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PAPER

Emerging Technologies in Learning: A Bibliometric Analysis of Technology Integration and Applications

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ABSTRACT

Smart learning, a field marked by rapid evolution and innovation, leverages emerging technologies to address modern educational challenges, transforming teaching methodologies and driving significant progress. This study analyzes the impact of key technologies, including artificial intelligence (AI), the Internet of Things (IoT), big data, and generative AI, between 2010 and 2024 using bibliometric and content analysis methods. Drawing from Scopus and Web of Science (WoS) databases, it highlights how these innovations foster personalized learning environments and dynamic educational content. The findings reveal exponential growth in research on AI and the IoT in education since 2015, with major contributions from Chinese and American researchers. The study profiles influential researchers, leading institutions, and pioneering countries, offering insights into the evolving landscape of smart education. By examining trends and the interplay between technology and educational reform, the paper underscores the importance of data-driven strategies for designing and implementing adaptive learning systems. It also anticipates future challenges and opportunities, proposing a framework to guide ethical integration of these technologies into education, ensuring they enhance global learning outcomes in an increasingly digital world.

KEYWORDS

artificial intelligence (AI), bibliometric, big data, generative AI, Internet of Things (IoT), smart learning, m-learning

1 INTRODUCTION

Smart learning represents a strategic evolution in educational methodologies, heavily influenced by the rapid advancement of digital technologies. At its core, smart learning refers to the integration of technological systems and tools designed to enhance learning environments [1]. These systems not only personalize educational experiences to meet the unique needs of individual learners but also improve the accessibility and effectiveness of educational resources across diverse contexts [2].

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Emerging technologies, such as artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), big data analytics, and generative AI, are central to this transformation. AI, for instance, powers adaptive learning platforms capable of analyzing real-time learner data to deliver personalized content and feedback. The IoT connects physical and digital environments, enabling immersive and interactive learning experiences. Big data analytics provides critical insights by exploring vast educational datasets, facilitating the continuous refinement of educational strategies and outcomes. Generative AI further enhances these systems by creating new educational content, such as text, images, or simulations, thus fostering innovative teaching methods. Together, these technologies are reshaping educational paradigms, making learning more interactive, accessible, and efficient.

This technological evolution is transforming traditional educational environments into dynamic, interactive, and personalized learning ecosystems [3, 4]. AI and ML are leading this transformation by enabling platforms that analyze student performance in real time and provide tailored content and feedback. IoT technologies complement these systems by integrating physical and virtual classrooms, creating seamless and immersive educational experiences [5]. The proliferation of big data analytics further enhances these advancements, offering educators actionable insights for continuous improvement of teaching methodologies [6]. These innovations not only increase learner engagement and retention but also empower educators with tools to monitor progress and identify areas requiring intervention.

As the adoption of these technologies grows, the educational landscape is increasingly characterized by more personalized, efficient, and accessible learning solutions. This heralds a new era of "mart learning," poised to redefine educational standards globally. The integration of these technologies not only prepares students to navigate the digital world proficiently but also equips them with the skills necessary to address the challenges of an ever-evolving digital era [7, 8].

This study aims to explore the technological innovations shaping education through a bibliometric analysis of scientific publications spanning 2010 to 2024. The objective is to map the evolution of educational technologies, identify key trends, and uncover research gaps. Section 2 provides a comprehensive literature review to establish a theoretical framework, contextualize the study, and highlight significant contributions and paradigm shifts in the adoption of educational technologies. Section 3 details the methodological approach, including the databases accessed, criteria for article selection, and statistical tools used for analysis, ensuring transparency and reproducibility. The results of the bibliometric analysis will then be presented, highlighting emerging trends, the most active regions, and the impacts of these technologies on pedagogical practices. Finally, the discussion will synthesize key findings, propose future research directions, and address the implications of technological integration in education.

2 LITERATURE REVIEW

The educational landscape is undergoing a profound transformation driven by the integration of advanced technologies such as AI, ML, the IoT, big data analytics, and generative AI. These innovations are reshaping how educational content is delivered and how students interact with learning materials. Beyond enhancing infrastructure and operational frameworks in educational institutions, these technologies are critical for personalizing learning experiences, improving educational outcomes, and streamlining processes [9]. This evolution highlights a pivotal research area in modern educational science, emphasizing the importance of understanding and effectively implementing these technologies.

The impact of advanced technologies is not limited to education but extends to various other fields. For instance, Igbinenikaro et al. discuss the use of cutting-edge tools in underwater surveys [10], while Zala et al. explore how Vision Transformer technology is revolutionizing fruit disease classification [11]. These examples demonstrate how innovative technologies are being adapted across disciplines to enhance efficiency and effectiveness.

In more complex contexts, Roy, Millican, and Agrawal highlight the potential of ML in testing electronic components, particularly for enhancing hardware security [12]. Similarly, Shi et al. illustrate how entity embedding learning can refine knowledge graph accuracy, significantly benefiting quality assessment in cybersecurity [13]. Such studies underline the transformative potential of emerging technologies across various professional domains.

In the educational sector specifically, these technologies are influencing early learning through digital audio and robotics, as explored by Y. Xu in preschool music education [14]. Intelligent e-learning systems exemplify how technology is driving educational reform. Arumugam et al. further extend this discussion by demonstrating how AI, big data, and ML are revolutionizing smart marketing and business strategies [15].

Other sectors are also witnessing the transformative power of these technologies. In healthcare, M.U. Tariq highlights the role of AI in advancing medical diagnostics [16], while Gökhan et al. demonstrate the application of neural networks and ML to improve outcomes in assisted reproductive technologies [17]. Liu et al. assess human-robot interaction in construction, emphasizing its potential to enhance efficiency [18]. However, the work of Singh and Rani on the ethical and legal challenges in applying ML to medical imaging underscores the need for robust regulatory frameworks to address privacy and ethical concerns [19].

Collectively, these studies underscore the diverse applications of AI and related technologies across sectors and their potential to transform educational practices. By enhancing learning environments, streamlining administrative processes, and optimizing pedagogical strategies, these technologies hold immense promise for education and beyond.

3 METHODOLOGY

This study employed a bibliometric analysis based on the recommendations of Aria and Cuccurullo [20, 21]. The research process was organized into three main steps. First, we collected the data by loading it and converting it into an appropriate format. During this phase, we identified potential sampling biases, particularly those arising from relying exclusively on databases such as Scopus and Web of Science (WoS), which might exclude relevant studies published in other languages or on less prominent platforms. To address this limitation, we diversified our keywords and encompassed a broad range of disciplines during data collection.

Next, we analyzed and synthesized the collected data to draw meaningful conclusions. Special attention was given to publication bias, which often favors studies reporting significant or innovative findings. To mitigate this, we ensured a transparent methodology, emphasizing inclusivity and cross-validation of results. Finally, the outcomes of our analysis were presented through visualizations to enhance comprehension and facilitate interpretation.

4 RESULTS AND DISCUSSION

4.1 Data collection: Loading and conversion of data

Our study began with the extraction of data from two major databases: Scopus and WoS. These datasets were then merged to facilitate the analysis of e-learning trends and the various technologies employed to enhance learning.

To collect the relevant data, we defined a set of search keywords, including terms such as smart learning, combined with emerging technologies such as the IoT, AI, generative AI, and big data. Our analysis covered the period from 2010 to 2024, focusing exclusively on research articles and conference papers. This process yielded a total of 289 documents. Table 1 provides an overview of the research protocol, detailing the specific keyword combinations used and the corresponding results.

Table 1. Advanced data search with criteria

Database	Criteria	Advanced Search	Results
Web of Science	• Advanced search, • Date of publication after 2009, • Relevant articles, • Articles in journals and conferences, • Documents written in English, • Articles limited to the fields of computer science, mathematics, education and engineering.	(TS=("smart learning") AND TS=("Internet of things" OR "Artificial intelligence" OR "Generative AI" OR "Big data" OR "IoT" OR "IA"))	**133**
Scopus		TITLE-ABS-KEY ("Smart learning") AND TITLE-ABS-KEY ("Internet of things" OR "IoT" OR "Big data" OR "Artificial intelligence" OR "IA" OR "Generative AI") AND ")) AND PUBYEAR > 2001 AND (LIMIT-TO (LANGUAGE, "English"))	**262**
106 duplicated documents were removed for this study			**289**

Extracting data in BibTeX format from the WoS and Scopus databases involves several key steps. First, access to the databases is obtained via their respective interfaces. The next step is to define precise search criteria to identify articles relevant to the study. Once the search results are retrieved, the articles meeting the specified criteria are selected and exported in BibTeX format [22]. This process may involve utilizing the export features built into the databases or employing third-party tools to convert the data into the desired format. Finally, the extracted BibTeX data was imported into RStudio, where bibliometric analysis software was employed to conduct more detailed and advanced analyses.

Table 2. Data conversion and merging steps

Steps	Instructions on How to Merge Data Using R-Studio
1	Extract data in BibTeX format from WoS and Scopus databases.
2	Save the data to a directory.
3	Install the Bibliometrix packages by running the following script:install.packages("bibliometrix").
4	Run the following script:library(bibliometrix) to import the Bibliometrix library.
5	Open the file created in step 2 by running the following script:setwd("C:/.../Name of file created in step 2").
6	Save the data in the same file created in step 2.

Following the completion of the steps outlined in Table 2, we executed the scripts shown in Figure 1:

Fig. 1. Script details

4.2 Data analysis and overview methods

Bibliometric analysis data. Table 3 presents a summary of the bibliometric analysis, showcasing the distribution of document types within the collected dataset. The results reveal that conference documents (n = 128) constitute the largest proportion, followed by journal articles (n = 104). The remaining document types, totaling 57, complete the dataset. To perform a more in-depth analysis, we examined the entire dataset using the advanced criteria outlined in Table 1. This approach enabled us to extract meaningful insights into the prevailing trends and themes within the research domain under investigation.

Table 3. Main information overview

Description	Results
Main Information about Data	
Timespan	2010:2024
Sources (Journals, Books, etc)	207
Documents	289
Annual Growth Rate %	18.68
Document Average Age	4
Average citations per doc	7.422
References	1315
Document Contents	
Keywords Plus (ID)	1486
Author's Keywords (DE)	848
Authors	
Authors	788
Authors of single-authored docs	31
Authors Collaboration	
Single-authored docs	47
Co-Authors per Doc	3.35
International co-authorships %	2.422

(Continued)

Table 3. Main information overview *(Continued)*

Description	Results
Document Types	
Article	104
Article conference paper	1
Article early access	1
Book	2
Book chapter	17
Conference paper	128
Conference paper article	1
Conference review	15
Proceedings paper	14
Review	6

The data analyzed offers a comprehensive view of the evolution of research and publications in the studied field over an extended period, spanning from 2010 to 2024. Drawn from a diverse array of sources totaling 207, the dataset underscores the richness and breadth of references utilized in this analysis. The scale of academic output is notable, with a total of 289 documents identified, reflecting sustained research activity over the years. The average annual growth rate of 18.68% is a compelling indicator of the dynamic nature and increasing prominence of this research area. This consistent growth highlights a rising interest in the topics explored, with new contributions continuously enriching the field. The average age of the papers, at just four years, further emphasizes the field's evolving nature, marked by the regular introduction of updated ideas and findings.

Citation activity within the dataset is substantial, with an average of 7.42 citations per document, signifying the high impact and relevance of the published works. This demonstrates the significant influence these studies exert on ongoing research and academic discussions in related domains. The dataset also reveals an extensive knowledge base, evidenced by a total of 1,315 cited references. This robust foundation illustrates the depth of existing scholarship on which researchers have built their work. Furthermore, the inclusion of additional and author-provided keywords highlights meticulous efforts in organizing and classifying information, facilitating easier access to relevant content.

Collaboration among researchers emerges as a key feature, with an average of 3.35 co-authors per document. While the majority of collaborations are domestic, the dataset also reflects a degree of international cooperation, albeit relatively modest, at 2.42%. This openness to global exchange indicates a growing but still limited emphasis on cross-border academic collaboration. In terms of document types, conference papers dominate, followed by journal articles and book chapters.

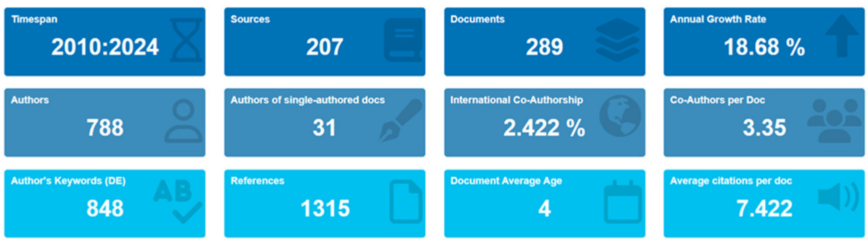

Fig. 2. Main information overview

Countries scientific production. Figure 3 presents the geographical distribution of scientific production in the field of innovative educational technologies. The varying shades of blue represent the volume of contributions, with China emerging as the leading contributor, indicated by the darkest shade. The United States, India, and several European countries also demonstrate substantial contributions, albeit to a lesser extent than China. This distribution underscores a concentration of research outputs in specific regions, suggesting a dominance of these countries in advancing the field.

region	Freq	region	Freq
CHINA	63	OMAN	3
INDIA	39	PAKISTAN	3
SPAIN	21	OUTH AFRIC	3
USA	18	THAILAND	3
PERU	17	BAHRAIN	2
SAUDI ARABIA	13	ANGLADESI	2
SERBIA	11	CYPRUS	2
UK	11	IRAN	2
SOUTH KOREA	10	IRELAND	2
CANADA	9	JORDAN	2
MOROCCO	9	MAURITIUS	2
BULGARIA	7	COLOMBIA	1
INDONESIA	7	DENMARK	1
TUNISIA	7	FINLAND	1
BRAZIL	6	ITALY	1
MALAYSIA	6	KENYA	1
MEXICO	6	LEBANON	1
RUSSIA	6	LITHUANIA	1
JAPAN	5	NAMIBIA	1
ROMANIA	5	PORTUGAL	1
CZECH REPUBLIC	4	SLOVAKIA	1
GREECE	4	SRI LANKA	1
SINGAPORE	4	WITZERLAN	1
UNITED ARAB EMIRATES	4	UKRAINE	1
AUSTRALIA	3	GERMANY	3
EGYPT	3	LATVIA	3

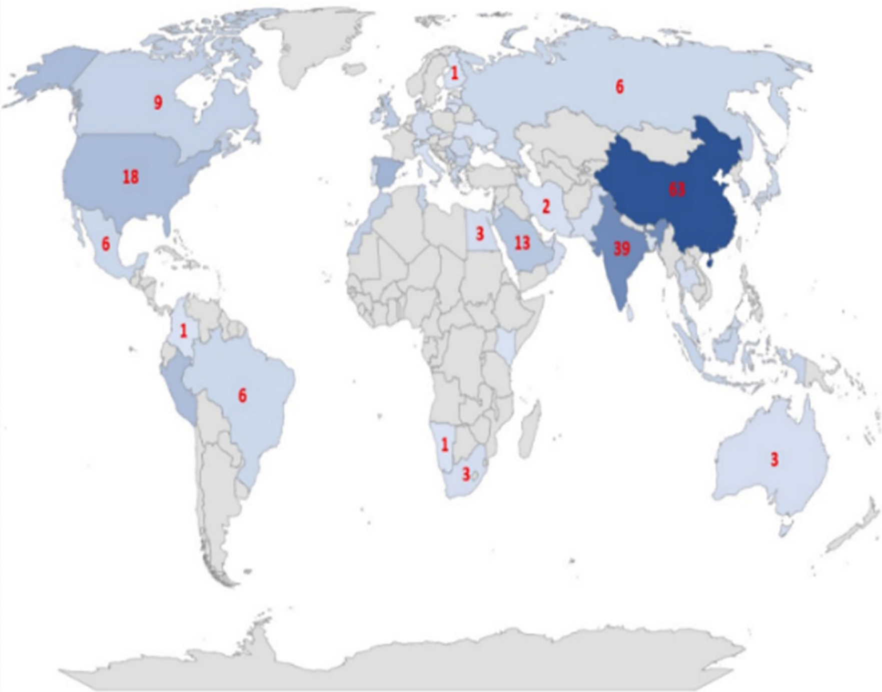

Fig. 3. Countries scientific production

Annual scientific production. Figure 4 depicts the annual production of scientific articles on intelligent learning, revealing a generally increasing trend from 2010 to a peak in 2019. This upward trajectory reflects the growing interest and investment in this research area during the decade. However, 2020 marked a sharp decline in publications, likely attributable to the widespread disruptions caused by the COVID-19 pandemic. By 2021, the scientific community demonstrated resilience and adaptation, as evidenced by a partial recovery in publication numbers. Despite this rebound, production levels have yet to return to their pre-pandemic peak.

The subsequent decline observed in 2022 raises pertinent questions about the current dynamics of research in intelligent learning. This downturn may indicate shifting academic priorities, saturation in certain research themes, or the influence of external factors affecting the pace of scholarly output. Understanding these trends warrants further investigation to identify underlying causes and assess the future trajectory of this evolving field.

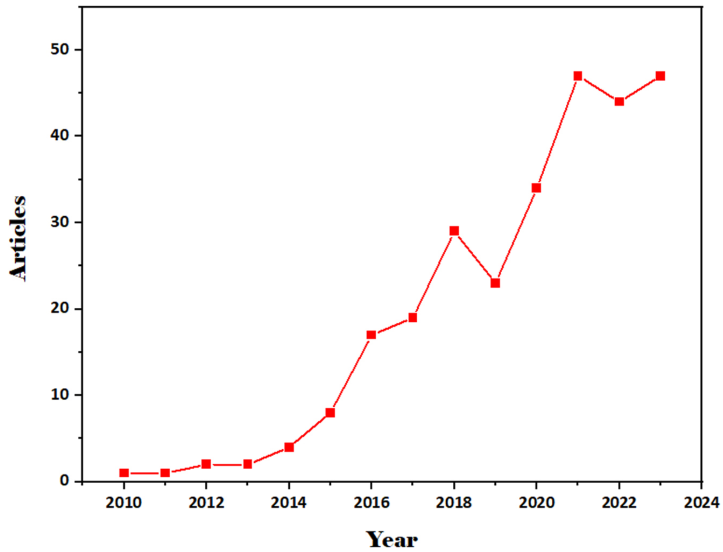

Fig. 4. Annual scientific production

Average number of citations per year. Figure 5 illustrates the average number of citations per year over the specified period. The data reveals considerable volatility in citation counts, with notable peaks and troughs throughout the timeline. For instance, after a peak in 2010, there was a subsequent decline, followed by further fluctuations in both upward and downward directions. A significant increase in citations is observed around 2020, but this surge was followed by an equally sharp decline in 2022. This pattern highlights the variability in the impact and recognition of published work, as measured by citations, suggesting that scholarly attention fluctuates from one year to the next.

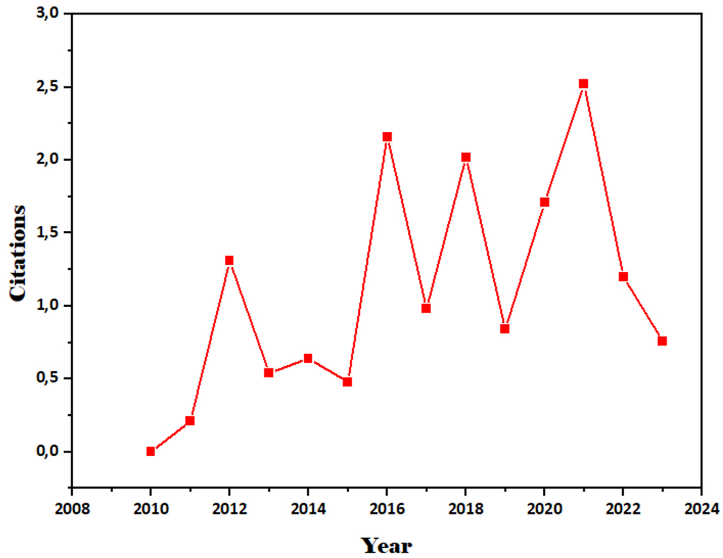

Fig. 5. Average number of citations per year

Three-field plot of active institutions and countries publishing articles related to keywords. Figure 6 highlights the dominant role of universities in China, India, and the United States within the e-learning field, reflecting their significant involvement in educational technologies. These institutions are closely linked to advanced domains such as AI and smart learning, with the varying thickness of the connections indicating the level of activity or strength of association in these areas. This visualization serves as a valuable analytical tool for identifying global trends in educational innovation, showcasing regions and institutions that are at the forefront of the evolution of educational technologies.

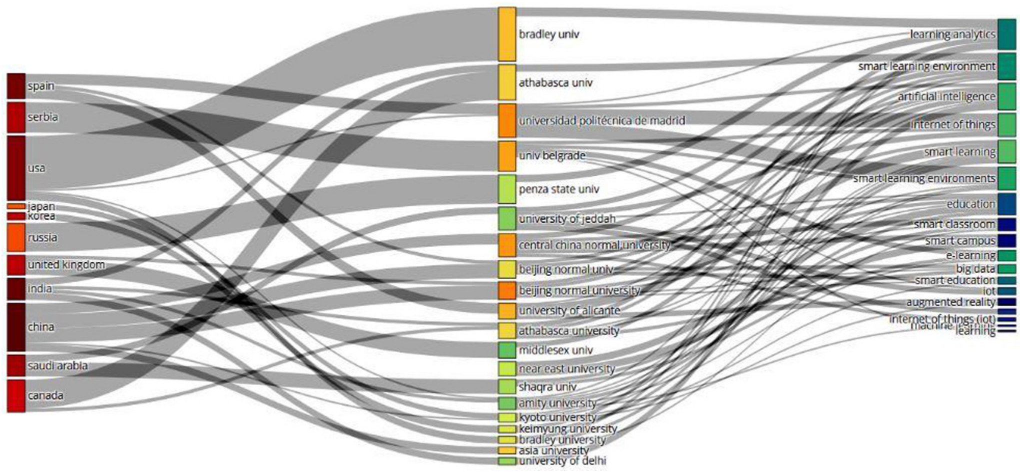

Fig. 6. Three-field plot of active institutions and countries publishing articles related to keywords

Three-field plot of active authors and countries publishing articles related to keywords. Figure 7 illustrates the relationships between countries, authors, and their research areas in advanced educational technologies. Countries such as Spain, the United States, and China are linked to authors contributing to research on topics like smart learning environments and the IoT. The connections between authors and keywords reflect their specific contributions to particular research niches.

The thickness of the lines appears to represent the volume of research or activity associated with each author, providing a visual indication of their level of involvement in the field. This chart serves as a valuable tool for identifying thought leaders and emerging trends in educational technology research. Additionally, it highlights potential areas for international collaboration between countries and researchers.

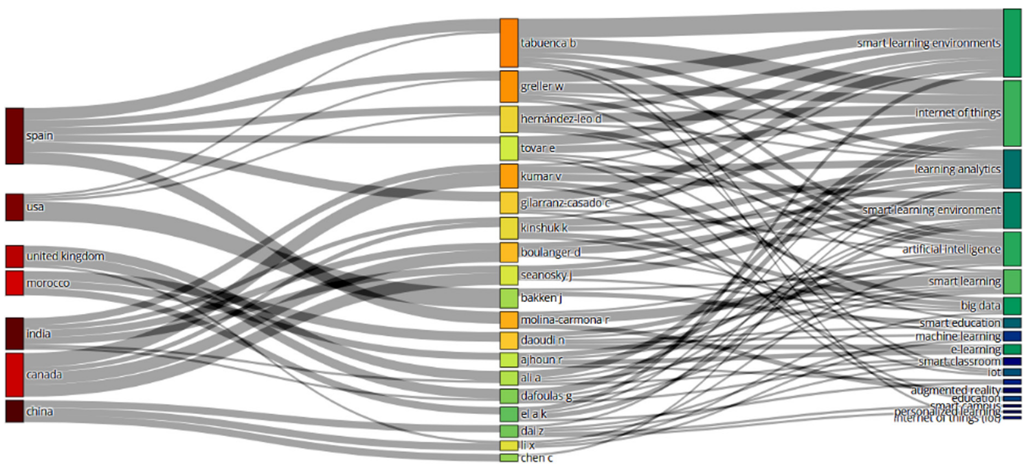

Fig. 7. Three-field plot of active authors and countries publishing articles related to keywords

Authors local impact. Figure 8 presents the authors' h-index, a metric used to assess their impact within their field of research. Several authors have an h-index of 3, while a few stand out with an h-index of 4, indicating that they have more highly cited publications. Larger circles represent a higher h-index, visually highlighting the greater impact of these authors compared to their peers.

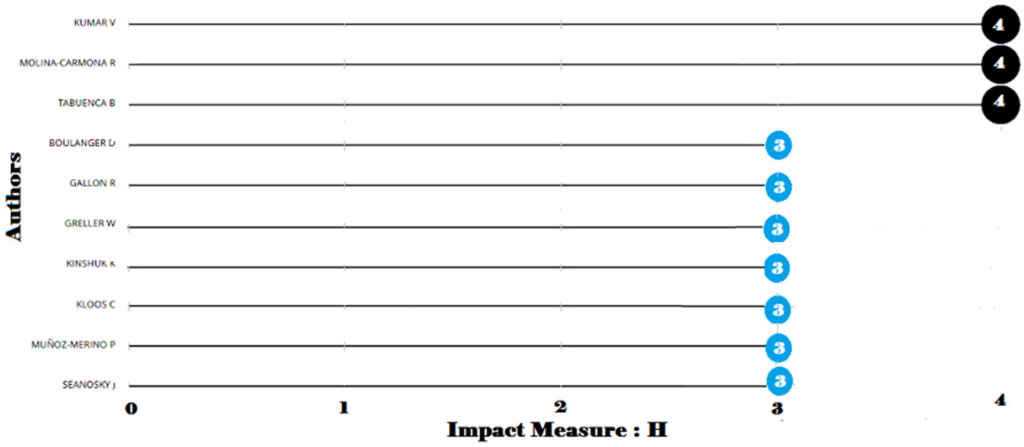

Fig. 8. Authors local impact

Most cited countries. Figure 9 presents a bubble chart illustrating the number of citations per country in a specific research area or academic publication. China stands out with the highest number of citations, represented by the largest bubble positioned farthest to the right of the graph, indicating its status as the most cited or influential country in this field. Other countries, including Pakistan, Spain, and Hong Kong, follow with notable citation counts, although significantly lower than China's. The size of each bubble is proportional to the number of citations, providing a clear visual representation of each country's relative impact in the field.

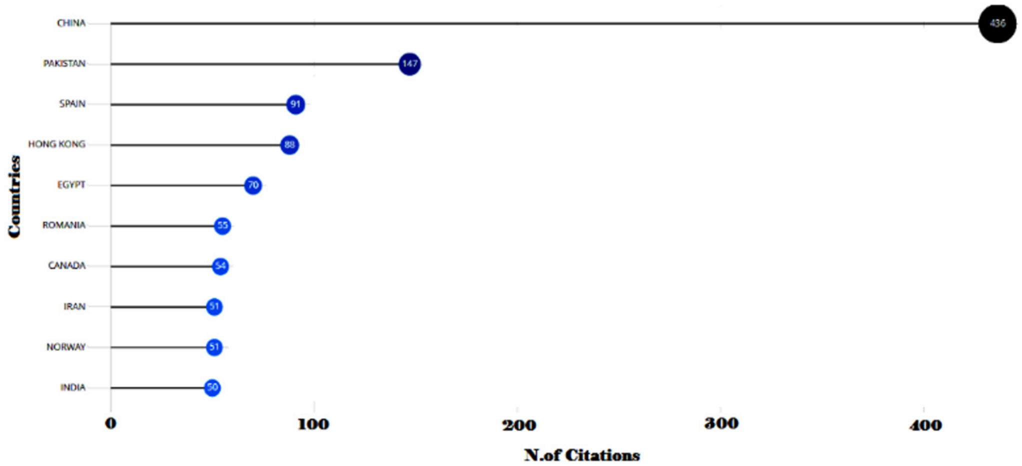

Fig. 9. Most cited countries

Reference spectroscopy. Figure 10 illustrates the evolution of the number of citations in the field of spectroscopy over the years. The chart reveals a generally stable and modest level of citations, followed by a noticeable increase at a certain point, signaling a renewed interest or significant advancements in this area of research. Distinct peaks in the graph suggest periods when spectroscopy was central to major scientific discoveries or innovative applications. More recently, there has been a sharp rise in citations, followed by a rapid decline. This fluctuation may reflect changes in publication practices or shifts in the popularity of specific spectroscopic methods over time.

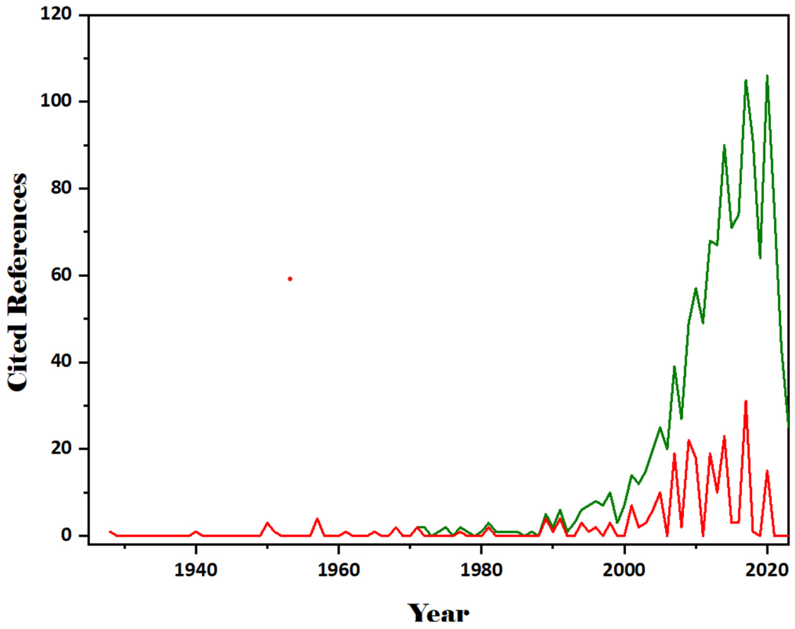

Fig. 10. Reference spectroscopy

Author productivity using Lotka's law. Figure 11 depicts author productivity in the field of smart learning, analyzed according to Lotka's law. Lotka's law suggests that the number of authors making *nnn* contributions is approximately inversely proportional to *n2n* ^ *2n2* [23]. The graph illustrates a steep decline in the percentage of authors as the number of documents increases. Specifically, a large proportion of authors have written only a single document, while very few authors have contributed a significant number of documents, as evidenced by the sharp drop-off in the curve after the first few publications. This trend highlights that in the domain of smart learning, a small number of prolific authors account for a substantial portion of the literature, while the majority of authors make minimal contributions.

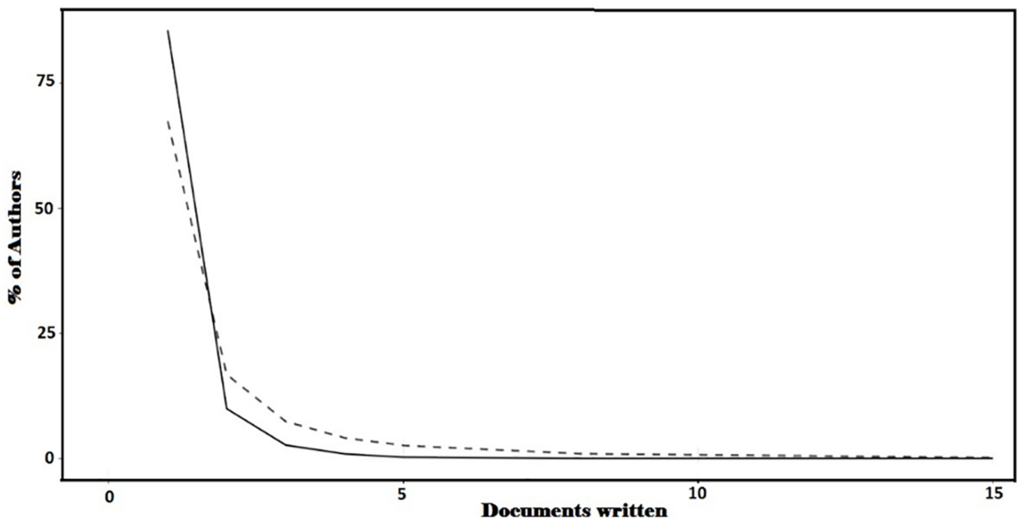

Fig. 11. Author's productivity using Lotka's law

Sources production over time. Figure 12 presents a comparison of cumulative trends on various topics from 2010 to 2024, with trajectories that reflect the degree of attention each topic has received over time. Some topics show a steady, sustained increase, indicating ongoing, gradual interest. Others exhibit explosive growth at certain points, likely driven by significant innovations or events. Additionally, the appearance of plateaus suggests a slowdown in interest or a stabilization following periods of growth. The diversity of the curves highlights the varying dynamics of each topic, illustrating the complexity and evolution of knowledge areas and their shifting prominence in both academic and public interest. This graphical overview serves as a valuable tool for analyzing trends and forecasting future developments in the research landscape and the popularity of specific topics.

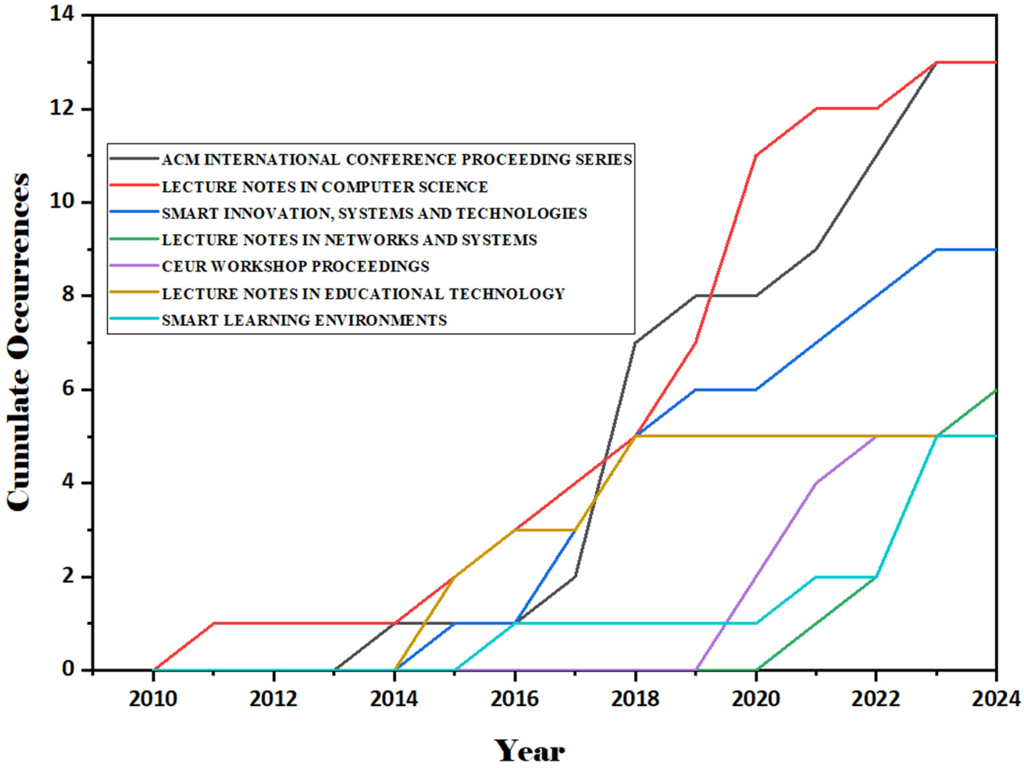

Fig. 12. Sources production over time

Sources local impact. Figure 13 presents a bar graph illustrating the scientific impact of various sources, such as journals and conference series, as measured by the H-index. The horizontal axis represents the H-index, an indicator that reflects both the quantity and impact of research published by these sources. The vertical axis lists the different sources.

The graph reveals that *Lecture Notes in Computer Science* has the highest H-index score of 6, suggesting a significant level of citations and, likely, considerable influence within its field. Other sources, such as *Advances in Intelligent Systems and Computing* and *Lecture Notes in Educational Technology*, show slightly lower H-index scores, indicating a somewhat less pronounced, but still notable, impact. Sources with an H-index of 2 appear to have a relatively lower impact within their respective domains.

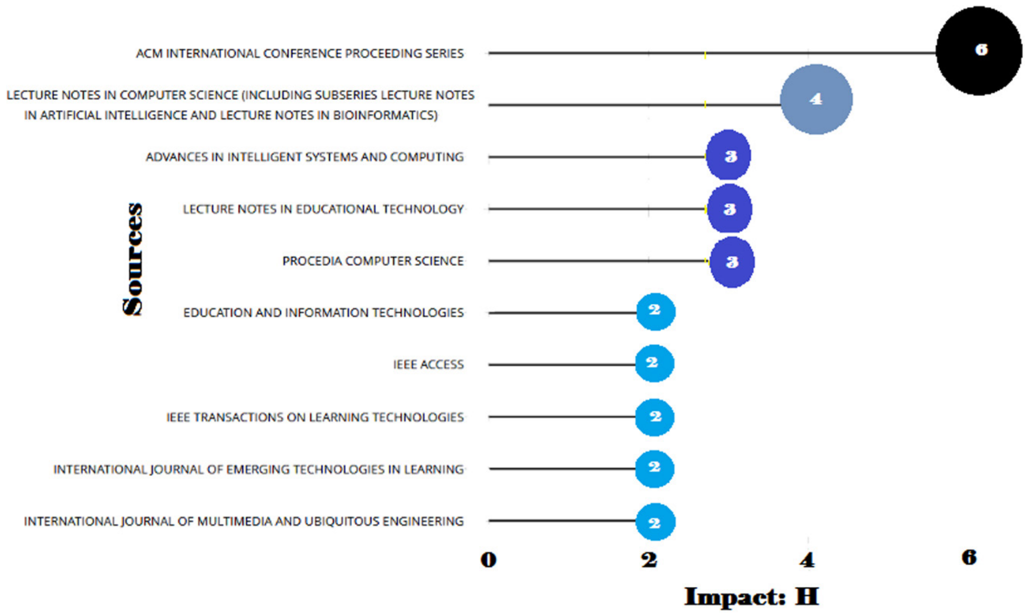

Fig. 13. Sources local impact

Core sources of Bradford's law. Figure 14 is similar to a Bradford chart, a common tool in bibliometric analysis used to assess the distribution of publications within a specific research field. This type of chart helps identify the most influential journals or conferences by displaying the number of articles published by each source. The shaded area, labeled "Core Sources," highlights the most prolific sources that typically dominate the literature in the given field. These sources contribute the highest number of publications, which are central to the development and dissemination of knowledge in the field.

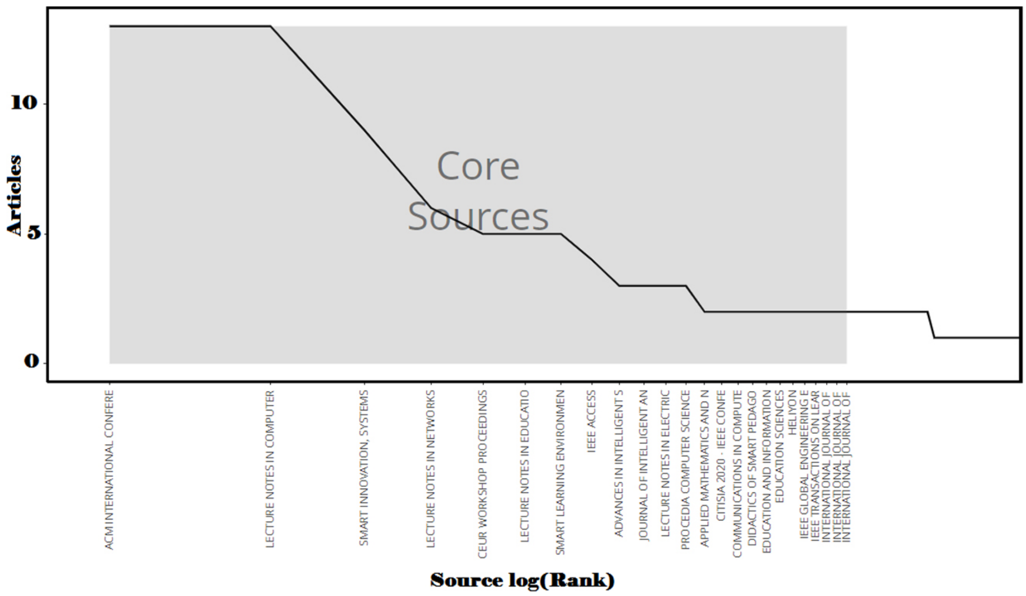

Fig. 14. Core sources of Bradford's law

Countries production over time. Figure 15 illustrates the production of scientific articles on innovative educational technologies in the top five countries.

There is a noticeable upward trend in article production across all countries, with China leading the way, reaching nearly 70 publications by 2024. India follows closely with around 50 publications. The United States and Spain show similar production levels, each with approximately 40 articles. Although Peru is less productive, it exhibits a notable increase post-2020, reaching around 25 articles by 2024. These trends highlight the global surge in interest and growth in research on smart and convergent educational technologies, with China and India making particularly strong contributions. The chart underscores the significance of these countries in advancing research and innovation in the field while also demonstrating a diverse geographical distribution of scientific production.

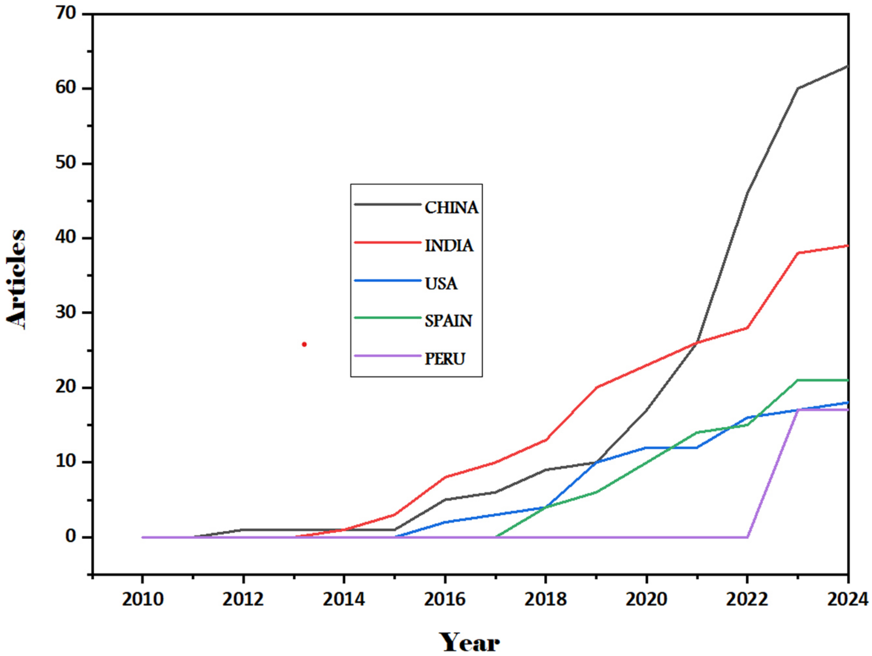

Fig. 15. Countries' production over time

4.3 Discussion

The integration of advanced technologies in education has led to transformative changes, particularly in teaching methodologies, learning environments, and educational outcomes. This study explores these advancements through a bibliometric analysis of the Scopus and WoS databases, identifying key developments and contributions in the field of education, particularly in relation to technological advancements over the years.

When comparing the impact of different technologies, AI and ML stand out for their ability to personalize learning experiences. AI-driven adaptive learning platforms can analyze student performance in real-time, offering personalized feedback and content tailored to individual needs [24]. This contrasts with traditional one-size-fits-all educational models and highlights a significant improvement in addressing diverse learning paces and styles. For example, AI in intelligent tutoring systems has been transformative, adapting to student responses and offering additional resources to facilitate understanding [25, 26]. In contrast, traditional educational methods rely on static resources that do not adapt to learner progress, potentially leading to disengagement and ineffective learning outcomes.

The IoT enhances educational environments by creating interconnected learning spaces. Smart classrooms, equipped with IoT devices, can monitor environmental conditions and adjust them for optimal learning [27]. Additionally, IoT facilitates the integration of physical and virtual learning spaces, promoting a blended learning approach that is both flexible and immersive [28]. Big data analytics also plays a crucial role in educational advancements. By analyzing vast amounts of educational data, educators can identify trends and patterns that inform teaching strategies and policy decisions [29], [30]. For instance, early identification of at-risk students through data analytics enables timely interventions, improving retention and success rates [31].

To assess the full potential of these technologies, it is critical to examine their long-term impact on educational outcomes and engagement. Longitudinal studies that track the sustained effects of AI, IoT, and big data over extended periods are essential for understanding how these technologies influence learning processes and outcomes. Such research can provide insights into the scalability and adaptability of these solutions in diverse educational contexts, helping stakeholders refine and optimize their implementation. Furthermore, exploring the impact of these technologies on teacher-student interactions and engagement levels will shed light on their ability to foster meaningful learning experiences and support sustained academic progress. These insights will guide the development of ethical frameworks and practical guidelines for integrating technology into education effectively.

To maximize the benefits of these technologies, several recommendations are proposed. First, teachers should receive comprehensive training on the use of AI, IoT, and big data tools to effectively integrate these technologies into their teaching practices. This training should include both technical skills and pedagogical strategies to ensure that technology enhances the learning process. Second, collaboration between technologists, educators, and policymakers is crucial for developing tools that address real educational needs. This collaborative approach ensures that technological solutions are both practical and scalable [32]. Third, it is essential to address ethical concerns such as data privacy, consent, and the potential for bias in AI algorithms. Establishing clear ethical guidelines and robust data protection measures will help maintain trust and integrity in educational technologies. Finally, governments and educational institutions should invest in the infrastructure needed to support the widespread adoption of smart technologies, including high-speed internet, reliable power supplies, and secure digital platforms.

Future research should focus on several key areas to advance the integration of technology in education. Longitudinal studies assessing the sustained impact of AI, IoT, and big data on educational outcomes will provide valuable insights into the effectiveness of these technologies over time [33]. Interdisciplinary approaches combining insights from education, psychology, computer science, and data analytics can lead to more holistic and effective technological solutions. Research should also explore ways to make advanced educational technologies scalable and accessible, particularly in underserved regions, by developing low-cost solutions and ensuring that technologies can be adapted to different educational contexts. Finally, understanding how these technologies affect the roles of teachers and students is crucial. Research should investigate how technology can enhance teacher-student interactions and promote active, engaged learning.

This bibliometric study on smart learning and related technologies highlights both the opportunities and challenges these advancements bring. As the educational landscape evolves, a thoughtful and informed approach is essential for integrating these technologies in ways that enrich education while upholding ethical standards and fostering inclusion. Our analysis specifically focuses on emerging technologies in education, revealing a more rapid adoption of the Internet of Things.

5 CONCLUSION

The bibliometric analysis conducted in this study highlighted key trends and the evolution of technologies in the field of smart learning, focusing on areas such as AI, the IoT, big data, and generative AI. These technologies are profoundly transforming teaching methods, making education more adaptive, personalized, and accessible. By integrating big data analytics and delivering generative educational content, these tools hold immense potential to enhance learning environments and provide innovative solutions that support educators. However, the deployment of these technologies also presents significant challenges, particularly in terms of data security, privacy, and the ethical implications of AI usage. To fully realize the benefits of these innovations in an equitable manner, it is crucial to establish clear regulations and provide comprehensive user training. Collaboration between educational institutions, policymakers, and technology developers is essential to create robust regulatory frameworks and develop tailored training programs that prepare students for an integrated digital future.

This study underscores that the thoughtful adoption and integration of advanced technologies can substantially enhance the learning experience. However, it is vital to continue exploring these technologies while proactively addressing the ethical concerns and practical challenges they present within educational settings. By doing so, we can ensure that technological innovation in education contributes positively to the development of future generations, equipping them with the skills necessary to thrive in an increasingly data-driven economy. Although our study offers a new perspective on the integration of technologies in education, it is limited by the selection of databases used for analysis. Future research could expand the scope by including additional databases to provide a more comprehensive view of the evolving landscape of educational technologies.

6 REFERENCES

[1] A. Dehbi, A. Bakhouyi, A. M. Khaddar, and M. Talea, "Education and smart technologies: Towards a new pedagogical paradigm," *International Journal of Evaluation and Research in Education,* vol. 14, no. 1, pp. 297–309, 2025. https://doi.org/10.11591/ijere.v14i1.30470

[2] A. Dehbi, A. Bakhouyi, R. Dehbi, and M. Talea, "MOOCs in smart education: Comparative study by applying AHP and COPRAS method," *International Journal of Emerging Technologies in Learning (iJET),* vol. 17, no. 8, pp. 61–74, 2022. https://doi.org/10.3991/ijet.v17i08.27871

[3] K. Palanivel, "Emerging technologies to smart education," *Int. J. Comput. Trends Technol (IJCTT),* vol. 68, no. 2, pp. 5–16, 2020. https://doi.org/10.14445/22312803/IJCTT-V68I2P102

[4] T. Karakose *et al.*, "Assessment of the relationships between prospective mathematics teachers' classroom management anxiety, academic self-efficacy beliefs, academic amotivation and attitudes toward the teaching profession using structural equation modelling," *Mathematics,* vol. 11, no. 2, p. 449, 2023. https://doi.org/10.3390/math11020449

[5] A. Dehbi, R. Dehbi, A. Bakhouyi, and M. Talea, "Survey analysis of students and teachers' perceptions of e-learning and m-learning in Morocco," *International Journal of Interactive Mobile Technologies (iJIM),* vol. 17, no. 3, pp. 102–122, 2023. https://doi.org/10.3991/ijim.v17i03.36325

[6] M. A. Ayanwale, R. R. Molefi, and S. Oyeniran, "Analyzing the evolution of machine learning integration in educational research: A bibliometric perspective," *Discover Education,* vol. 3, 2024. https://doi.org/10.1007/s44217-024-00119-5

[7] A. Dehbi, A. Bakhouyi, R. Dehbi, and M. Talea, "Smart evaluation: A new approach improving the assessment management process through Cloud and IoT technologies," *International Journal of Information and Education Technology,* vol. 14, no. 1, pp. 107–118, 2024. https://doi.org/10.18178/ijiet.2024.14.1.2030

[8] S. Papadakis, "MOOCs 2012–2022: An overview," *Advances in Mobile Learning Educational Research,* vol. 3, no. 1, pp. 682–693, 2023. https://doi.org/10.25082/AMLER.2023.01.017

[9] A. Haleem, M. Javaid, M. A. Qadri, and R. Suman, "Understanding the role of digital technologies in education: A review," *Sustainable Operations and Computers,* vol. 3, pp. 275–285, 2022. https://doi.org/10.1016/j.susoc.2022.05.004

[10] O. P. Igbinenikaro, O. O. Adekoya, and E. A. Etukudoh, "Emerging underwater survey technologies: A review and future outlook," *Open Access Research Journal of Science and Technology*, vol. 10, no. 2, pp. 71–84, 2024. https://doi.org/10.53022/oarjst.2024.10.2.0052

[11] S. Zala, V. Goyal, S. Sharma, and A. Shukla, "Transformer based fruits disease classification," *Multimedia Tools and Applications*, vol. 84, pp. 1627–1647, 2024. https://doi.org/10.1007/s11042-024-19172-1

[12] S. Roy, S. K. Millican, and V. D. Agrawal, "A survey and recent advances: Machine intelligence in electronic testing," *Journal of Electronic Testing*, vol. 40, pp. 139–158, 2024. https://doi.org/10.1007/s10836-024-06117-7

[13] Z. Shi, H. Li, D. Zhao, and C. Pan, "Research on quality assessment methods for cybersecurity knowledge graphs," *Computers & Security*, vol. 142, p. 103848, 2024. https://doi.org/10.1016/j.cose.2024.103848

[14] L. Yu and J. Ding, "Application of music artificial intelligence in preschool music education," *IOP Conference Series: Materials Science and Engineering*, vol. 750, 2020. https://doi.org/10.1088/1757-899X/750/1/012101

[15] S. Kalogiannidis, D. Kalfas, E. Loizou, O. Papaevangelou, and F. Chatzitheodoridis, "Smart sustainable marketing and emerging technologies: Evidence from the Greek business market," *Sustainability,* vol. 16, no. 1, p. 312, 2023. https://doi.org/10.3390/su16010312

[16] M. U. Tariq, "The transformation of healthcare through AI-driven diagnostics," in *Enhancing Medical Imaging with Emerging Technologies*, Avinash Kumar Sharma *et al.*, Eds., IGI Global, 2024, pp. 250–264. https://doi.org/10.4018/979-8-3693-5261-8.ch015

[17] A. Gökhan, K. D. Kilic, T. Çavuşoğlu, and Y. Uyanıkgil, "Basics of artificial intelligence for assisted reproductive technologies," in *Enhancing Medical Imaging with Emerging Technologies*, 2024, pp. 1–12. https://doi.org/10.4018/979-8-3693-5261-8.ch001

[18] Z. Liu, M. Zhu, and S. Wang, "Safety behavior analysis and risk evaluation method of human-construction robotics and automation interaction in intelligent construction scenarios driven by deep learning and digital twin," *SSRN*, 2024. https://doi.org/10.2139/ssrn.4795420

[19] V. Singh and S. Rani, "Machine learning in medical imaging: Ethico-legal and privacy issues," in *Enhancing Medical Imaging with Emerging Technologies*, Avinash Kumar Sharma *et al.*, Eds., IGI Global, 2024, pp. 34–50. https://doi.org/10.4018/979-8-3693-5261-8.ch003

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

[21] M. M. S. Missen *et al.*, "Scientometric analysis of social science and science disciplines in a developing nation: A case study of Pakistan in the last decade," *Scientometrics*, vol. 123, pp. 113–142, 2020. https://doi.org/10.1007/s11192-020-03379-8

[22] A. Dehbi, R. Dehbi, A. Bakhouyi, and M. Talea, "Interoperability in smart Education: A systemic review based on bibliometric and content analysis methods," *Journal of Theoretical and Applied Information Technology,* vol. 100, no. 24, pp. 7211–7221, 2022. https://www.jatit.org/volumes/Vol100No24/2Vol100No24.pdf

[23] A. J. Lotka, "The frequency distribution of scientific productivity," *Journal of the Washington Academy of Sciences,* vol. 16, no. 12, pp. 317–323, 1926. https://www.jstor.org/stable/24529203

[24] I. Gligorea, M. Cioca, R. Oancea, A. T. Gorski, H. Gorski, and P. Tudorache, "Adaptive learning using artificial intelligence in E-learning: A literature review," *Education Sciences,* vol. 13, no. 12, p. 1216, 2023. https://doi.org/10.3390/educsci13121216

[25] A. Alam, "Harnessing the power of AI to create intelligent tutoring systems for enhanced classroom experience and improved learning outcomes," in *Intelligent Communication Technologies and Virtual Mobile Networks,* ICICV 2023, in Lecture Notes on Data Engineering and Communications Technologies, G. Rajakumar, K. L. Du, and Á. Rocha, Eds., Springer, Singapore, vol. 171, 2023, pp. 571–591. https://doi.org/10.1007/978-981-99-1767-9_42

[26] M. Ouadoud, T. Chafiq, N. Rida, and M. Y. Chkouri, "Generate a meta-model content for collaboration space of learning management system compatible with IMS-LD," *International Journal of Interactive Mobile Technologies (iJIM),* vol. 13, no. 1, pp. 37–52, 2019. https://doi.org/10.3991/ijim.v13i01.9440

[27] V. Terzieva, S. Ilchev, and K. Todorova, "The role of internet of things in smart education," *IFAC-PapersOnLine*, vol. 55, no. 11, pp. 108–113, 2022. https://doi.org/10.1016/j.ifacol.2022.08.057

[28] A. Badshah, A. Ghani, A. Daud, A. Jalal, M. Bilal, and J. Crowcroft, "Towards smart education through internet of things: A survey," *ACM Computing Surveys*, vol. 56, no. 2, pp. 1–33, 2023. https://doi.org/10.1145/3610401

[29] C. Fischer *et al.*, "Mining big data in education: Affordances and challenges," *Review of Research in Education*, vol. 44, no. 1, pp. 130–160, 2020. https://doi.org/10.3102/0091732X20903304

[30] A. Dehbi, A. Bakhouyi, A. M. Khaddar, and M. Talea, "Education and smart technologies: Towards a new pedagogical paradigm," *International Journal of Evaluation and Research in Education,* vol. 14, no. 1, pp. 297–309, 2025. https://doi.org/10.11591/ijere.v14i1.30470

[31] N. Cele, "Big data-driven early alert systems as means of enhancing university student retention and success," *South African Journal of Higher Education,* vol. 35, no. 2, pp. 56–72, 2021. https://doi.org/10.20853/35-2-3899

[32] T. Karakose, I. Kocabas, R. Yirci, S. Papadakis, T. Y. Ozdemir, and M. Demirkol, "The development and evolution of digital leadership: A bibliometric mapping approach-based study," *Sustainability*, vol. 14, no. 23, p. 16171, 2022. https://doi.org/10.3390/su142316171

[33] N. Cavus, S. E. Mrwebi, I. Ibrahim, T. Modupeola, and A. Y. Reeves, "Internet of Things and its applications to smart campus: A systematic literature review," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 16, no. 23, pp. 17–35, 2022. https://doi.org/10.3991/ijim.v16i23.36215

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