact: A bibliometric analysis. *Sustainability, 12*(22), 9389. https://doi.org/10.3390/su12229389

Bartram, S. M., Branke, J., De Rossi, G., & Motahari, M. (2021). Machine learning for active portfolio management. *The Journal of Financial Data Science*, *3*(3), 9-30. https://doi.org/10.3905/jfds.2021.1.071

Blikstein, P., & Worsley, M. (2016). Multimodal learning analytics and education data mining: Using computational technologies to measure complex learning tasks. *Journal of Learning Analytics*, *3*(2), 220-238. https://doi.org/10.18608/jla.2016.32.11

Caputo, A., & Kargina, M. (2022). A user-friendly method to merge Scopus and Web of Science data during bibliometric analysis. *Journal of Marketing Analytics*, *10*(1), 82-88. https://doi.org/10.1057/s41270-021-00142-7

Chaipidech, P., Srisawasdi, N., Kajornmanee, T., & Chaipah, K. (2022). A personalized learning system-supported professional training model for teachers' TPACK development. *Computers and Education: Artificial Intelligence*, *3*, 100064. https://doi.org/10.1016/j.caeai.2022.100064

Darling-Hammond, L. (2017). Teacher education around the world: What can we learn from international practice? *European Journal of Teacher Education*, *40*(3), 291-309. https://doi.org/10.1080/02619768.2017.1315399

Díaz Redondo, R. P., Caeiro Rodríguez, M., López Escobar, J. J., & Fernández Vilas, A. (2021). Integrating micro-learning content in traditional e-learning platforms. *Multimedia Tools and Applications*, *80*(2), 3121-3151. https://doi.org/10.1007/s11042-020-09523-z

Dong, F., & Zhang, Y. (2016). Automatic features for essay scoring-an empirical study. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing* (pp. 1072-1077). https://doi.org/10.18653/v1/D16-1115

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, *133*, 285-296. https://doi.org/10.1016/j.jbusres.2021.04.070

Ellegaard, O., & Wallin, J. A. (2015). The bibliometric analysis of scholarly production: How great is the impact? *Scientometrics*, *105*(3), 1809-1831. https://doi.org/10.1007/s11192-015-1645-z

Fidan, M. (2023). The effects of microlearning-supported flipped classroom on pre-service teachers' learning performance, motivation and engagement. *Education and Information Technologies*, *28*(10), 12687-12714. https://doi.org/10.1007/s10639-023-11639-2

Fu, S. (2022). A reinforcement learning-based smart educational environment for higher education. *International Journal of E-Collaboration*, *19*(6), 1-17. https://doi.org/10.4018/IJeC.315019

Garcia-Garcia, J. M., Penichet, V. M. R., Lozano, M. D., Garrido, J. E., & Law, E. L. C. (2018). Multimodal affective computing to enhance the user experience of educational software applications. *Mobile Information Systems*, *2018*, 8751426. https://doi.org/10.1155/2018/8751426

Gardner, J., O'Leary, M., & Yuan, L. (2021). Artificial intelligence in educational assessment: 'Breakthrough? Or buncombe and ballyhoo?' *Journal of Computer Assisted Learning*, *37*(5), 1207-1216. https://doi.org/10.1111/jcal.12577

Garnelo, M., Rosenbaum, D., Maddison, C. J., Ramalho, T., Saxton, D., Shanahan, M., Whye Teh, Y., Rezende, D. J., & Eslami, S. M. A. (2018). Conditional neural processes. In *Proceedings of the International Conference on Machine Learning* (pp. 1704-1713).

He, Z., Xia, W., Dong, K., Guo, H., Tang, R., Xia, D., & Zhang, R. (2022). Unsupervised learning style classification for learning path generation in online education platforms. In *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining* (pp. 2997-3006). ACM. https://doi.org/10.1145/3534678.3539107

Hellas, A., Ihantola, P., Petersen, A., Ajanovski, V. V., Gutica, M., Hynninen, T., Knutas, A., Leinonen, J., Messom, C., & Liao, S. N. (2018). Predicting academic performance: A systematic literature review. In *Proceedings of the Annual Conference on Innovation and Technology in Computer Science Education* (pp. 175-199). https://doi.org/10.1145/3293881.3295783

Hilbert, S., Coors, S., Kraus, E., Bischl, B., Lindl, A., Frei, M., Wild, J., Krauss, S., Goretzko, D., & Stachl, C. (2021). Machine learning for the educational sciences. *Review of Education*, *9*(3), e3310. https://doi.org/10.1002/rev3.3310

Inyega, H. N., & Inyega, J. O. (2020). Machine learning: The future of sustainable teacher education is here. *Journal of Pedagogy, Andragogy and Heutagogy in Academic Practice*, *1*(2), 115-133.

Jing, Y., Wang, C., Chen, Y., Wang, H., Yu, T., & Shadiev, R. (2023). Bibliometric mapping techniques in educational technology research: A systematic literature review. *Education and Information Technologies*. https://doi.org/10.1007/s10639-023-12178-6

Kotsiantis, S. B., Zaharakis, I. D., & Pintelas, P. E. (2006). Machine learning: A review of classification and combining techniques. *Artificial Intelligence Review*, *26*(3), 159-190. https://doi.org/10.1007/s10462-007-9052-3

Mousavi, S. S., Schukat, M., & Howley, E. (2018). Deep reinforcement learning: An overview. In *Proceedings of SAI Intelligent Systems Conference*. https://doi.org/10.1007/978-3-319-56991-8_32

Murphy, R. F. (2019). *Artificial intelligence applications to support K-12 teachers and teaching: A review of promising applications, opportunities, and challenges*. RAND Corporation. https://doi.org/10.7249/PE315

Namoun, A., & Alshanqiti, A. (2021). Predicting student performance using data mining and learning analytics techniques: A systematic literature review. *Applied Sciences*, *11*(1), 237. https://doi.org/10.3390/app11010237

Nawaz, R., Sun, Q., Shardlow, M., Kontonatsios, G., Aljohani, N. R., Visvizi, A., & Hassan, S. U. (2022). Leveraging ai and machine learning for national student survey: Actionable insights from textual feedback to enhance quality of teaching and learning in UK's higher education. *Applied Sciences*, *12*(1), 514. https://doi.org/10.3390/app12010514

Nye, B. D. (2015). Intelligent tutoring systems by and for the developing world: A review of trends and approaches for educational technology in a global context. *International Journal of Artificial Intelligence in Education*, *25*(2), 177-203. https://doi.org/10.1007/s40593-014-0028-6

Osisanwo, F. Y., Akinsola, J. E. T., Awodele, O., Hinmikaiye, J. O., Olakanmi, O., & Akinjobi, J. (2017). Supervised machine learning algorithms: Classification and comparison. *International Journal of Computer Trends and Technology*, *48*(3), 128-138. https://doi.org/10.14445/22312803/IJCTT-V48P126

Purnama Sari, I., & Hanif Batubara, I. (2021). Cluster analysis using k-means algorithm and fuzzy C-means clustering for grouping students' abilities in online learning process. *Journal of Computer Science, Information Technology and Telecommunication Engineering*, *2*(1), 139-144.

Sajjadi, M., Javanmardi, M., & Tasdizen, T. (2016). Regularization with stochastic transformations and perturbations for deep semi-supervised learning. In *Proceedings of the 30th Conference on Neural Information Processing Systems* (pp. 1-9).

Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. *SN Computer Science*, *2*, 160. https://doi.org/10.1007/s42979-021-00592-x

Sen, P. C., Hajra, M., & Ghosh, M. (2020). Supervised classification algorithms in machine learning: A survey and review. In J. Mandal, & D. Bhattacharya (Eds.), *Emerging technology in modelling and graphics: Advances in intelligent systems and computing* (pp. 99-111). Springer. https://doi.org/10.1007/978-981-13-7403-6_11

Shetty, S. H., Shetty, S., Singh, C., & Rao, A. (2022). Supervised machine learning: Algorithms and applications. In P. Singh (Ed.), *Fundamentals and methods of machine and deep learning* (pp. 1-16). Wiley. https://doi.org/10.1002/9781119821908.ch1

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT press.

Tammets, K., & Ley, T. (2023). Integrating AI tools in teacher professional learning: A conceptual model and illustrative case. *Frontiers in Artificial Intelligence*, *6*. https://doi.org/10.3389/frai.2023.1255089

Taylor, D. L., Yeung, M., & Bashet, A. Z. (2021). Personalized and adaptive learning. J. Ryoo, & K. Winkelmann (Eds.), *Innovative learning environments in STEM higher education* (pp. 17-34). Springer. https://doi.org/10.1007/978-3-030-58948-6_2

Touretzky, D., Gardner-McCune, C., Martin, F., & Seehorn, D. (2019). Envisioning ai for K-12: What should every child know about ai? *Proceedings of the AAAI Conference on Artificial Intelligence, 33*(01), 9795-9799. https://doi.org/10.1609/aaai.v33i01.33019795

Waheed, H., Hassan, S. U., Aljohani, N. R., & Wasif, M. (2018). A bibliometric perspective of learning analytics research landscape. *Behaviour and Information Technology, 37*(10-11), 941-957. https://doi.org/10.1080/0144929X.2018.1467967

Yakubu, M. N., & Abubakar, A. M. (2022). Applying machine learning approach to predict students' performance in higher educational institutions. *Kybernetes, 51*(2), 916-934. https://doi.org/10.1108/K-12-2020-0865

Please cite: Demir, S. (2023). Bibliometrics Analysis on Using Machine Learning Algorithms in Teacher Education Researches. *Journal of Research in Didactical Sciences, 2*(1), 14202. https://doi.org/10.51853/jorids/14202

Received: 07 October 2022 ● Accepted: 25 December 2023

Journal of Research in Didactical Sciences
ISSN: 2997-5905 (Online)

VOL. 2, ISSUE 1, 2023
Article No: 14204

REVIEW ARTICLE

OPEN ACCESS

Constructs in the Institutional E-Learning Readiness Models: A Literature Review

Donnalyn Blacer Bacolod [1*]

[1] Palawan State University, Philippines
* Corresponding author: dbacolod@psu.palawan.edu.ph

Abstract: Learning continuity amidst the COVID-19 pandemic is being advocated by many. As a result, many educational institutions worldwide are turning to e-learning or online learning as a solution. Nevertheless, many of them have never used e-learning before. Accordingly, this literature review aims to gather pertinent data about the constructs existing institutional e-learning readiness models. There were 42 models found in various databases between the year 2000 and January 2021, according to the search keywords "(institution or institutionalize) and readiness and (online learning or e-learning)." This review discusses the most frequently cited constructs in various models and other relevant information which are critical for the development of a new model and/or the adoption of an existing model to assess an institution's readiness for e-learning delivery.

Keywords: online learning, readiness models, e-learning constructs, higher education

INTRODUCTION

Distance education, such as e-learning or online education, was most frequently used as a mitigation strategy during the COVID-19 pandemic (Widodo et al., 2020). To combat this pandemic, the demand for an alternative method of educating learners increased dramatically. However, many educational institutions in developing countries encountered a variety of difficulties due to their unfamiliarity with e-learning, in comparison to more advanced schools. As a result, assessing an organization's readiness for e-learning is critical.

Even before the pandemic, many educational institutions were planning to implement e-learning. It is estimated that around 1,000 educational institutions in 50 countries are currently employing e-learning (Bhuasiri et al., 2012). Other researchers have also noted the widespread use of e-learning in higher education institutions all over the world (e.g., Kituyi & Tusubira, 2013; Tarus et al., 2015; Mosa et al., 2016). The use of e-learning also results in an increase in the number of students enrolled. In an e-learning environment, students can access a wide range of educational opportunities that were previously limited by factors such as age restrictions, availability of time, work schedules, and other cultural and socioeconomic constraints, among other things (Adebisi & Oyeleke, 2018). Some developing countries have expressed an interest in using e-learning, but they have been hampered by various issues such as inadequate infrastructure, cultural and policy frameworks, and a lack of resources (Usagawa, 2018). Such barriers continue to be a significant concern for many who are considering adopting e-learning now. The organization, including its stakeholders, must be prepared for the implementation of e-learning. When it comes to the adoption and effectiveness of e-learning, Zamani et al. (2016) found that readiness is a critical factor. Similarly, Albarrak (2010), Mosadegh et al. (2011) and Mirabolghasemi et al. (2019) emphasized the readiness of institutions for the adoption of e-learning.

In his definition of e-learning readiness, Bowles (2004) stated that it is the assessment of an institution's readiness to use and implement e-learning technologies. Similarly, Mirabolghasemi et al. (2019) stated that e-learning readiness refers to an organization's level of preparedness for various aspects of e-learning prior to its implementation. Alem et al. (2016) define e-learning readiness as a measure of a learner's readiness to participate in online courses. For Nwagwu (2020), e-learning readiness refers to the level of preparedness of stakeholders in terms of psychological, physical, and infrastructure factors that will result in a beneficial e-learning activity.

E-learning readiness assessment is crucial to the success of an institution that wants to embark on e-learning. When it comes to implementing e-learning programs successfully in higher education, Rohayani et al. (2015) identified readiness for e-learning as a critical component. It enables organizations to develop comprehensive strategies and achieve their ICT objectives (Kaur & Zoraini Wati, 2004). Organizations can also develop strategies to cater to specific learning groups because of their readiness to use e-learning technology (Nyoni, 2014). The e-readiness assessment assists developed countries, such as Saudi Arabia, in preparing for e-learning initiatives (Alshammari, 2019).

Institutional e-learning readiness should be carefully considered prior to implementation to avoid or at the very least mitigate the negative consequences. When it comes to implementing e-learning, Adiyarta et al. (2018) believe that an organization must have a sound strategy and plan in place to ensure that the desired result occurs. Unfortunately, some institutions that have implemented e-learning have failed to achieve their goals. Many organizations have failed in their attempts to implement e-learning. In higher education institutions, this is mainly due to the school's unpreparedness to implement e-learning (Al-araibi et al., 2019; Odunaike & Dehinbo, 2009). For Schreurs et al. (2012) this failure stems from the lack of an assessment of institutional e-learning preparedness. Through a readiness assessment, they said, the risk of failure could be reduced to a minimum.

This study recognizes the value and necessity of e-learning during this period of new normal of education. The available literature cautions against adopting and implementing such a program without first conducting a readiness assessment. As a result, it is critical to assess the level of preparedness; however, the availability of the instrument presents a new challenge for the institution. According to Hill et al. (2002), "borrowed models" are often not tailored to the specific needs of the educational setting, and as a result, become a source of difficulties. Even though most educational institutions are eager to implement e-learning technology, the criteria for determining whether they are ready for e-learning are still undefined (Omoda-Onyait & Lubega, 2011).

The purpose of this literature review is to gather relevant information about constructs of the institutional or organizational e-learning readiness models that can be used for future development of e-learning assessment instrument. As such, the following research questions were formulated:

1. What are the constructs used in each institutional or organizational e-learning readiness model?
2. What are the most cited constructs in the literature of institutional or organizational e-learning readiness models and in the previous studies from 2000-2021?

METHODS

The search words used in this literature review were "(institution or institutionalize) and readiness and (online learning or e-learning)." Most of the databases searched were Google Scholar, Science Direct-Elsevier, IEEE Xplore, ERIC, DOAJ, LearnTechLib, and Wiley. The following inclusion were observed in this search:

1. works published from year 2000 up to January 2021,
2. works published in English language,
3. thesis and dissertation manuscripts,
4. research articles, conference papers and other literature review papers,
5. works pertaining to institutional or organizational e-learning or online learning readiness, and
6. original or revised constructs of institutional e-learning or online learning readiness models.

Meanwhile, the exclusion observed were, as follows:

1. works that adopted or directly copied the constructs or models of institutional or organizational e-learning or online readiness,
2. repeated articles with the same versions, and
3. works that pertain to teacher, staff, or student e-learning readiness.

More than 400 works from various databases were discovered during the initial search; however, only 42 works fall within the scope of the current study. The Zotero application was used for data management. After finishing reading all the collected studies, data were analyzed and reported in paragraphs and tabular forms.

RESULTS

Description of 42 Institutional or Organizational E-Learning Readiness Models

Below are the brief descriptions of the 42 models from the literature searched. The description includes the constructs and other important information.

Chapnick (2000) developed a model for assessing an institution's readiness for e-learning. In the proposed model, eight constructs such as "psychological readiness, sociological readiness, environmental readiness, human resource readiness, financial readiness, technological skill readiness, equipment readiness, and content readiness" are used to examine the e-learning readiness. She used 66 factors written in question form and grouped them according to the said constructs. There are multiple-choice answers to every question, and managers should pick one of those that best represents their companies. At the end of each response, a point value is indicated in parenthesis. After responding to all questions in a section, managers are expected to add up the points for that section. According to Chapnick's model, the lower a user's grade, the more prepared their organization is for e-learning. The model does not only assist managers in determining whether their organizations are prepared for e-learning but also in determining which areas of their organizations require improvement and which areas are successful. Her model had been utilized by various institutions across the globe for e-learning readiness assessments.

Rosenberg (2000) was concerned with constant experimentation with regards to e-learning. He devised a set of 20 key-questions that were divided into seven categories such as "business or entrepreneurial readiness, changing nature of learning and e-learning, the value of teaching and information design, management of change, re-invention of educational organization, the industry of e-learning, and personal commitment." He created a tool to determine whether an institution is prepared to offer e-learning courses. This measurement tool was designed for non-educational organizations that intend to make a profit through their operations.

Engholm and McLean (2001) contended that organizations must analyze specific organizational and individual "readiness" criteria in order to achieve a seamless and effective transition to e-learning. Numerous elements associated with e-learning preparedness are discovered in the literature, and these factors are further studied using a qualitative multiple case study approach. A model of e-learning readiness is created based on the information found, which includes all the potential barriers discovered to be impediments to a successful e-learning experience in the future. This model may be useful to assist managers and trainers in their respective organizations in the determination of the readiness of their organization's e-learning systems. Their model is composed of five constructs, namely the organization's culture, learners, technology, organizational and industry factors, and learning content. They used three different organizations in Australia as the respondents of his study. There was a "charitable non- profit organization in the health sector, a government agency in the natural resources industry, and a private organization in the financial sector."

Anderson (2002) examined five critical success factors that will assist businesses in making sound e-learning decisions in the hope of avoiding failure. According to him, successful programs should adhere to these 5Cs: "culture, content, capability, cost, and clients." These 5Cs are the main determinants of e-learning readiness and success.

Haney (2002) studies the body of knowledge on organizational readiness for e-learning providing managers with directives and readiness tools for e-learning. Haney (2002) advised that managers should self-assess their organizational readiness using the 70 questions about organizational readiness. These questions were categorized into seven constructs such as human resources, learning management system, learners, content, information technology, finance, and vendor.

Khan (2002) identified the issues in the following areas: "pedagogical, institutional, technological, interface design, evaluation, management, resource support, and ethical considerations" to consider in assessing the e-learning readiness of any institution. Each dimension can be broken down into various subdimensions, and each subdimension is comprised of issues pertaining to a specific aspect of an e-learning environment.

Gachau (2003) aimed to measure the e-learning implementation readiness of Kenya Polytechnic in Nairobi, Kenya by indicating five dimensions namely students, administration, content, technical, and the future of e-learning. The results of her study revealed that factors such as learners' computer literacy, character, and motivation are the most important factors to consider for the readiness of students. For administration, the e-learning management support and e-learning culture are considered as the crucial determinants while the learning mechanisms and e-learning delivery methodology are for the content dimension. Technical support factor should be part of the technical readiness. Lastly, the future of e-learning must be planned as well.

Borotis and Poulymenakou (2004) proposed a model, which has seven components based on previous research and personal experience to confront the issue of incongruence in predefined components in readiness models of Rosenberg (2000), Chapnick (2000), and Haney (2002). He examined the aspects of "business, technology, content, training process, culture, human resources, and finances," respectively. Each construct is clearly defined in their paper. The Business dimension speaks to alignment of the e-learning strategy with the HEI's global strategy and goals, the external environment, and the degree of commitment level and support of the HEI's top-level administration. The Technology dimension examines the technological infrastructure of higher education institutions, as well as the extent to which students have access to that infrastructure and the Internet. The Content dimension is concerned with the availability of existing content, the format in which it is presented, the levels of interactivity, reusability, and interoperability with other systems. The Culture dimension encompasses the habits and perceptions of higher education institutions regarding the adoption and use of e-learning. The Human Resources dimension has to do with the number and skill sets of all of the stakeholders involved in the e-learning experience, such as faculty and students, administrative staff, and support personnel. The Financial Dimension examines the allocation of funds by the higher education institution to the e-learning strategy. According to them, this readiness model applies to any type of organization, but some adjustments are required when applied to a higher education institution.

Kaur and Zoraini Wati (2004) employed a study to determine the readiness of Open University Malaysia receivers (students) and enablers (tutors). The instrument consists of a 60-item questions for which 16 items asked about relevant demographic data and 44 items explored the 8 constructs of Kaur and Zoraini Wati (2004) e-learning readiness model. The said constructs are the "learner, management, personnel, content, technical, environmental, cultural and financial readiness." The e-learning readiness research tool was used to collect information from a sample of 93 receivers and 35 enablers who participated in the study. According to the findings of the study, policymakers and regulatory bodies must work together to improve the image of e-learning programs to encourage greater participation in a technology-driven teaching and learning environment.

Aydın and Tasci (2005) posited in their study that many tools are available in the market to assess a learning program's readiness for e-learning. However, most of these tools are designed for use in countries with an established human resource development sector. In particular, the available instruments cannot be used in institutions in emerging countries which just started to employ human resources. In their study, they devised an e-learning readiness tool suited for companies situated in such countries. While this has been developed to fit the cultural characteristics of Turkish companies, they believed that it can be easily customized to other emerging countries. Their study examines the readiness of the first 100 companies listed on the Istanbul Chamber of Industry's 2001 Turkey's Top 500 Major Industrial Enterprises List. They gathered their data from directors or managers involved in managing human resources departments in their respective companies. This tool is not devised for educational institutions. The instrument they used is divided into two sections: section 1 asked for the demographic characteristics and section two consisted of 30 items (in Likert scale) asking about their perceptions of the company's readiness for e-learning. Aydın and Tasci (2005) proposed a model consisting of seven categories: "human resources, learning management system, learners, content, information technology, finance, and vendor". These constructs are supported by Roger's diffusion of innovation theory which has four factors namely technology, innovation, people, and self- development.

Psycharis (2005) proposed three broad categories: resources, education, and environment, each with its own set of criteria. These three variables emerge from previous studies. Within the category of "resources, technological readiness, economic readiness, and human resource readiness" are deemed to be the primary determinants while the education category entails both content readiness and educational readiness. Lastly, environmental readiness encompasses "entrepreneurial readiness, leadership readiness and readiness of culture." According to Psycharis (2005), researching the organization's preparedness in terms of e-learning probes both those who are eager to incorporate it into their educational strategy, as well as those who have already implemented e-learning and are seeking reasons for subpar results. In his paper, he attempted to establish a connection between the factors that are present in various e-learning models and those that pertain to an organization's readiness for e-learning adoption. He showed that these factors are constituent parts of the overall model of the organization. Thus, he concluded that the success of e-learning is inextricably linked to its resources, educational processes, and context. His model has been adopted in Greece.

So and Swatman (2006) noted that the models for e-learning readiness that have been proposed up to this point have primarily been proposed for higher education institutions, with the intent of filling a gap in the literature. They proposed a model for e-learning readiness that would apply to primary and secondary educational institutions. Under the model, the readiness for e-learning for primary and secondary schools is comprised of six dimensions: "students' preparedness, teachers' preparedness, IT infrastructure, management support, school culture, and preference to meet face to face."

Lopes (2007) presented an evaluation model for assessing a higher education institution's readiness for e-learning. She used six factors such as technology, content, culture, human resource, financial, and business in her model. The data were gathered through a review of documentation, observation, and the use of two questionnaires. The first questionnaire collected data on students' abilities, access to equipment, and attitudes toward e-learning. Students and professors served as the respondents of her study. Results revealed that the "business, content and culture, and human resource" dimensions are classified as being in the medium (3) level of e-learning readiness while a low (1) readiness for e-learning is assigned to the technology dimension. The financial aspect has a low (0) e-learning readiness.

Al-Osaimi et al. (2008) used STOPE-based approach to conduct practical e-readiness assessment case studies in their study. STOPE stands for "strategy, technology, organization, people, and environment" dimensions. Among the case studies considered are those of three Saudi organizations: a government-owned organization, an international bank, and a private sector company. Each dimension has sub-factors or issues to examine.

Mercado (2008) pointed out in her study that online learning success stems from understanding and meeting the needs and readiness of significant stakeholders in the online learning environment. Addressing and assessing first the educational problems are necessary for considering the e-learning solutions or tools. She further added that the likelihood of successfully implementing an online learning-ready environment increases by recognizing these critical factors that promote online learning. With these issues, she came up with her study attempting to compile a readiness assessment tool along with an examination of existing readiness levels to implement an e-learning environment effectively. The constructs she used for institutional readiness are administrative and resource support. Under administrative, 3 aspects are explored such as commitment, policies, and instructional while for resource support, factors like financial, human, and technical are included. She believes that institutional readiness should consider the existence of processes that support both students and teachers. Teachers, students, and administrators should all have access to instructional and technical resources as part of their support systems. Special support must be given because of the online environment's unique circumstances. All resources, including financial, human, infrastructure, and technical resources, must be included. The instrument consists of 30 descriptions, equally divided to the said constructs. Also, it is answerable by yes or no. One major drawback for her assessment tool is the lack of further validation and application.

Schreurs et al. (2008) set out to determine whether Dutch hospitals were ready for e-learning. They came up with a measurement tool comprising of "learner characteristics, organization and management of e-learning, availability of qualitative technological facilities for e-learning, and the e-learning process and solutions/courses dimensions." In the dimension of learner characteristics, various characteristics, such as motivation, internet experience, and information and communication technology (ICT) skills, are measured. The organizational and management dimension of e-learning entails adjusting work hours to accommodate e-learning as well as investing in physical and e-learning infrastructure. The availability of high-quality technology facilities is measured in terms of Internet connectivity, ICT infrastructure, and a flexible learning management system. The process and solutions/courses in e-learning embrace the use of e-learning systems and course design that is tailored to students' learning styles.

Odunaike and Dehinbo (2009) assessed the e-learning readiness of Tshwane University of Technology (TUT) using the following dimensions in their instrument: business readiness, stakeholders readiness, technology readiness, content management readiness, training process readiness, culture readiness, and financial readiness.

Srichanyachon (2010) identified technology, human resources, and culture as essential components for colleges and universities to consider prior to implementing online education. His constructs of institutional readiness have been discussed only in his article. No data collection has been done to report the validity and reliability of his instrument. Also, his research article is formulated according to Thailand's educational context of online education. He noted additionally the importance of having a proportional number of computers with internet access to students, the frequency of teacher training, and recommendation for the adoption of e-learning and face-to-face instruction in a single course to increase the learning effectiveness.

Darab and Montazer (2011), initially, proposed the e-learning readiness model aimed to develop an appropriate e-learning model that can be used to assess the Iranian higher education institution based on comparative studies and the perspectives of national experts. Their model consists of 14 constructs which are grouped into three dimensions. Hard readiness includes equipment and network infrastructures; Soft readiness include regulations, management, culture, content, human resources (professors, staff, and students), policy, security, standards, and finance; lastly, Coordination, Supervision, and Support readiness are composed of supervision, support, and assessment aspects. Two of the nine indicators listed under soft readiness (laws and regulations and management) were considered the most critical indicators for the implementation of e-learning systems in Iranian universities. Later, their model was applied to Tarbiat Modares University, one of the prestigious universities in Iran, to provide an accurate and comprehensive assessment of e-learning.

Omoda-Onyait and Lubega (2011) attempted to determine the e-learning readiness of higher education institutions in Uganda using their proposed model. They noted that existing models are geared toward developed countries; thus, they offered a model for emerging economies. Their model consists of five constructs such as content, pedagogy, technology, culture, and awareness which are arranged from top to bottom of the pyramid. They collected their data from the eight public and private universities in Uganda. The questionnaire was administered to students and staff.

Saekow and Samson (2011) reviewed success factors in e-learning adoptions derived from a survey conducted in Thailand and the USA. The five constructs they used for their model are "policy, technology, finance, human resources and infrastructure" dimensions. They adopted their e-learning readiness components from Borotis and Poulymenakou's (2004) model. According to them, to have successful online programs, administrative support (under the policy dimension) at the top level is essential for the success of online programs. They mentioned that the most frequently cited success factors included the allocation of support resources to online programs, the development of a clear, well-defined project plan, the careful selection of introductory curriculum offerings, and training and workshop sessions of teachers to assist in the development of effective teaching styles.

Djamaris et al. (2012) determined the e-learning system readiness of PT Petarmina, in Indonesia, by using the framework proposed by Aydın and Tasci (2005). Djamaris et al. also used technology, innovation, people, and self-development dimensions to achieve such a goal. Findings revealed that, in general, the said university demonstrated e-learning readiness, although the aspect of their human resources need some improvements.

Ojwang (2012) assessed the level of preparedness of public secondary schools in Kisumu County in Kenya for the implementation of e-learning to improve access, equity, and quality in secondary education. He used seven constructs, namely infrastructure, electricity, computer resources, experienced personnel, internet connectivity, e-learning awareness, and level of computer literacy, in establishing his framework. The results of his study reported several inadequacies and challenges regarding e-learning implementation.

Schreurs and Al-Huneidi (2012) believed that numerous organizations have failed to implement e-learning successfully. One significant factor leading to this failure is the absence of assessment of the readiness of an organization for e-learning. Hence, they developed a model to assess whether an organization is prepared for e-learning. The model consists of five categories such as "facilities and infrastructure for e-learning, management, organization of e-learning function/department, learners' characteristic, and e-learning course and process." They used the model in KBC, a Belgian bank and insurances company, to assess the readiness of the company in implementing e-learning.

Azimi (2013) conducted a descriptive study to ascertain the readiness of university administrations for e-learning. He incorporated the factors of "ICT infrastructure, human resources, budget and finance, psychology, and content." A sample of 35 receivers and 31 university leaders from education institutions affiliated with the University of Mysore was surveyed using the enumerated factors.

Alshaher (2013) presented a new methodology for determining if an institution is ready to embark on an e-learning system project by incorporating fuzzy logic analysis into the McKinsey 7S model. He employed seven dimensions as a framework for examining the organization's current state prior to system installation to identify areas of vulnerability that could result in the project's failure. Seven dimensions are reviewed to assess the current condition of the organization before system adoption to identify possible weaknesses. These dimensions are strategy, structure, systems, style/culture, staff, skills, and shared values.

Oketch (2013) developed a model to measure the e-learning readiness of Kenya's higher education institutions. Specifically, his study investigated the e-learning readiness of the University of Nairobi's lecturers. He proposed a model with three primary constructs: technology, culture, and content. Each construct measures specific variables. Technological readiness is designed to measure the accessibility to eLearning resources, technological competencies, and attitude towards eLearning of the lecturers. Cultural readiness of the lectures assesses the attitude and management support towards e-learning. Content readiness asks about course material availability in the e-learning system, the need for training, and lecturers' satisfaction.

Okinda (2014) was able to determine the level of e-learning readiness at the Kenya Technical Teachers College (KTTC) by reviewing numerous models for assessing e-readiness using the ADDIE instructional design model and adopting Engholm and McLean's (2001) readiness framework. The five variables that he used were individual learners, content, ICT, organizational culture, and organization and industry.

Nisperos (2014) aimed to assess the e-learning readiness of some universities in Sudan. She proposed a model composing four dimensions: "perceived e-readiness of teachers and students, level of technology acceptance, the need for training, and the readiness of the technological infrastructure of the university to support e-learning". She administered her questionnaire to 60 faculty members and 200 students. Using such a readiness instrument, the results of her study indicated that, in general, Sudanese universities are not yet ready to implement e-learning. They need to improve the areas of training and technological infrastructure.

Sae-Khow (2014) aimed to create e-learning indicators that could be used as a baseline for higher education institutions' e-learning performance. In his model, he utilized seven institutional e-learning indicators such as "institute/organization, curricular program/teaching and instructional design, resource/technology/information technology, teaching/learning, learner, faculty and supporting personnel, and measurement/evaluation." The identified indicators were evaluated by specialists (university lecturers who are doctorate degree holders and have more than nine years of service) based on their content validity and their suitability for use in subsequent competency comparisons. All indicators were deemed appropriate by the experts to varying degrees, ranging from high to extremely high. According to them, all the indicators obtained could be used as criteria or benchmarks model in higher education institutions to evaluate the effectiveness of e-learning initiatives.

Demir and Yurdugül (2015) proposed models for e-learning readiness for institutions, students, and teachers by conducting a literature review. His study examined 30 models of readiness tools. Findings indicate that "finance, ICT infrastructure, human resources, management and leadership, content, culture, and competency of technology use" have become key components of models of preparation for institutional e-learning readiness, and thus, become his constructs for his proposed model.

Wibowo and Laksitowening (2015) believed that the readiness of institutions for e-learning becomes the key to guiding them through the implementation preparation process. The maturity of all factors affecting the implementation of e-learning cannot be separated from its readiness. Hence, in their study, they identified the constructs for e-learning readiness and proposed a model for such a concern. The model classified e-learning readiness factors into five constructs and grouped these into three layers based on levels of importance for institutions. The five constructs are the organization, financial, content, academic, and technology. The three layers comprise of supporting layer, core layer, and presentation layer. First, the core layer of this model, which includes organizations and academic domains, was devoted to institutions and is known to be critical to e-learning readiness. Second, the supporting layer was used to be an enabler for both organizational and academic entities in the core layer. The supporting layer includes the financial aspect. Third, the next layer to be prepared by institutions in implementing e-learning is the presentation layer, as a result of preparation in the core layer and supporting layer. The presentation layer depicts an institution's readiness for e-learning from the perspective of external stakeholders who are directly involved in the use of e-learning in the learning process. Technology and content compose this layer. In a separate study, Laksitowening et al. (2016) implemented this model at Telkom University.

Doculan's (2016) paper entitled "E-learning readiness assessment tool for Philippine higher education" utilized 22 different studies for literature review. She patterned her questionnaire from Mercado (2008) and included some aspects found in other studies. She then came up with her own assessment instrument, which includes three main constructs: "student, teacher, and institution." Each construct contains sub-categories.

Thaufeega (2016) investigated the level of e-learning readiness among Maldivian college students and their respective institutions. The schools' readiness was determined through semi-structured interviews with the two senior staff members of each college. The model he proposed is composed of Student Readiness (SR), Institutional Readiness (IR), Facilitator Readiness (FR), Societal Readiness (SCR), and National Readiness (NR). As for institutional readiness, the factors considered were access, study habits and skills (independent and self-directed learning), lifestyle factors (e-learning awareness), teaching style (student-centered), infrastructure, and human resources.

Villarica (2016) conducted a study to determine the viability of eLearning readiness at the Laguna State Polytechnic University (LSPU) main campus by interviewing faculty and students. She used the Akaslan and Law's (2011) e-learning readiness model for teachers and devised a 62-item questionnaire for readiness assessment. She explored the dimensions of "e-learning readiness, acceptance, training, technological infrastructure, and tools awareness." The results revealed that the LSPU needs to prioritize critical success factors, including ICT applications in the academic environment, e-learning training and education for faculty, students, technical and administrative personnel, and for the development of on-campus technological infrastructure before moving forward with its expansion.

Abdullah and Toycan (2017) contribute significantly to theory and practice regarding the implementation of sustainable e-learning systems for private universities in Northern Iraq and other developing countries. The first contribution of their study is identifying sustainable e-learning application factors from education providers' perspectives. With this, they created a readiness model using six dimensions: technological, human resource, content, educational, leadership, and cultural. University staff was interviewed and investigated to learn about the readiness factors.

Adiyarta et al. (2018) devised an e-learning readiness model composed of 13 variables such as "psychological, sociological, environmental, human resource, financial, technological skill, equipment, content, innovation, institution, leadership, culture, and policy". Their model was implemented at an unnamed university. Results revealed that 3 out 13 factors (human resource, technology skill, and content) show unreadiness and need improvement in the university.

Alshammari and Adaileh (2018) established the e-readiness of Saudi Arabian higher education institutions for e-learning by using seven dimensions such as "policy, pedagogy, technology, interface design, management, administrative support, evaluation, and continual improvement." The research instrument was developed from items generated from literature and then confirmed with exploratory factor analysis, confirmatory factor analysis, making its scale valid and reliable for e-readiness assessment. This research used various attributes of teachers, students, and administrators, to accomplish meaningful comparisons and show results with cross-group equivalence. The findings of the study reveal that five out of seven constructs ("technology, management, pedagogy, interface design and, administrative and resource support") are critical factors and should be considered for e-readiness measurement. Two variables in the scale were left unconfirmed. Additional emphasis should be placed on evaluation and continual improvement in the e-learning process, although previous research demonstrates the critical nature of policy and institutional business strategy development, and evaluation and continuous improvement in readiness assessment.

Irene and Zuva (2018) investigated the readiness of secondary schools in Gauteng, South Africa. They employed the STIPC model, which stands for strategy, technology, institution, people, and content. The STIPC model was derived from the STOPE model of Al-Osaimi et al. (2008). They collected the data from educators and students through a closed-ended survey questionnaire.

Alshammari (2019) assessed teachers, students, and administrators in institutions of higher education based on their individual characteristics. Seven dimensions were identified as e-readiness component factors: "policy and institutional business strategy, pedagogy, technology, interface design, management, administrative and resource support, and evaluation and continuous improvement." Included in his study are the components constituting e-learning success. These include "system, information and service qualities, use and user satisfaction, and net benefits."

Nwagwu (2020) examined the e-learning readiness of the University of Ibadan Nigeria by collecting the perceptions of the university lecturers. Believing that university lecturers are vital to the success of online learning at their respective institutions, the lecturers became his study's sole participants, with the findings restricted to the latter's perspectives. Nwagwu utilized eight components to assess the readiness of the premier university – i.e., "lecturers' readiness, public/society readiness, students' readiness, human resources readiness, financial readiness, training readiness, ICT equipment readiness, and e-learning materials/ content readiness".

Saintika et al. (2021) studied the advancement of information technology, which has permeated numerous sectors, including education. The development of e-learning is an example of how ICT is being used in education. Only 6% of the Indonesian universities have begun using e-learning systems. Implementing e-learning is still only moderately optimized. Other experts have warned all organizations that will adopt e-learning to prepare thoroughly to avoid costly overruns. Saintika et al. proposed an e-learning readiness framework for universities and colleges. The model is divided into two parts: the university's side and the students' side. The former contains four factors such as "lecturer's characteristics, e-learning facilities, learning environment, and learning management," while the latter consists of "self-learning, motivation, learner's control, and student's characteristic." They tested their framework to selected Indonesian tertiary institutions. Using their assessment tool, they found out that these institutions are level three ready but needing a few improvements in some areas.

The 42 institutional or organizational e-learning readiness models searched and collected from this study used different constructs. A total of 246 main constructs has been tallied from the 42 models; however, considering their sub-factors or sub-constructs, there are about 268 constructs all in all (**Table 1**). These constructs are mainly categorized into technological infrastructure, technical skills, human resources, students, content, culture, management, strategy, financial, psychological, and sociological aspects. A construct is a variable that is "abstract and latent rather than concrete and observable (such as the rating itself)" or "such a variable is literally something that scientists 'construct' (put together from their own imaginations) and which does not exist as an observable dimension of behavior..." (Nunnally & Bernstein, 1994). In other words, constructs are criteria, aspects or dimensions being assessed in an institution or university to indicate its level of readiness.

Table 2 reveals the most used or cited constructs from the different models. Among the categories, the infrastructure construct is the most cited. Infrastructure construct includes ICT, technology equipment and tools, internet connectivity, software, and electricity. The content construct is mentioned 42 times in the different models. The content is comprised of curricular programs, pedagogical, and e-learning processes among others. The management is mentioned 35 times while the human resources is 32 times. All in all, these are the constructs that constitute mostly the institutional or organizational e-learning readiness models.

Table 1. List of constructs used in institutional e-Learning readiness models

Model	Main constructs	Sub-constructs
Chapnick (2000)	1. Psychological readiness 2. Sociological readiness 3. Environmental readiness 4. Human resource readiness 5. Financial readiness 6. Technological skill readiness 7. Equipment readiness 8. Content readiness	None
Rosenberg (2000)	1. Business readiness 2. Changing nature of learning and e-learning 3. Value of instructional and informational design 4. Change management 5. Reinventing the training organization 6. E-learning industry 7. Personal commitment	None
Engholm and McLean (2001)	1. Organization's culture 2. Individual readiness 3. Technology 4. Content 5. Organizational and industrial factors	None
Anderson (2002)	1. Culture 2. Content 3. Capability 4. Cost 5. Clients	None
Haney (2002)	1. Human resources 2. Learning management system 3. Learners 4. Content 5. Information technology 6. Finance 7. Vendor	None
Khan (2002)	1. Pedagogical 2. Institutional 3. Technological 4. Interface design 5. Evaluation 6. Management 7. Resource support 8. Ethical considerations	None
Gachau (2003)	1. Students 2. Administration/organization 3. Content 4. Technical 5. The future of e-learning	None
Borotis and Poulymenakou (2004)	1. Business 2. Technology 3. Content 4. Training process 5. Culture 6. Human resources 7. Financial	None

Table 1 (Continued).

Model	Main constructs	Sub-constructs
Kaur and Zoraini Wati (2004)	1. Learner 2. Management 3. Personnel 4. Content 5. Technical 6. Environmental 7. Cultural 8. Financial readiness	None
Aydın and Tasci (2005)	1. Human resources 2. Learning management system 3. Learners 4. Content 5. Information technology 6. Finance 7. Vendor	None
Psycharis (2005)	1. Resource 2. Education 3. Environment	None
So and Swatman (2006)	1. Students' preparedness 2. Teachers' preparedness 3. IT infrastructure 4. Management support 5. School culture 6. Preference to meet face to face	None
Lopes (2007)	1. Technology 2. Content 3. Culture 4. Human resource 5. Financial 6. Business	None
Al-Osaimi et al. (2008)	1. Strategy 2. Technology 3. Organization 4. People 5. Environment	None
Mercado (2008)	1. Administrative 2. Resource support	1.1. Commitment 1.2. Policies 1.3. Instructional 2.1. Resource support 2.2. Financial 2.3. Human 2.4. Technical
Schreurs et al. (2008)	1. Learner characteristics 2. Organization and management of e-learning 3. Availability of qualitative technological facilities for e-learning 4. E-learning process and solutions/courses	None
Odunaike and Dehinbo (2009)	1. Business readiness 2. Stakeholders readiness 3. Technology readiness 4. Content management readiness 5. Training process readiness 6. Culture readiness 7. Financial readiness	None

Table 1 (Continued).

Model	Main constructs	Sub-constructs
Srichanyachon (2010)	1. Technology readiness 2. Human resources readiness (teachers and students) 3. Culture readiness	None
Darab and Montazer (2011)	1. Network 2. Equipment 3. Regulations 4. Standards 5. Financial 6. Security 7. Culture 8. Content 9. Policy 10. Human resources 11. Supervision 12. Support 13. Assessment 14. Management	None
Omoda-Onyait and Lubega (2011)	1. Awareness 2. Culture 3. Technology 4. Pedagogy 5. Content	None
Saekow and Samson (2011)	1. Policy 2. Technology 3. Financial 4. Human resource 5. Infrastructures	None
Djamaris et al. (2012)	1. Technology 2. Innovation 3. People 4. Self-development	None
Ojwang (2012)	1. Infrastructure 2. Electricity 3. Computer resources 4. Experienced personnel 5. Internet connectivity 6. E-learning awareness 7. Level of computer literacy	None
Schreurs and Al-Huneidi (2012)	1. Facilities and infrastructure for e-learning 2. Management 3. Organization of e-learning function/department 4. Learners' characteristic 5. E-learning course and process	None
Azimi (2013)	1. ICT infrastructure 2. Human resources 3. Budget and finance 4. Psychology 5. Content	None

Table 1 (Continued).

Model	Main constructs	Sub-constructs
Alshaher (2013)	1. Strategy 2. Structure 3. Systems 4. Style/Culture 5. Staff 6. Skills Shared values	None
Oketch (2013)	1. Technological 2. Culture 3. Content	None
Okinda (2014)	1. Individual learners 2. Content 3. ICT 4. Organizational culture 5. Organization and industry	None
Nisperos (2014)	1. E-readiness perception 2. Acceptance 3. Training 4. Infrastructure	None
Sae-Khow (2014)	1. Institute/organization 2. Curricular program/teaching and instructional design 3. Resource/technology/information technology 4. Teaching/learning 5. Learner 6. Faculty and supporting personnel 7. Measurement/evaluation	None
Wibowo and Laksitowening (2015)	1. Organization a. Policy b. Human resource c. Culture d. Management 2. Academic a. Curriculum b. Learning method c. Administration 3. Financial a. Budgeting b. Business 4. Technology a. Hardware b. Software c. Network 5. Content a. Learning content	1.1. Policy 1.2. Human resource 1.3. Culture 1.4. Management 2.1. Curriculum 2.2. Learning method 2.3. Administration 3.1. Budgeting 3.2. Business 4.1. Hardware 4.2. Software 4.3. Network 5.1. Learning content
Demir and Yurdugul (2015)	1. Finance 2. ICT infrastructure 3. Human resources 4. Management and leadership 5. Content 6. Culture 7. Competency of technology use	None

Table 1 (Continued).

Model	Main constructs	Sub-constructs
Doculan (2016)	1. Student 2. Teacher 3. Institution	1.1. Technology access 1.2. Technological confidence 1.3. Training 1.4. Social support 1.5. Study habits 1.6. Abilities 1.7. Motivation 1.8. Time management 1.9. Perceived usefulness 2.1. Technology access 2.2. Technological confidence 2.3. Training 2.4. Teaching styles and strategies 2.5. Abilities 2.6. Motivation 2.7. Time management 2.8. Perceived usefulness 3.1. ICT infrastructure 3.2. Administrative support (policies an commitment) 3.3. Human, financial and technological support
Thaufeega (2016)	1. Access 2. Study habits and skills (independent and self-directed learning) 3. Lifestyle factors (e-learning awareness) 4. Teaching style (student-centered) 5. Infrastructure 6. Human resources	None
Villarica (2016)	1. E-learning readiness 2. Acceptance 3. Training 4. Technological infrastructure 5. Tools awareness	None
Abdullah and Toycan (2017)	1. Technological 2. Human resource 3. Content 4. Educational 5. Leadership 6. Cultural	None
Adiyarta et al. (2018)	1. Psychological 2. Sociological 3. Environmental 4. Human resource 5. Financial 6. Technological skill 7. Equipment 8. Content 9. Innovation 10. Institution 11. Leadership 12. Culture 13. Policy	None
Alshammari and Adaileh (2018)	1. Pedagogy 2. Technology 3. Interface design 4. Management 5. Administrative support	None

Table 1 (Continued).

Model	Main constructs	Sub-constructs
Irene and Zuva (2018)	1. Strategy 2. Technology 3. Organization 4. People 5. Content	None
Alshammari (2019)	1. Policy and institutional business strategy 2. Pedagogy 3. Technology 4. Interface design 5. Management 6. Administrative and resource support 7. Evaluation and continual improvement	None
Nwagwu (2020)	1. Lecturers' readiness 2. Public/society readiness 3. Students' readiness 4. Human resources readiness 5. Financial readiness 6. Training readiness 7. ICT equipment readiness 8. E-learning materials/content readiness	None
Saintika et al. (2021)	1. University's side 2. Student's side	1.1. Lecturer's characteristic 1.2. E-learning facilities 1.3. Learning environment 1.4. Learning management 2.1. Self-learning 2.2. Motivation 2.3. Learner's control 2.4. Student's characteristic

Table 2. Frequently cited constructs in institutional e-Learning models

Constructs	Examples	Frequency of Mentions/Citations from Different Models
Infrastructure	ICT, Technology, Network, Internet connectivity, Electricity, and Software	46
Technical skills	Tool awareness, Technical skills, Computer literacy, and Capability	10
Students	Characteristics, Learning method, Learner's preparedness, Motivation, and Preference	21
Human resources	Teachers, Staff, Personnel, Their preparedness, and experiences	32
Content	Content, Content management, Curricular program, Pedagogical, and E-learning process and courses	42
Management	Management, Leadership, Administrative support and Training	35
Financial	Financial and Cost	16
Culture	Culture and Organization's culture	17
Strategy	Vision, Mission, and Policies	18

Different models are comprised of various constructs. Some of them only used 2 constructs (e.g., Saintika et al., 2021; Mercado, 2008). However, each of the constructs has sub-factors, for instance, the administrative construct of Mercado (2008) includes commitment, policies, and instructional. Saintika et al. (2021) used university's side and student's side as their main constructs. Under the student's side are the student's characteristics, learner control, motivation, and self-learning. Most of the models (n = 21) involve 4 to 6 constructs and common to them are the constructs pertaining to students, infrastructure (e.g., Engholm & McLean, 2001; So et al., 2006; Schreurs et al., 2012) Fourteen of the models have 7 to 9 constructs (e.g., Alshammari, 2019; Nwagwu, 2020; Odunaike & Dehinbo, 2009) while there is no model containing 10 to 12. The models of Adiyarta et al. (2018) and Darab and Montazer (2011), have the greatest number of constructs, which are 13 and 14, respectively (**Table 2**).

CONCLUSION

Models of institutional or organizational readiness for e-learning are critical to the adoption and implementation of e-learning successfully. The pieces of literature provide valuable insight into how readiness is determined. Numerous constructs can be used to assess an organization's readiness level. Some institutions might require a different kind of readiness model from the rest. Because the model was developed in a different location or country, it may not work in the context of another school. It is possible that a model from a developed country may not be appropriate for an institution in a developing country, and vice versa. Hence, different models have different set of constructs.

During this period of pandemic, many institutions, particularly those in the educational sector, will be forced to shift their paradigm from face-to-face instruction to distance learning and flexible learning, and they will need to determine their level of e-learning readiness to make this transition. Thus, this research is critical for such initiatives to ensure the success of e-learning program delivery. However, while the pandemic has caused uncertainty and delays in the education sector, it has also paved the way to realize the need to transform the educational landscape of many institutions that continue to rely on traditional face-to-face classroom settings despite technological advancement, internet connectivity, and the introduction of new educational paradigms. The critical importance of institutional e-learning readiness models for assessment purposes has become apparent in recent years. This paper aspires for the development of additional institutional e-learning readiness models, as there are currently only a few available studies in the extant of literature.

REFERENCES

Abdullah, M. S., & Toycan, M. (2017). Analysis of the factors for the successful e-learning services adoption from education providers' and students' perspectives: A case study of private universities in Northern Iraq. *EURASIA Journal of Mathematics, Science and Technology Education, 14*(3), 1097-1109. https://doi.org/10.12973/ejmste/81554

Adebisi, T. A., & Oyeleke, O. (2018). Promoting effective teaching and learning in online environment: A blend of pedagogical and andragogical models. *Bulgarian Journal of Science & Education Policy, 12*(1), 153-172.

Adiyarta, K., Napitupulu, D., Rahim, R., Abdullah, D., & Setiawan, M. I. (2018). Analysis of e-learning implementation readiness based on integrated ELR model. *Journal of Physics: Conference Series, 1007*, 012041. https://doi.org/10.1088/1742-6596/1007/1/012041

Akaslan, D., & Law, E. L. (2011). Measuring teachers' readiness for e-learning in higher education institutions associated with the subject of electricity in Turkey. In *Proceedings of the 2011 IEEE Global Engineering Education Conference (EDUCON)* (pp. 481-490). IEEE. https://doi.org/10.1109/EDUCON.2011.5773180

Al-araibi, A. A. M., Naz'ri bin Mahrin, M., & Yusoff, R. C. M. (2019). Technological aspect factors of E-learning readiness in higher education institutions: Delphi technique. *Education and Information Technologies, 24*, 567-590. https://doi.org/10.1007/s10639-018-9780-9

Albarrak, A. I. (2010). Designing e-learning systems in medical education: A case study. *International Journal of Excellence in Healthcare Management, 3*(1).

Alem, F., Plaisent, M., Zuccaro, C., & Bernard, P. (2016). Measuring e-Learning readiness concept: Scale development and validation using structural equation modeling. *International Journal of e-Education, e-Business, e-Management and e-Learning, 6*(4), 193-207. https://doi.org/10.17706/ijeeee.2016.6.4.193-207

Al-Osaimi, K., Alheraish, A., & Bakry, S. H. (2008). STOPE-based approach for e-readiness assessment case studies. *International Journal of Network Management, 18*(1), 65-75. https://doi.org/10.1002/nem.657

Alshaher, A. A. F. (2013). The McKinsey 7S model framework for e-learning system readiness assessment. *International Journal of Advances in Engineering & Technology, 6*(5), 1948-1966.

Alshammari, A. (2019). *The impact of e-readiness on e-learning success in Saudi Arabian higher education institutions* [PhD thesis, De Montfort University].

Alshammari, A. F., & Adaileh, M. J. (2018). E-learning readiness: A scale development in Saudi higher education institutions. *International Journal of Economics & Management Sciences, 7*(5), 1000553. https://doi.org/10.4172/2162-6359.1000553

Anderson, T. (2002). Is e-learning right for your organization? *Learning Circuits: ASTD's Online Magazine All About E-Learning*. http://www.learningcircuits.org/2002/jan2002/anderson.html

Aydın, C. H., & Tasci, D. (2005). Measuring readiness for e-learning: Reflections from an emerging country. *Journal of Educational Technology & Society, 8*(4), 244-257.

Azimi, H. M. (2013). Readiness for implementation of e-learning in colleges of education. *Journal of Novel Applied Sciences, 2*(12), 769-775.

Borotis, S., & Poulymenakou, A. (2004). E-learning readiness components: Key issues to consider before adopting e-learning interventions. In *Proceedings of the E-Learn: World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education* (pp. 1622-1629). Association for the Advancement of Computing in Education (AACE).

Bowles, M. S. (2004). *Relearning to e-learn: Strategies for electronic learning and knowledge*. Melbourne University Publishing.

Chapnick, S. (2000). Are you ready for e-learning. *Learning Circuits: ASTD's Online Magazine All About E-Learning*. https://nurhadiw.files.wordpress.com/2010/08/are_you_ready_for_elearning.pdf

Darab, B., & Montazer, G. A. (2011). An eclectic model for assessing e-learning readiness in the Iranian universities. *Computers & Education, 56*(3), 900-910. https://doi.org/10.1016/j.compedu.2010.11.002

Demir, Ö., & Yurdugül, H. (2015). The exploration of models regarding e-learning readiness: Reference model suggestions. *International Journal of Progressive Education, 11*(1), 173-194.

Djamaris, A., Priyanto, A. B., & Jie, F. (2012). Implementation of e-learning system readiness: Indonesia context. In *Proceedings of the 2012 IEEE International Conference on Management of Innovation & Technology (ICMIT)* (pp. 314-319). IEEE. https://doi.org/10.1109/ICMIT.2012.6225824

Doculan, J. A. D. (2016). E-learning readiness assessment tool for Philippine higher education institutions. *International Journal on Integrating Technology in Education, 5*(2), 33-43. https://doi.org/10.5121/ijite.2016.5203

Đurek, V., & Reðep, N. B. (2016). Review on e-readiness assessment tools. In *Proceedings of the Central European Conference on Information and Intelligent Systems* (p. 161). Faculty of Organization and Informatics Varazdin.

Engholm, P., & McLean, J. (2001). *What determines an organisation's readiness for e-learning* [Bachelor thesis, Monash University].

Gachau, A. M. (2003). *A survey of e-learning readiness in tertiary institutions: A case study of Kenya polytechnic* [Doctoral dissertation, University of Nairobi].

Haney, D. (2002). Assessing organizational readiness for e-learning: 70 questions to ask. *Performance Improvement, 41*(4), 8-13. https://doi.org/10.1002/pfi.4140410404

Hill, J. R., Raven, A., & Han, S. (2002). Connections in web-based learning environments: A research-based model for community building. *Quarterly Review of Distance Education, 3*(4), 383-393.

Irene, K., & Zuva, T. (2018). Assessment of e-learning readiness in South African schools. In *Proceedings of the 2018 International Conference on Advances in Big Data, Computing and Data Communication Systems (icABCD)* (pp. 1-7). IEEE. https://doi.org/10.1109/ICABCD.2018.8465444

Kaur, K., & Zoraini Wati, A. (2004). An assessment of e-learning readiness at Open University Malaysia. *Open University Malaysia*. http://library.oum.edu.my/repository/115/1/an_assessment.pdf

Khan, B. H. (2002). Dimensions of e-learning. *Educational Technology, 42*(1), 59-60.

Kituyi, G., & Tusubira, I. (2013). A framework for the integration of e-learning in higher education institutions in developing countries. *International Journal of Education and Development Using Information and Communication Technology, 9*(2), 19-36.

Laksitowening, K. A., Wibowo, Y. F. A., & Hidayati, H. (2016). An assessment of e-learning readiness using multi-dimensional model. In *Proceedings of the 2016 IEEE Conference on e-Learning, e-Management and e-Services (IC3e)* (pp. 128-132). IEEE. https://doi.org/10.1109/IC3e.2016.8009053

Lopes, C. T. (2007). Evaluating e-learning readiness in a health sciences higher education institution. In *Proceedings of the IADIS International Conference E-Learning* (pp. 59-67). IADIS.

Mercado, C. (2008). Readiness assessment tool for an e-learning environment implementation. *International Journal of the Computer, the Internet and Management, 16*, 11-18.

Mirabolghasemi, M., Choshaly, S. H., & Iahad, N. A. (2019). Using the HOT-fit model to predict the determinants of e-learning readiness in higher education: A developing country's perspective. *Education and Information Technologies, 24*(6), 3555-3576. https://doi.org/10.1007/s10639-019-09945-9

Mosa, A. A., Naz'ri bin Mahrin, M., & Ibrrahim, R. (2016). Technological aspects of e-learning readiness in higher education: A review of the literature. *Computer and Information Science, 9*(1), 113-127. https://doi.org/10.5539/cis.v9n1p113

Mosadegh, H., Kharazi, K., & Bazargan, A. (2011). Conducting feasibility of e-learning in gas companies in Yazd Province. *Journal of Science and Technology Information, 26*(3), 547-569.

Nisperos, L. S. (2014). Assessing the e-learning readiness of selected Sudanese universities. *Asian Journal of Management Sciences & Education, 3*(4), 45-59.

Nunnally, J., & Bernstein, I. (1994). *Psychometric theory*. McGraw-Hill.

Nwagwu, W. E. (2020). E-learning readiness of universities in Nigeria–What are the opinions of the academic staff of Nigeria's premier university? *Education and Information Technologies, 25*(2), 1343-1370. https://doi.org/10.1007/s10639-019-10026-0

Nyoni, J. (2014). E-readiness of open and distance learning (ODL) facilitators: Implications for effective mediation. *Perspectives in Education, 32*(3), 78-91.

Odunaike, A., & Dehinbo, J. (2009). Institutional e-learning readiness (a case study of TUT). In *Proceedings of the Information Systems Education Conference*.

Ojwang, C. O. (2012). *E-learning readiness and e-learning adoption among public secondary schools in Kisumu County, Kenya* [Doctoral dissertation, University of Nairobi].

Oketch, H. A. (2013). *E-learning readiness assessment model in Kenya's higher education institutions: A case study of University of Nairobi* [Doctoral dissertation, University of Nairobi].

Okinda, R. A. (2014). Assessing e-learning readiness at the Kenya Technical Teachers College. *Journal of Learning for Development, 1*(3). https://doi.org/10.56059/jl4d.v1i3.32

Omoda-Onyait, G., & Lubega, J. T. (2011). E-learning readiness assessment model: A case study of higher institutions of learning in Uganda. In *Proceedings of the International Conference on Hybrid Learning* (pp. 200-211). Springer. https://doi.org/10.1007/978-3-642-22763-9_19

Psycharis, S. (2005). Presumptions and actions affecting an e-learning adoption by the educational system-Implementation using virtual private networks. *European Journal of Open, Distance and E-learning, 8*(2).

Rohayani, A. H., Kurniabudi, & Sharippudin (2015). A literature review: Readiness factors to measuring e-learning readiness in higher education. *Procedia Computer Science, 59*, 230-234. https://doi.org/10.1016/j.procs.2015.07.564

Rosenberg, M. J. (2000). *The e-learning readiness survey: 20 key strategic questions you and your organisation must answer about the sustainability of your e-learning efforts*. http://www.books.mcgrawhill.com/training/elearning/elearning_survey.pdf

Sae-Khow, J. (2014). Developing of indicators of an e-learning benchmarking model for higher education institutions. *Turkish Online Journal of Educational Technology, 13*(2), 35-43.

Saekow, A., & Samson, D. (2011). E-learning readiness of Thailand's universities comparing to the USA's cases. *International Journal of e-Education, e-Business, e-Management and e-Learning, 1*(2), 126-131.

Saintika, Y., Astiti, S., Kusuma, D. J. A., & Muhammad, A. W. (2021). Analysis of e-learning readiness level of public and private universities in Central Java, Indonesia. *Register Jurnal Ilmiah Teknologi Sistem Informasi* [*Register of Information Systems Technology Scientific Journal*], *7*(1), 15-30. https://doi.org/10.26594/register.v7i1.2042

Schreurs, J., & Al-Huneidi, A. (2012). E-learning readiness in organizations. *International Journal of Advanced Corporate Learning, 5*(1), 4-7. https://doi.org/10.3991/ijac.v5i1.1885

Schreurs, J., Ehlers, U. D., & Sammour, G. (2008). E-learning readiness analysis (ERA): An e-health case study of e-learning readiness. *International Journal of Knowledge and Learning, 4*(5), 496-508. https://doi.org/10.1504/IJKL.2008.022066

So, T., & Swatman, P. M. C. (2006). e-learning readiness of Hong Kong teachers. *WordPress*. https://nurhadiw.files.wordpress.com/2010/08/swatman.pdf

Srichanyachon, N. (2010). Key components of e-learning readiness. *Bangkok University Academic Review, 9*(1), 55-61.

Tarus, J. K., Gichoya, D., & Muumbo, A. (2015). Challenges of implementing e-learning in Kenya: A case of Kenyan public universities. *International Review of Research in Open and Distributed Learning, 16*(1), 120-141. https://doi.org/10.19173/irrodl.v16i1.1816

Thaufeega, F. (2016). *Institutional and learner readiness for e-learning in the Maldives* [Doctoral dissertation, Brunel University]. https://doi.org/10.21125/inted.2016.1417

Usagawa, T. (2018). A comparative study of students' readiness on e-learning education between Indonesia and Myanmar. *American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS), 40*(1), 113-124.

Villarica, M. V. (2016). Mining student academic performance on ITE subjects using descriptive model approach. *Research Journal of Computer and Information Technology Sciences, 4*(11), 1-15.

Wibowo, Y. F. A., & Laksitowening, K. A. (2015). Redefining e-learning readiness model. In *Proceedings of the 3rd International Conference on Information and Communication Technology (ICoICT)* (pp. 552-557). IEEE. https://doi.org/10.1109/ICoICT.2015.7231484

Widodo, S. F. A., Wibowo, Y. E., & Wagiran, W. (2020). Online learning readiness during the COVID-19 pandemic. *Journal of Physics: Conference Series, 1700*, 012033. https://doi.org/10.1088/1742-6596/1700/1/012033

Zamani, B. E., Esfijani, A., & Damaneh, S. M. A. (2016). Major barriers for participating in online teaching in developing countries from Iranian faculty members' perspectives. *Australasian Journal of Educational Technology, 32*(3), 38-49. https://doi.org/10.14742/ajet.2678

Please cite: Bacolod, D. B. (2023). Constructs in the Institutional E-Learning Readiness Models: A Literature Review. *Journal of Research in Didactical Sciences, 2*(1), 14204. https://doi.org/10.51853/jorids/14204

Received: 28 December 2022 ● Accepted: 03 October 2023

Journal of Research in Didactical Sciences
ISSN: 2997-5905 (Online)
VOL. 2, ISSUE 1, 2023
Article No: 14205

EDITORIAL

OPEN ACCESS

Ethical Considerations in Using AI in Educational Research

Nuri Balta [1*]

[1] Suleyman Demiral University, Kazakhstan
* Corresponding author: baltanuri@gmail.com

Abstract: This editorial explores the ethical challenges associated with integrating artificial intelligence into educational settings. They highlight key ethical principles to guide AI use in educational research, including transparency, accountability, fairness, and authenticity. The author emphasizes the need for ethical frameworks to address complex issues around biases, attribution, and the human-AI division of labor.

Keywords: artificial intelligence, educational research, ethical considerations

INTRODUCTION

In the age of technological advancement, the integration of artificial intelligence (AI) has revolutionized various aspects of education, including research and scholarly writing. While AI offers remarkable opportunities to enhance the efficiency and quality of educational research, it also raises profound ethical considerations. The work by Akgun and Greenhow (2022) provides an insightful analysis into the ethical challenges faced in K-12 educational settings with the integration of AI. As custodians of academic integrity and ethical scholarship, it is imperative for authors and publishers to critically reflect on the ethical implications of AI utilization in educational research.

ETHICAL PRINCIPLES IN AI-DRIVEN EDUCATIONAL ARTICLE WRITING

At the heart of ethical AI application in educational research lie principles of transparency, accountability, fairness, and authenticity (Floridi et al., 2021; Porayska-Pomsta & Rajendran, 2019). Transparency demands that authors disclose the extent of AI involvement in the writing process, including the use of AI-generated content or language assistance tools. Accountability requires authors to take responsibility for the accuracy, integrity, and originality of the content produced with AI assistance, ensuring that it adheres to scholarly standards and citation practices. Fairness mandates that AI-driven articles do not unduly advantage or disadvantage authors based on their access to AI technologies, resources, or expertise. Authenticity emphasizes the importance of maintaining the author's voice, style, and intellectual contribution in educational research, thereby preserving academic integrity and authorship rights.

CHALLENGES AND COMPLEXITIES

Despite the ethical imperatives outlined above, navigating the intersection of AI and educational research presents numerous challenges and complexities. One such challenge is the potential for AI-generated content to inadvertently perpetuate biases or misinformation, particularly if the underlying algorithms are not adequately trained or validated (Zhou et al., 2023). Additionally, the outsourcing of writing tasks to AI systems raises questions about the appropriate division of labor, intellectual ownership, and academic credit (Oprysk, 2023). Moreover, the use of AI language assistance tools may blur the boundaries between original authorship and automated content generation, posing challenges to scholarly attribution and citation practices.

GUIDING ETHICAL FRAMEWORKS

To address these challenges and uphold ethical standards in using AI in educational research, authors and publishers can draw upon existing frameworks and guidelines. The Committee on Publication Ethics (COPE), for instance, provides ethical guidelines for authors and publishers, emphasizing the importance of transparency, integrity, and accountability in scholarly communication. Similarly, the principles for responsible AI in educational research, can be developed by leading experts and organizations, offer guiding principles for the ethical design, deployment, and evaluation of AI technologies in educational research contexts. By adhering to such frameworks and integrating ethical considerations into every stage of the research process, stakeholders can mitigate risks, foster trust, and maximize the societal benefits of AI in educational research.

CONCLUSION

As AI continues to transform the landscape of educational research, it is incumbent upon authors, editors, and publishers to prioritize ethical considerations and uphold the highest standards of scholarly integrity. By embracing principles of transparency, accountability, fairness, and authenticity, we can harness the transformative potential of AI technologies while safeguarding the integrity of educational research and publication. Moving forward, it is essential for all stakeholders to engage in critical reflection, dialogue, and collaboration to ensure that using AI in educational research serves the greater good and advances the pursuit of knowledge and understanding in our global community.

REFERENCES

Akgun, S., & Greenhow, C. (2022). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. *AI and Ethics, 2*(3), 431-440. https://doi.org/10.1007/s43681-021-00096-7

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2021). An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. In L. Floridi (Ed.), *Ethics, governance, and policies in artificial intelligence* (pp. 19-39). Springer. https://doi.org/10.1007/978-3-030-81907-1_3

Oprysk, L. (2023). Intellectual property rights and data ownership. In M. Ebers, & P. K. Tupay (Eds.), *Artificial intelligence and machine learning powered public service delivery in Estonia* (pp. 173-189). Springer. https://doi.org/10.1007/978-3-031-19667-6_10

Porayska-Pomsta, K., & Rajendran, G. (2019). Accountability in human and artificial intelligence decision-making as the basis for diversity and educational inclusion. In J. Knox, Y. Wang, & M. Gallagher (Eds.), *Artificial intelligence and inclusive education: Speculative futures and emerging practices* (pp. 39-59). Springer. https://doi.org/10.1007/978-981-13-8161-4_3

Zhou, J., Zhang, Y., Luo, Q., Parker, A. G., & De Choudhury, M. (2023). Synthetic lies: Understanding AI-generated misinformation and evaluating algorithmic and human solutions. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (pp. 1-20). ACM. https://doi.org/10.1145/3544548.3581318

Please cite: Balta, N. (2023). Ethical Considerations in Using AI in Educational Research. *Journal of Research in Didactical Sciences, 2*(1), 14205. https://doi.org/10.51853/jorids/14205