

Mapping Artificial Intelligence for Personalised Learning based on Learning Style: Scopus-Based Bibliometric Analysis (2006-2026)

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Abstract. The aims of this study is to conduct a bibliometric analysis of the development of learning style-based personalisation. The rapid advancement of AI-based learning personalisation has been accompanied by growing research attention to the role of learning style in the modern learning ecosystem. The research methodology involves a bibliometric analysis of 604 Scopus-indexed publications from the period 2006 to 2026 that were analyzed and visualized using Biblioshiny, VOSviewer and Open Refine. The results of the study indicate a significant increase in publications beginning in 2020, reflecting growing research attention to AI-based personalisation, the keywords patterns indicate an increasing association between learning style and machine learning analytics. Random Forest is one of the most commonly reported machine learning methods in the literature to identify learning styles. The findings further indicate that AI and learning style are increasingly discussed with the same research landscape. This study contributes by mapping the evolution of this field and demonstrating the convergence of educational theory and computational approaches. Further research should be extended beyond the Scopus database, combining bibliometric analysis and systematic literature review, and investigating the integration of learning styles with learner behavioral and cognitive data in AI-powered personalised learning systems.

Keywords: learning style, personalised learning, AI in education, bibliometric analysis, Scopus

1. INTRODUCTION

Over the past few decades, the rapid evolution of digital technologies has catalysed a profound paradigm shift within global educational systems, particularly through the assimilation of e-learning, learning analytics, and artificial intelligence (AI). This transformation is characterised by a fundamental reorientation from traditional teacher-directed instruction toward learner-centred educational frameworks which emphasise individual differences in the learning process [1]. Within this context, personalised learning has emerged as an approach that seeks to tailor learning experiences to individual learner characteristics. Personalised learning is an instructional approach that tailors teaching strategies and learning activities to the unique needs, interests, abilities and goals of individual learners [2].

In digital learning environments, personalisation can be operationalised by adapting instructional content, learning routes, recommendations, feedback, and learning support according to learner characteristics such as knowledge level and learning style [3] [4].

Artificial intelligence has increasingly been incorporated into personalised learning to support the identification of learner characteristics and the computational adaptation of learning experiences. Rather than treating AI as separate from personalisation, this study considers AI as a technological mechanism through which learner-related information can be analysed and used to support personalised learning.

An essential learner characteristic frequently employed in the development of personalised learning is learning style. It illustrates how people take in, process, and understand information, which is impacted by both affective elements [5]. Kolb, Honey, Mumford, and Felder-Silverman are just a few of the learning style models that have been proposed. Because of its extensive dimensions and the availability of a validated measuring tool, the Felder-Silverman model is one of the most popular in learning style research [6]. The incorporation of learning style into personalisation enables customisation of content presentation, including the use of spoken or visual elements and the order in which information is delivered, to suit personal preferences [7], [8], [9].

Although the learning style model is widely used in adaptive learning research, its pedagogical effectiveness is still the subject of debate. In adaptive e-learning systems,

learning style models such as Felder-Silverman and VARK are generally used as parameters in learner profiles that trigger adaptation [10], determine material presentation modalities [11], and support the development of personalised learning paths [12]. These characteristics can be obtained through questionnaires filled out by students or detected automatically from learning patterns and interactions using machine learning techniques such as decision trees, artificial neural networks, and Bayesian networks. However, the use of computational learning style profiles does not necessarily prove their pedagogical validity. The identification of learning modalities from digital behaviour can suffer from misclassification, and improper adaptation can limit the variety of material presented to learners. In addition, reported empirical results remain mixed: personalisation does not necessarily lead to significant improvements in academic performance, and short-term post-test gains do not necessarily indicate deeper conceptual understanding or long-term persistence [13]. Excessive reliance on algorithmically determined learning styles can also limit learning agency and self-regulated learning abilities.

Research developments related to the application of intelligence in learning personalisation have been extensively examined through various bibliometric mapping studies and systematic literature reviews (SLR). Bibliometrically, [14] maps the landscape of personalised and adaptive learning research for the period 2001–2025, which includes the analysis of publication sources, authors and leading countries, keyword patterns, conceptual structures, and the integration of learning styles with modern technology. An in-depth study of the patterns and trends of AI publication in personalised learning was also conducted by [15] for the period 2000–2022, which highlighted research fronts and research hotspots, while [16] identified geographical distribution, mapping of publication outlets, and the dominance of the types of technology used in the personalisation of learning. From the perspective of SLR, various studies focus on specific domains, such as the analysis of content recommendation systems in adaptive learning environments [17] as well as investigations of learning style models, machine learning techniques for automatic identification, evaluation metrics, and learning style-based learning support [7]. In engineering education, [18] assessed the readiness and impact of the application of machine learning for learning style prediction and recommendation systems, which was refined by [18] analysing and summarising learning personalisation research in terms of components, features, development methods, learning theories used, and the impact of its implementation in higher education. Furthermore, [19] identified, assessed, and synthesised

the literature on the development of Adaptive Personalised Learning Environments from 2019 – 2023, especially Activity Theory and Personalised Learning Design Framework, and evaluated the effectiveness of Adaptive Learning Environments in increasing the learning size of students. Meanwhile, [20] researches machine learning methods in real time, from the data collection stage to the evaluation of student behaviour in learning personalisation. The complexity of this domain is also demonstrated by [21] through the integration of Educational Data Mining (EDM) for intelligent multi-agent modelling, and [22] which proposes a mobile-based adaptive e-learning design for Industry 4.0 and Society 5.0. Reflects on the role of artificial intelligence as the main driver of personalised learning.

Although previous bibliometric and SLR studies have mapped the development of learning personalisation and the implementation of artificial intelligence in general, the existing literature still shows fundamental limitations, namely that it has not given a special focus on the domain of Artificial Intelligence for Personalised Learning based on Learning Style. The majority of previous studies have mapped publication trends, author productivity, state networks, and artificial intelligence in learning personalisation without in-depth analysis of the interaction between artificial intelligence and learning styles. Therefore, there is a need for research to specifically examine the mapping of intellectual structure, conceptual structure, and evolutionary dynamics of research themes regarding the integration of artificial intelligence with learning styles over time.

The main objective of this study is to conduct a bibliometric analysis of global literature during the period 2006 to 2026 on research related to personalised learning based on learning styles. The analysis focuses on identifying research trends, thematic structure, scientific collaboration network, leading publication sources, employed technologies, and the conceptual relationship between AI techniques and learning styles, without evaluating the effectiveness of AI integration into personalised learning based on learning styles. Through this approach, the study is expected to present a meticulous map of the field's development and to map out potential agendas for subsequent studies. Specifically, this study is guided by the following research questions (RQs):

- 1) RQ1: What are the main research trends, thematic structure, and evolutionary patterns in personalised learning based on learning style?
- 2) RQ2: Who are the leading authors, publications, countries and collaboration network in personalised learning research based on learning style

- 3) RQ3: What learning style identification approaches and AI/ML-driven technologies are used in learning-style-based personalised learning?
- 4) RQ4: What is the relationship between AI techniques and learning style models in personalised learning based on learning style?

This study's main contribution is a thorough bibliometric mapping that explains research advancements as well as the conceptual framework and connection between important elements of learning style-based personalised learning during the 2006-2026 period. The results contribute to highlighting the major research fronts in this growing area and revealing potential future Work.

2. METHODS

This study employs a bibliometric analysis approach to explore the development of research in the field of learning style-based personalised learning. This approach is selected because it enables a quantitative and systematic mapping of publication trends, scientific collaboration structures, and conceptual relationships within a research domain [23]. Figure 1 illustrates the overall research workflow.

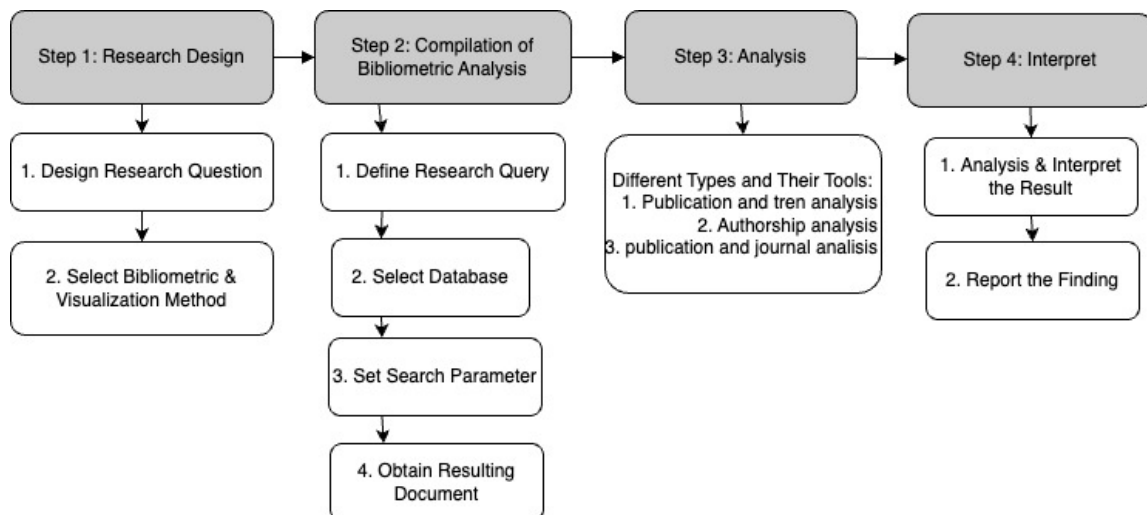


Figure 1. Research workflow outline

The research framework (Figure 1) consists of four main stages of bibliometric analysis: research design, data compilation, analysis, and mapping interpretation, systematically structured to produce a scientific mapping. The research design stage involves formulating

research questions and selecting appropriate analytical and visualisation methods. The data compilation stage includes defining keyword-based search queries, selecting databases, setting search parameters, and collating relevant publication datasets. Subsequently, the analysis stage applies various techniques such as publication trends analysis, authorship and collaboration (co-authorship) analysis, as well as publication and journal analysis, to identify patterns in research development. The final stage, interpretation, aims to critically interpret the analytical results and report them systematically.

2.1. Search Strategy

The data source for this study is the Scopus database. The process of collecting and selecting literature data was carried out in a structured manner following the PRISMA framework (Figure 2) to ensure transparency and validity of the bibliometric analysis. Publication search was conducted on April 10, 2026, using the *TITLE-ABS-KEY* combination with the following search query:

("Adaptive learning" OR "personalized learning" OR "adaptive e-learning" OR "personalised e-learning" OR "adaptive personalised e-learning" OR "adaptive personalized e-learning" OR "personalised learning" OR "individualized learning") AND ("machine learning" OR "artificial intelligence" OR AI) AND ("learning style" OR "learning preference" OR "student behavior")

This initial identification stage yielded 842 documents. The literature filtering was applied based on inclusion and exclusion criteria outlined in Table 1.

Table 1. Inclusion and exclusion criteria of publication

Inclusion criteria	Exclusion criteria
1. Publication period 2006–2026,	1. Publish before 2006,
2. Document type: journal article or proceeding,	2. Document other than journals and proceedings,
3. Written in English	3. Article not written in English,
4. Relate to the topic of AI/ML integration in learning style-based personalization.	4. Not related to AI/ML integration in learning style-based personalization.

The remaining 671 documents were exported as a CSV file. To maintain integrity and validity, the Scopus dataset was cleaned using software. OpenRefine excluded 37 duplicate documents, and 30 documents were review articles or previous bibliometric studies. Review articles and previous bibliometric studies were excluded because the analysis was designed to focus on primary research publications rather than secondary syntheses or previous mappings of the literature. Excluding these document types also helped prevent this study from being influenced by secondary interpretations and overlapping bibliometric evidence.

We read the full text of articles for which it was difficult to determine the topic's relevance based on the title and abstract. This was done to ensure that the literature dataset only contained primary research findings that provided new scientific findings directly related to the topic being examined in this study. The final selection resulted in a dataset of 604 relevant documents for analysis.

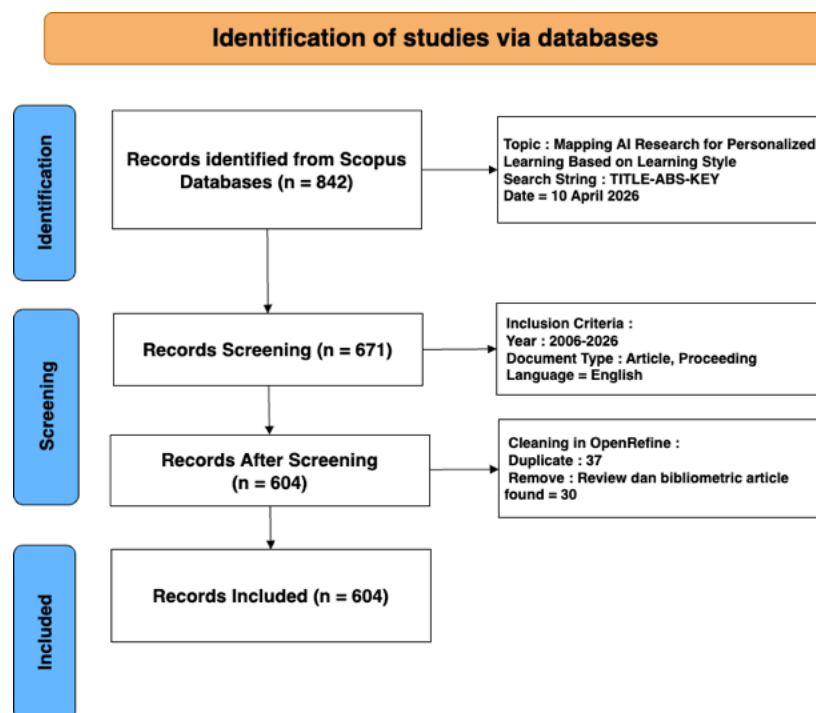


Figure 2. PRISMA Flowchart of Study Selection Process

2.2. Data Processing, Analysis, and Visualisation

OpenRefine is used for data pre-processing. This stage includes removing duplicate records, normalisation of the author names, and standardising author keywords to reduce

data inconsistencies. Both author keywords and author names were standardised through the "Cluster and Edit" feature in OpenRefine by combining key collision methods (Fingerprint, n-gram fingerprint, Metaphone 3, Cologne phonetic, Daitch-Mokotoff, Braider-Morse) with nearest-neighbour based on Levenshtein and PPM distance functions. For example, variations of writing such as:

"Artificial intelligence, artificial-intelligence, AI" standardised to *"artificial intelligence"*

"Personalised Learning" standardised to *"Personalized Learning"*

"Felder-Silverman model", "Felder Silverman model", "FSLSM" standardised to *"Felder Silverman Learning Style Model"*.

A similar procedure is applied to normalise author name variations. This process is very important because data quality directly affects the reliability of subsequent bibliometric analyses and interpretation of science mapping results [24]. Data analysis was carried out using a combination of RStudio with the Bibliometrics/Biblioshiny, Biblioplot and VOSviewer packages, using the same cleaned dataset. Biblioplots were used to visualise the Y-direction co-occurrence of author keywords. VOSviewer was used to visualise collaboration networks (co-authorship), author keyword occurrence and country collaboration [25]. To ensure a clear and legible network visualisation, the number of clusters was limited to 5 by setting a minimum cluster size threshold of 10 in the author keyword co-occurrence analysis, using the full counting method, and setting the minimum keyword occurrence threshold to 5. To determine the spatial distribution and clustering terms, the association strength method was applied for normalisation, operated under a cluster resolution of 1.00, an attraction parameter of 2, and a repulsion parameter of 0.

3. RESULTS AND DISCUSSION

3.1. RQ1: What are the main research trends, thematic structure, and evolutionary patterns in personalised learning based on learning style?

Table 2 presents the main characteristics of the dataset used in this study. A total of 604 documents published during the period 2006–2026 were successfully collected from 382 sources of publications indexed by Scopus.

Table 2. Main Information About Data

Description	Results
Timespan	2006:2026
Number of Document	604
Number of Sources	382
Annual Growth Rate %	25,77
Document Average Age	2,5
Average citations per doc	8,609
AUTHORS:	
Authors	1938
Authors of single-authored docs	71
AUTHORS COLLABORATION:	
Single-authored docs	75
Co-Authors per Doc	3,55
International co-authorships %	15,89
DOCUMENT TYPES:	
Article	197
Conference Paper	407

Figure 3 shows the annual development of publications on this topic during the period 2006–2026. There is an increasing trend in the number of publications, which shows the rapid development in this field, especially after 2020. The surge in productivity shows that research on the integration of artificial intelligence with learning style-based learning personalisation has entered a very rapid growth phase and is becoming one of the topics that is getting more and more attention. Almost all publications published up to 2023 have obtained citations, as indicated by 97% of the documents of 2023 and 100% in most of the previous years. However, that proportion has declined to 83% in 2024, 47% in 2025, and just 15% in 2026. This decline reflects more of the phenomenon of citation delay than a decline in the quality of research, considering that newer publications have a shorter time to be cited by subsequent studies. The most frequently cited reference is Sajja R, who presents a new framework, intelligent assistants powered by artificial intelligence and NLP, for personalised and adaptive learning in higher education.

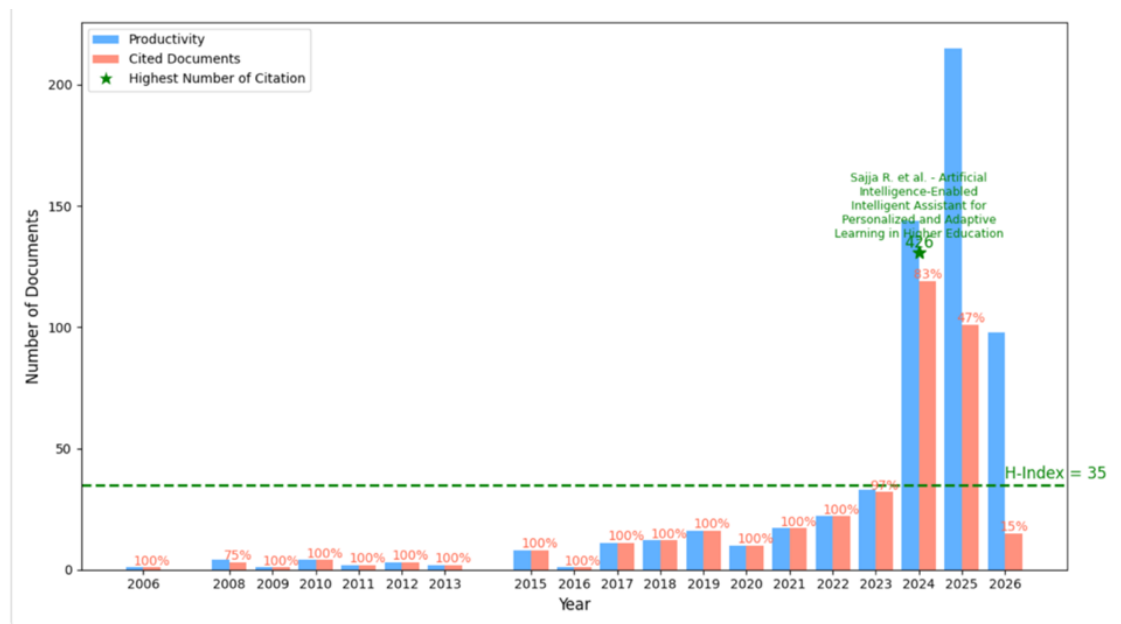


Figure 3. Research Productivity and Cited Document Over the Years



Figure 4. Network visualisation (minimum number of occurrences of keyword= 5 of the 1493 keywords; 87 meet the threshold)

The co-occurrence analysis (Figure 4) also produced 5 clusters that were interconnected to form a thematic group of intellectual structure research on Artificial Intelligence for Personalised Learning based on Learning Style.

Cluster 1 (red), focuses on the theme of machine learning for learning style identification that utilises machine learning algorithms to identify learner characteristics as the basis for personalising learning. This theme is built by author keywords such as machine learning, adaptive learning, learning style, classification, decision tree, K-means, support vector machine, random forest, and deep learning. The articles in the dataset show that the research in this cluster is dominated by the development of classification models to recognise learning styles using learning behaviour data [26], activity logs [27], and physiological data [28],[29]. Thus, this cluster represents a computational foundation that allows the personalisation process to be carried out automatically [30].

Cluster 2 (green) focuses on Intelligent Techniques in E-Learning, specifically the development of adaptive e-learning systems through the application of artificial intelligence techniques. Keywords such as recommender systems, knowledge tracing, reinforcement learning, personalised learning path, student performance prediction, and MOOC indicate that the focus of research has shifted from identifying student characteristics to dynamically optimizing learning paths. The various studies in the dataset utilize reinforcement learning, recommendation systems [31], and knowledge tracing [32] to adjust the order of materials, learning activities, and content recommendations based on individual needs, so that personalisation no longer stops at the process of identifying learning styles, but develops into a mechanism for continuous learning adaptation [33].

Cluster 3 (blue) represents the theme Artificial Intelligence in Personalised Learning, is also the center of conceptual networking. The dominance of the keywords artificial intelligence, personalised learning, intelligent tutoring systems, learning analytics, educational technology, natural language processing, and large language models shows that artificial intelligence has evolved from just a classification tool to a core technology in the implementation of personalised learning systems. The central position of this cluster connects almost all other research themes, thus showing that AI serves as an integration between learning theory, data analysis, and educational technology. The emergence of large language models and generative AI also indicates the expansion of research towards

learning systems that are able to provide adaptive feedback and natural language-based interactions [34].

Cluster 4 (yellow) represents the Learning Analytics theme, characterised by keywords such as student engagement, academic performance, learning outcomes, learner models, predictive analytics, ethical considerations, and data privacy. The presence of these terms indicates increased research attention to learning outcomes, learner engagement, predictive analytics, and governance issues. This shift reflects the growing need for AI systems that are not only technically accurate, but also transparent, ethical, and accountable in educational settings [34]. However, their presence in the keyword network does not constitute evidence that AI-based personalisation improves learning outcomes or engagement.

Cluster 5 (purple) represents the theme of Educational Data Mining in Education, which connects educational data mining, learning management systems, learning preferences, online education, curriculum design, and personalised recommendations. In contrast to the Learning Analytics cluster which emphasizes learning evaluation, this cluster is oriented towards the exploration of educational data to support decision-making in a learning personalisation system [35]. The existence of the keyword educational data mining with a learning management system shows that the integration of data from the digital learning environment is an important component in producing more precise learning recommendations.

The five themes form a conceptual trajectory that shows the evolution of research from the identification of learning styles using machine learning, to the development of intelligent techniques in e-learning, then developing into the implementation of Artificial Intelligence as the core of the personalised learning system, which is further strengthened by learning analytics and educational data mining as a data-based analysis and decision-making mechanism. This structure shows that the learning style remains a visible research construct while Artificial Intelligence is increasingly represented as a computational mechanism for personalised learning.

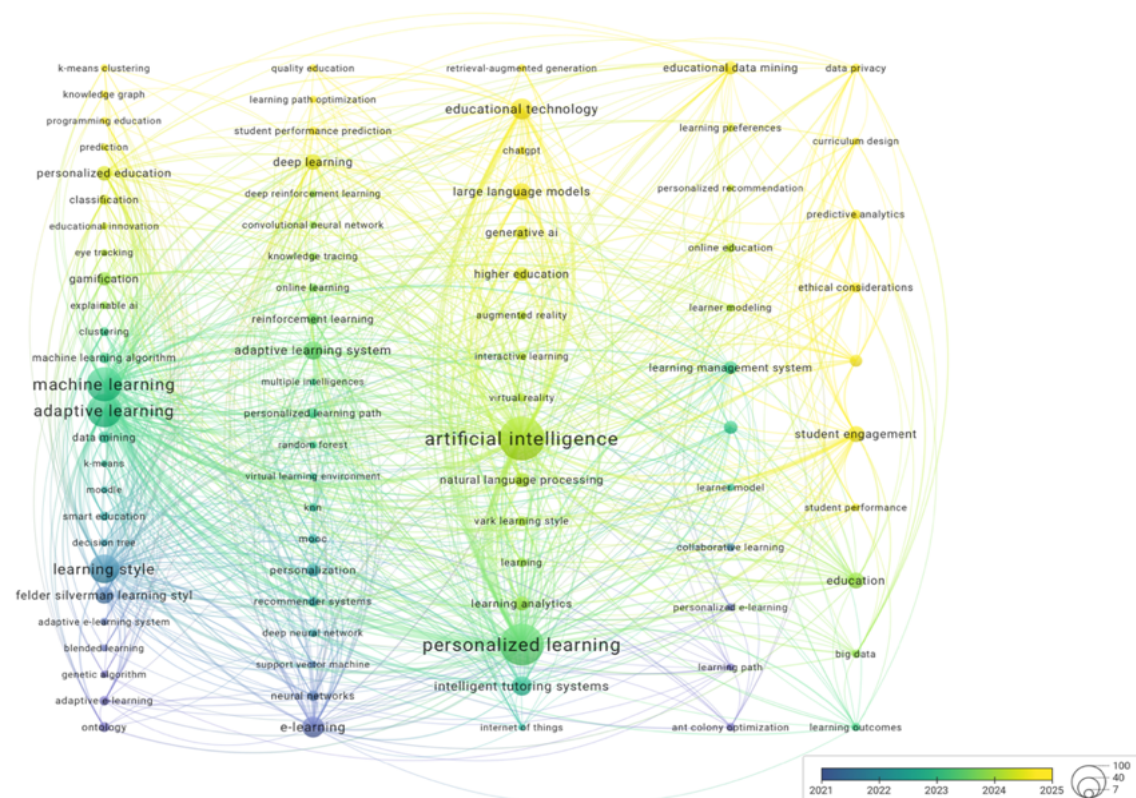


Figure 5. Overlay visualisation (minimum number of occurrences of keyword= 5 of the 1493 keyword; 87 meet the threshold)

An analysis of the visualisation overlay (Figure 5) shows the temporal dynamics of the development of this topic. The visualisation shows that keywords such as learning style, adaptive learning, machine learning, e-learning, and personalised learning emerged as themes that developed earlier. In contrast, the keywords large language models, generative AI, educational technology, educational data mining, student engagement, predictive analytics, ethical considerations, and data privacy were dominated by yellow and published between 2024 and 2025, indicating that these topics are starting to gain greater attention in the current research period. The colour range overlay was set to mean score = 2021 and max score = 2025 to see how the emergence of artificial intelligence technology affects learning styles in learning personalisation in the latest research. This bibliometric pattern indicates that the research focus is evolving from the development of personalised models based on student characteristics to the use of more advanced AI technology, while expanding attention to learning analytics, evaluation of learning outcomes, and ethical aspects in the implementation of AI in the field of education. These findings are in line with [7] who shows the increasing use of AI techniques in adaptive learning systems, as

well as Kasneci et al. who explain that the development of large language models opens up new opportunities for learning personalisation through natural language-based interaction and adaptive feedback.

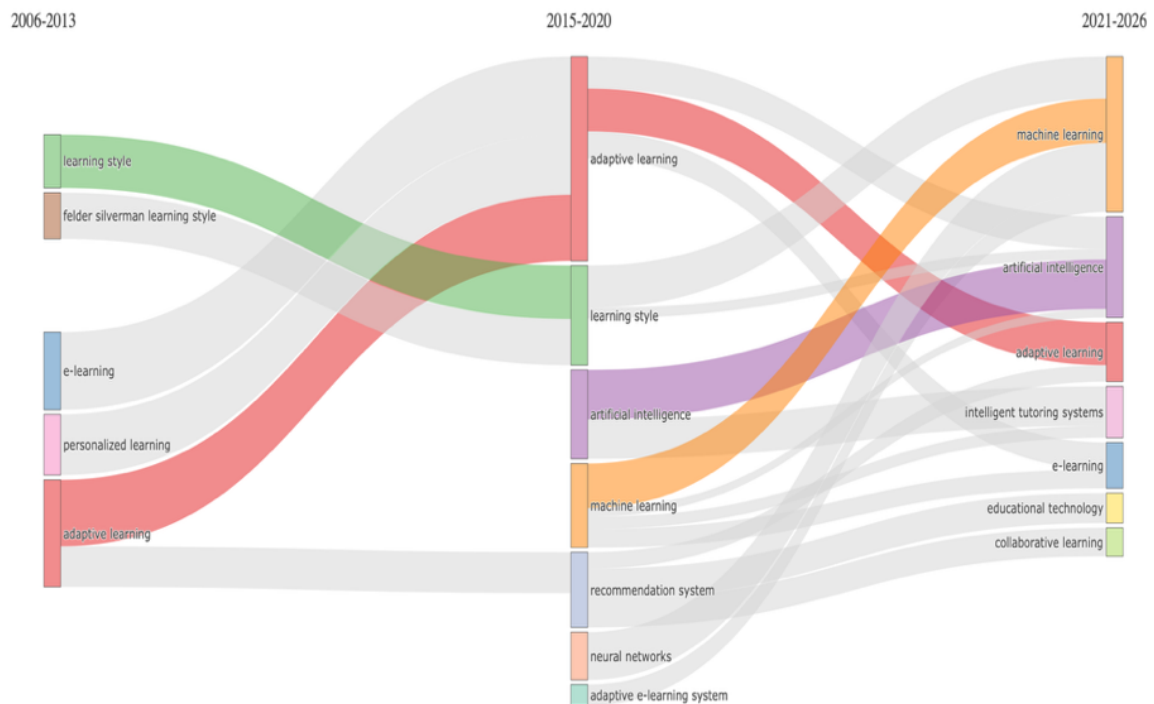


Figure 6. Thematic Evolution (number of word = 300, min cluster frequency per thousand docs = 1, α parameter (balancing occurrence vs. centrality = min weight index = 0.05, number of cutting point = 3)

In contrast to the overlay visualisation, which only shows the latest research developments on this topic, the thematic evolution (Figure 6) indicates a gradual reconfiguration of research themes, rather than a complete disappearance of research related to learning styles. In the period 2006–2013, learning styles, adaptive learning, personalised learning, e-learning, and Felder–Silverman learning styles were strongly associated with the initial research landscape. During the period 2015–2020, these themes became increasingly connected to machine learning and artificial intelligence. In the period 2021–2026, AI, machine learning, intelligent learning systems, educational technology, and collaborative learning became more prominent. This pattern suggests that learning styles remain visible in the research landscape while also becoming increasingly embedded within broader computing and technology themes. Learning styles remain the conceptual basis for

personalising learning, while AI is evolving as an increasingly adaptive and data-driven computational mechanism [36].

The relatively peripheral position of "learning style" in a keyword network needs to be interpreted in relation to the broader scope of computing and learning terms represented in the network. Figure 4 shows that, in addition to terms related to learning style, the research landscape also includes machine learning, artificial intelligence, learner models, learning analytics, recommender systems, predictive analytics, and educational technology. Figure 5 further shows the emergence of large language models, generative AI, student engagement, ethical considerations, and data privacy in more recent periods. The increasing representation of these broader themes places learning styles in an increasingly diverse thematic structure, where learning styles remain represented, but occupy a less central position compared to broader themes of computing and educational technology. This thematic diversification is also reflected in the increasing visibility of learner modelling concepts beyond the classification of learning styles. The co-emergence of learner models, learning analytics, student engagement, academic performance, predictive analytics, recommender systems, and knowledge tracing shows that the attention of the research has expanded and encompasses various dimensions of student behaviour, performance, and interaction. In this broader thematic context, learning style is represented as one of a number of constructs related to learners, along with other dimensions in learner modelling, rather than as the only basis for representing learner characteristics. Thus, bibliometric evidence suggests an expansion of research attention towards broader learner modelling, although the findings do not prove that learning style classifications have been replaced in all areas of research.

These keyword-based findings need to be interpreted within the scope of the author keywords and metadata indexed by Scopus used in this study. The analysed metadata represents the indexed terminology and thematic information for the included documents. Therefore, keyword frequency, co-occurrence patterns, and positions in the network reflect the research themes captured through indexed metadata. Variations in terminology between documents can also affect the representation and degree of interconnectedness of related concepts in the keyword network.

3.2. RQ2: Who are the leading authors, publications, countries and collaboration network in personalised learning research based on learning style

1) Leading Author and Collaboration

Figure 7 shows the development of the authors' productivity during the period 2006–2026. In general, no authors dominate the number of publications significantly, with most authors producing only between one and four articles. In addition, the majority of publication activities are concentrated in the period 2023–2025, while only a few authors, such as Santosa P.I., Zhang M., and Li B., show continuity of contributions over a longer span of time. This pattern shows that research on Artificial Intelligence for Personalised Learning based on Learning Style is still in a growth phase with wider researcher involvement, but has not yet formed a very dominant core group of authors.

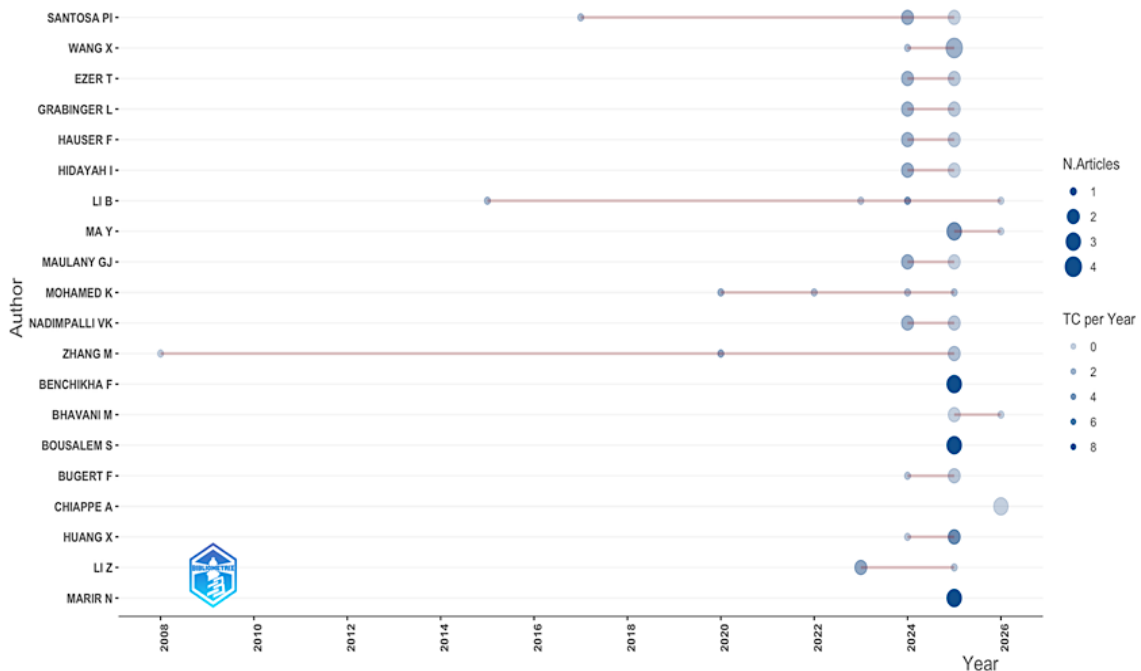


Figure 7. Author's Production Over Times (number of author = 20)

In contrast to the productivity pattern, Figure 8 shows that the scientific influence in the research network is more concentrated on a small number of authors. Oughdir L is the author with the highest local citations (15 citations), followed by Ali M (12 citations), and Bajaj R and Sharma V (11 citations each). Other authors obtained between 7 and 9 local citations, suggesting that conceptual contributions in this field still rest on a relatively limited group of authors.

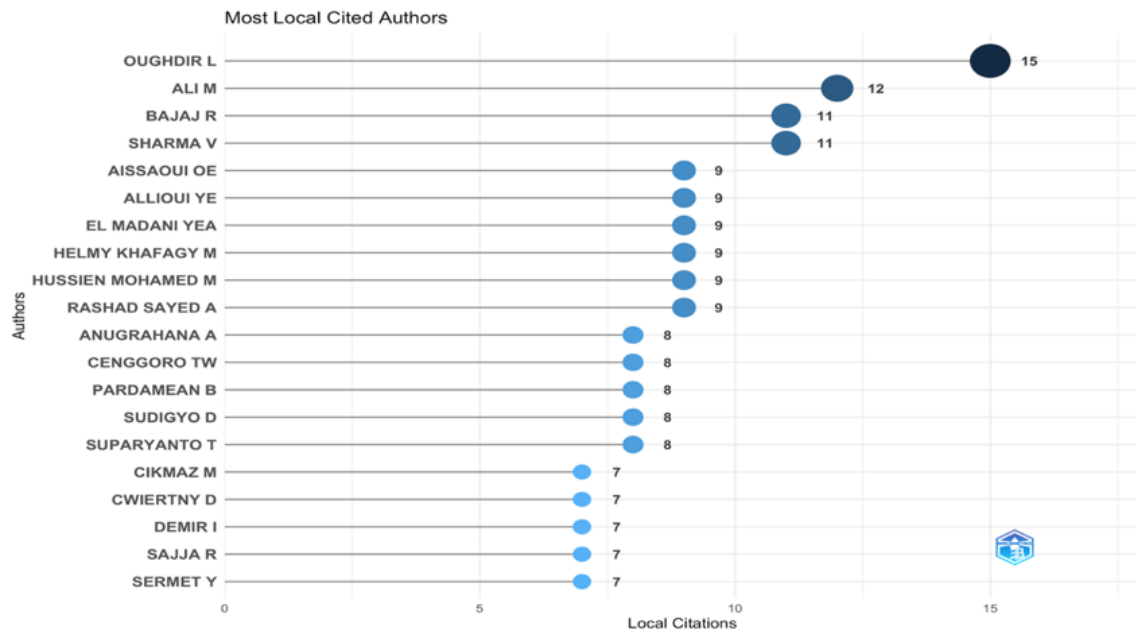


Figure 8. Most Local Cited Authors (number of author = 20)

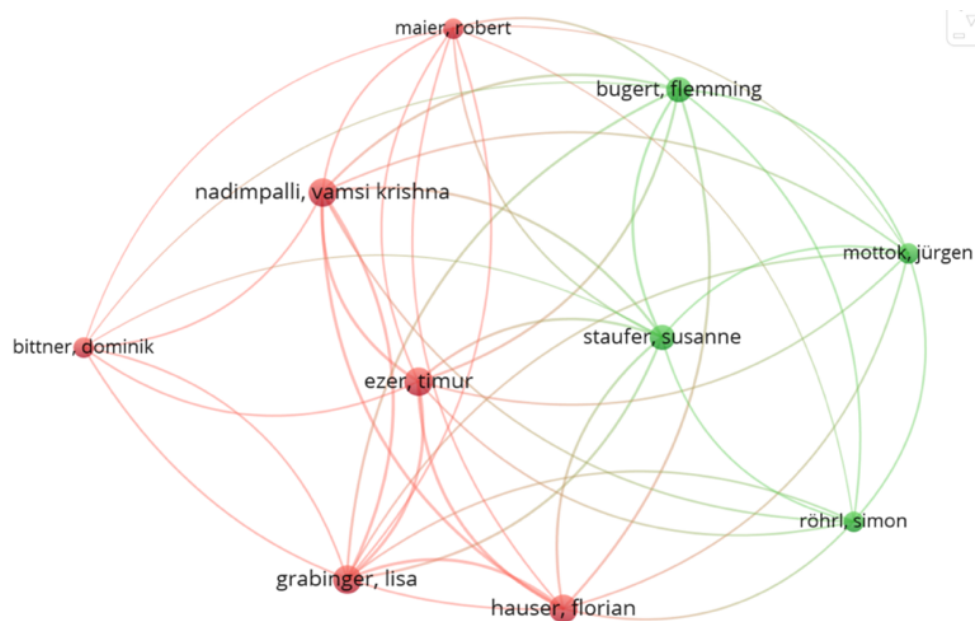


Figure 9. Co-Authorship Collaboration (minimum number of document of an author = 2, minimum number of citation of an author = 1)

Analysis of collaboration networks (Figure 9) shows the formation of two main collaboration groups that are interconnected through several cross-cluster relationships. In the first cluster, East Ezer and Nadimpalli Vamsi Krishna played the role of the main liaison among the group members, while in the second cluster the central role was shown

by Staufer Susanne and Bugert Flemming. Despite the existence of intergroup relationships, the relatively small size of the network suggests that scientific collaboration is still developing at the heart of a particular community and has not yet formed a broad global network of collaboration.

Comparisons between productivity, citations, and collaboration show that the most productive writers aren't always the most influential writers. In contrast, the authors with the highest local citations do not always generate the highest number of publications or occupy a central position in the collaborative network. These findings indicate that scientific leadership in the field of Artificial Intelligence for Personalised Learning based on Learning Style has not been centralized on a specific individual, but is still spread among several research groups that contribute through productivity, conceptual influence, and scientific collaboration.

2) Leading Publication

The analysis of publication sources with the greatest impact in the field of learning style-based personalised learning was conducted by analysing the most relevant sources and the most cited sources. The analysis of most relevant sources (Figure 10) indicates that publication outlets in the field of learning style-based personalised learning are predominantly dominated by computer science and information technology-oriented venues and dominated by conference proceedings rather than scientific journals. Based on Figure X, Lecture Notes in Networks and Systems was the most prolific source with 31 documents, followed by the ACM International Conference Proceedings Series (21 documents), AIP Conference Proceedings (17 documents), and Communications in Computer and Information Science (15 documents). Meanwhile, IEEE Access, Lecture Notes in Computer Science, and Procedia Computer Science each published 11 papers. The dominance of proceedings shows that this field is still developing dynamically with a high rate of innovation, so that research results are more widely disseminated through conference forums, which allow the dissemination of findings faster than journal publications. This pattern is a common characteristic in fields that are at the intersection of artificial intelligence and computer science, where conferences are often the primary medium for introducing new technologies and methods [37].



Figure 10. Most Relevant Source (number of documents = 20)

Table 3. Most Influential Source

Source	h_index	g_index	m_index	TC	NP	PY_start
IEEE Acces	7	11	1,4	306	11	2022
Procedia Computer Science	7	11	0,77777778	506	11	2018
Acm Int. Conf. Proceeding Series	6	7	0,5	86	21	2015
Lecture Notes in Computer Science (Including Subseries						
Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	6	9	0,28571429	97	11	2006
International Conference on Advance Computing and Innovative Technologies in Engineering	5	8	1,66666667	95	8	2024
Applied Sciences (Switzerland)	4	5	0,57142857	68	5	2020
Communications in Computer and Information Science	4	6	0,4	44	15	2017
Sustainability (Switzerland)	4	4	0,44444444	229	4	2018

Source	h_index	g_index	m_index	TC	NP	PY_start
Advances in Intelligent Systems and Computing	3	4	0,3	48	4	2017
AIP Conference Proceedings	3	4	1	18	17	2024
Education Sciences	3	3	0,75	89	3	2023
IEEE Global Engineering Education Conference, Educon	3	3	1	14	5	2024
Ifip Advances in Information and Communication Technology	3	3	0,2	56	3	2012
Information (Switzerland)	3	3	1	432	3	2024
International Journal of Electrical and Computer Engineering	3	3	0,375	41	3	2019
International Journal of Emerging Technologies in Learning	3	3	0,5	96	3	2021
International Journal of Interactive Mobile Technologies	3	4	1	20	5	2024
Lecture Notes in Networks and Systems	3	4	0,6	32	31	2022
Int.Conf. on Advanced Computing and Communication Systems	2	2	0,66666667	21	2	2024

Nevertheless, publication productivity does not fully reflect the scientific influence of a source. Table 3 shows that IEEE Access and Procedia Computer Science share the highest index of 7 among the list source. IEEE Access also has a g-index of 11, while Procedia Computer Science has the highest local citation count (506) among the list source. These differences demonstrate that the ranking of publication source varies depending on the bibliometric indicator used. Therefore, no single source can be identified as the most influential solely on the basis of one indicator; source influence should instead be interpreted multidimensionally using productivity, h-index, g-index, m-index, publication volume, and publication age. This consideration is particularly important for recent sources, whose citation counts may be constrained by the shorter period available for subsequent studies to cite their publications.

In contrast, Lecture Notes in Networks and Systems, despite being the most prolific source (31 documents), has only an h-index = 3, a g-index = 4, and 32 citations. This difference

shows that a high number of publications is not always followed by a strong scientific influence, so the evaluation of publication sources needs to consider productivity and quality indicators simultaneously. These findings are in line with [38] who assert that a combination of bibliometric indicators, such as the h-index, g-index, and total citations, provides a more comprehensive picture of the influence of a source than just using the number of publications. Overall, these results indicate that the development of Artificial Intelligence for Personalised Learning based on Learning Style research is still driven by conference publications as an early dissemination medium. At the same time, scientific contributions with higher citation impact tend to come from reputable international journals.

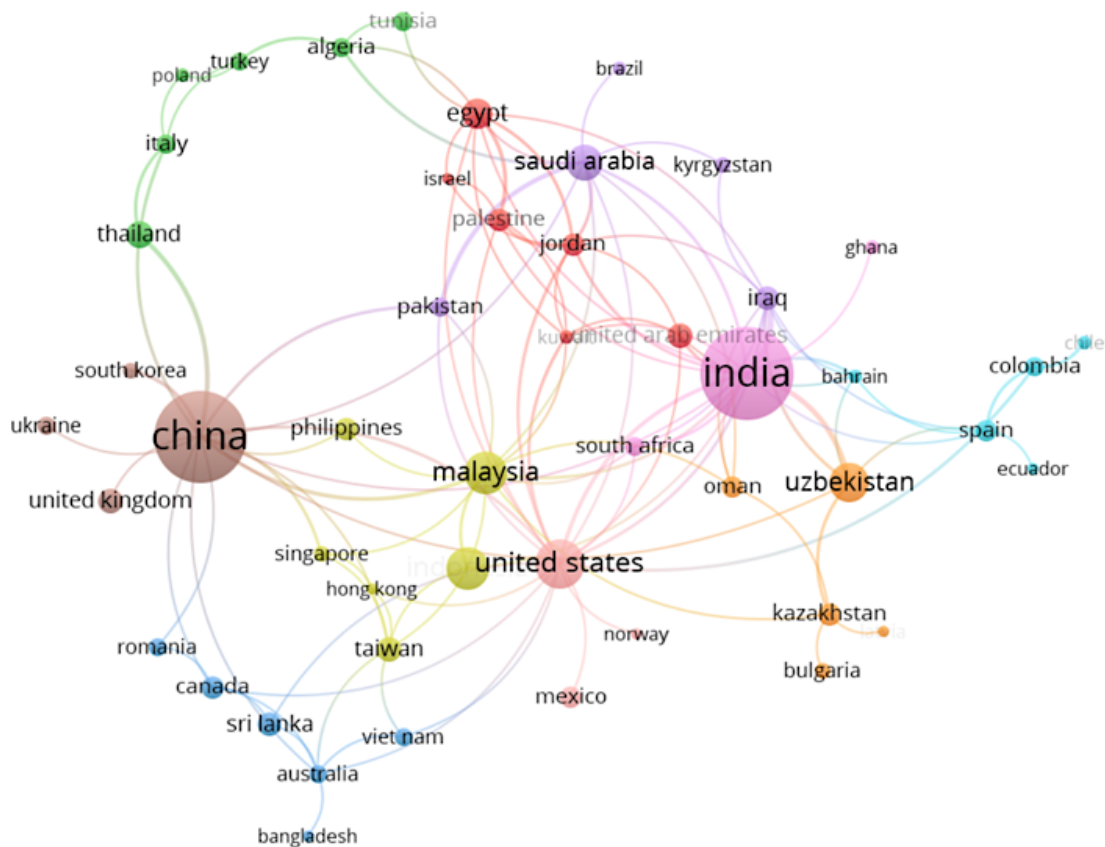


Figure 11. Country collaboration network (minimum number of documents of country = 2, minimum number of citation of country = 0, number of country to be selected = 60, number of cluster = 10)

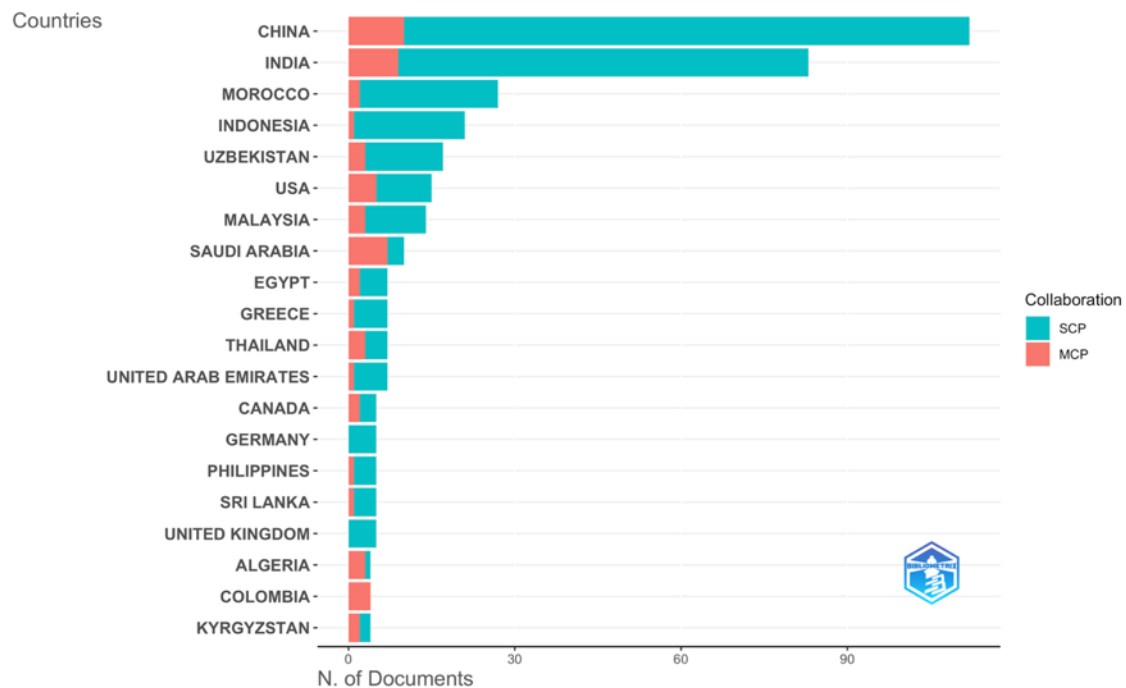


Figure 12. Corresponding Author's Countries (number of countries = 20)

The country collaboration networks analysis (Figure 11) shows that countries such as China, India, and the United States play a central role in research production and collaboration. China emerges as the dominant hub, characterised by an extensive network of collaboration, followed by India and other emerging countries such as Indonesia and Malaysia. Meanwhile, Western countries, particularly the United Kingdom and the United States, function as global connectors within the collaboration network. Nevertheless, collaboration patterns continue to exhibit a regional orientation, indicating that international collaboration has not yet reached its full potential.

These findings are further reinforced by the analysis of corresponding authors' countries (Figure 12), which shows that the majority of publications are still dominated by single-country publications. Rather than a multiple-country publication. China and India contribute the highest number of publications. However, most studies are conducted within a national context. A key insight from this finding is that, despite the substantial growth in research output, the level of international collaboration remains limited and should be strengthened to enhance both the quality and the scientific impact of study in this field.

The field of learning style has a robust theoretical foundation that underpins personalised learning. However, it continues to face challenges related to global integration and scientific collaboration. The dominance of a limited number of countries, coupled with the fragmentation of collaboration networks, suggests substantial opportunities to foster a more collaborative and multidisciplinary research ecosystem, particularly in advancing AI-driven personalised learning systems in the future.

3.3. RQ3: What learning style identification approaches and AI/ML-driven technologies are used in learning-style-based personalised learning?

Analysis of the 604-article dataset used in this study shows that the most widely used learning style identification approach is LMS log interaction (52 articles in the dataset). This approach utilises user interaction data in the learning system, such as content access activities, task processing time, and navigation patterns that can be downloaded and used as a dataset to detect learning styles [39]. The dominance of LMS-based approaches reflects a shift towards more contextual and behaviour-based identification of learning styles, going beyond reliance on subjective questionnaire data reported in the articles and datasets used in this study.

Table 4. Learning styles identification approaches

Methods	Number of Document in dataset
Indeks Learning Style/questionnaire	19
LMS Interaction Log	52
EEG (Electroencephalography)	4
Eye-Tracking	3
Game based	4

Methods based on Electroencephalography (EEG), eye tracking, and game-based approaches show a comparatively lower level of use than ILS and LMS; however, these methods remain an important contribution as an innovative approach. EEG allows the identification of learning styles based on brain activity [28]. Eye tracking is used to analyse learners' visual attention patterns [40] the same time, game-based integrates learning style concepts into an educational play environment that allows implicit identification of learning styles through user interaction [41]. These approaches reflect the evolving direction of research towards more objective and real-time methods for understanding

individual learning characteristics. A key insight from these findings is that classic questionnaire-based approaches such as ILS highlight the strong theoretical foundations of this field. However, the increasing use of LMS-based approaches and sensor-based methods, such as EEG, eye tracking, and game-based methods, indicates a shift towards a more dynamic, contextual, and data-driven approach, which has significant potential for the development of personalised learning systems in the future.

The use of AI in learning style identification is not only increasing quantitatively but also reflects the research community's methodological preference for specialised algorithms. The number of documents in Table 5 was obtained through a structured metadata filtering procedure. First, documents containing the author keyword 'learning styles' were retained as the initial filtering population. Next, the titles and abstracts of these documents were examined to identify explicit references to the specified AI/ML algorithms. An algorithm was counted if the title or abstract indicated the use, application, development, training, classification, prediction, or identification of learning styles. If the use of an AI/ML algorithm was not found in the title and abstract, the search continued to the full text, specifically the research methods section.

The distribution of AI/ML algorithms in Table 5 shows that research on learning style identification is not concentrated on a single computational approach, but develops through a combination of various machine learning paradigms. Learning style identification using Support Vector Machine (SVM) was used in 14 documents, followed by Neural Network with 13 documents and Random Forest with 9 documents. The high number of uses of all three algorithms in the dataset used in this study shows that research attention is mainly directed to methods that can be used to classify or model student characteristics from available data, so that learning style identification is increasingly positioned as a problem that can be operationalised computationally.

Table 5. AI/ML-driven algorithm to identify learning style

AI/ML Algorithm	Number of Document in dataset
Decision Tree (DT)	7
Naive Bayes	3
Support Vector Machine (SVM)	14
K-Nearest Neighbor (KNN)	8

AI/ML Algorithm	Number of Document in dataset
Artificial Neural Network (ANN)	8
Logistic Regression (LR)	5
K-Means	7
Random Forest (RF)	9
Deep Belief Network (DBN)	1
Convolutional Neural Networks (CNN)	2
Genetic Algorithms (GA)	1
Ant Colony Optimization (ACO)	3
Multilayer Perceptron	1
Deep Learning	6
Neural Network	13
Bagging Ensemble	1
MCDM	1
Ensemble Tree	1
Semantic web	1
Long Short Term Memory (LSTM)	1
Fuzzy Inference	3
Gaussian Mixture Model	1

The next pattern shows the use of K-Nearest Neighbour (KNN) and Artificial Neural Network (ANN), in 8 documents, respectively, as well as Decision Tree and K-Means in 7 documents each. The existence of these approaches suggests that the research does not only rely on specific classification algorithms, but also explores approaches based on data proximity, decision structures, and groupings to model the characteristics of learning styles. Meanwhile, Deep Learning appears in 6 documents and Logistic Regression in 5 documents. These findings indicate a methodological diversification, from conventional machine learning algorithms to neural and deep learning approaches, although the adoption of more complex approaches is still relatively limited compared to more established machine learning methods.

In contrast, a number of approaches have very low frequency. Naive Bayes, Ant Colony Optimisation (ACO), and Fuzzy Inference are each found in only 3 documents, whereas CNN is found in 2 documents. DBN, GA, Multilayer Perceptron, Bagging Ensemble, MCDM,

Ensemble Tree, Semantic Web, LSTM, and Gaussian Mixture Model each appear in only one document. This pattern suggests that although the algorithmic landscape is quite diverse, research attention is still stronger on classification algorithms and relatively established neural networks, whereas optimisation, ensemble, fuzzy, multimodal, and specific deep learning architecture methods have not received the same attention in the context of learning style identification.

The findings also provide an important indication of the direction of computational development in learning style research. The high number of documents using SVM, Neural Network, RF, KNN, ANN, and DT in the datasets used in this study indicates a tendency to treat learning style as a characteristic of learners that can be identified or predicted from data, rather than simply as an attribute determined through measurement instruments. At the same time, the emergence of K-Means, Deep Learning, CNN, LSTM, and a variety of other approaches—albeit with a lower number of documents indicates an expansion of exploration of techniques capable of handling more complex data patterns. Thus, the distribution of algorithms in the literature indicates a shift in attention from the use of learning style models to the exploration of computational mechanisms to identify and model learner characteristics.

However, the number of documents in the dataset used in this study does not indicate the effectiveness or superiority of an algorithm. For example, the higher number of studies using SVM than RF indicates that SVM receives greater research attention in the dataset being analysed, but it cannot be interpreted that SVM results in more accurate identification of learning styles. Similarly, the existence of low-frequency algorithms does not mean that they are less effective. Therefore, the findings in this table are more appropriately understood as mapping algorithmic attention in the literature, whereas algorithm performance evaluation requires experimental analysis and evaluation metrics that are outside the scope of this bibliometric analysis.

3.4. RQ4: What is the relationship between AI techniques and learning style models in personalised learning based on learning style?

The literature shows an increasing integration of learning style models with data-driven computational approaches in personalised learning research. Learning style models, specifically the Felder–Silverman Learning Style Model (FSLSM) and VARK, have been used

in several AI-powered systems to define learner profile categories and classification targets [42],[43],[44]. Previous studies have shown that these models can be computationally operationalised by mapping observable learner behaviours, such as interaction patterns, media preferences, and navigation sequences, into measurable features [42],[45]., This operationalisation allows AI techniques to process learner data and associate observed patterns with predefined learning style categories [12][45], [46]. However, the computational operationalisation of learning style models does not constitute validation of the underlying learning style theory or demonstrate that learning style-based adaptation is pedagogically effective. The role of AI in this literature is more precisely understood as enabling the identification and computational application of predefined learner profile constructions.

One of the key contributions of AI in this field is the transformation from a static approach to a dynamic and data-driven approach. If previously identification was done through explicit questionnaires [47], [48], then AI techniques allow implicit detection through the analysis of user interaction data. Activity logs are processed using algorithms like Decision Tree, Support Vector Machine, and Neural Networks in real-time [49],[30], so that learning styles can be identified without direct intervention from the user. In addition, in large-scale learning environments such as MOOCs [50],[51], advanced techniques such as Deep Belief Networks (DBN) [52],[27] and BiLSTM are used to handle high-dimensional and complex data, which cannot be processed effectively with traditional statistical methods. Once learning styles are identified, AI leverages the pedagogical principles of the model to adjust the learning environment. AI techniques are used to optimise learning path sequencing through optimisation approaches such as Ant Colony Optimisation (ACO) and Genetic Algorithms (GA) [53], which model the material selection process as an optimisation problem. In addition, AI-based systems also allow for personalised content presentation, where materials are tailored to learning style preferences, such as the use of visuals for visual learners or text for verbal learners. AI is also used to predict the most appropriate evaluation methods, so that the assessment process can be tailored to the individual characteristics of learners.

Recent developments suggest that AI is also being used to overcome the limitations of subjectivity in learning style models through the integration of physiological data. Electroencephalography-based techniques (EEG) allow the identification of patterns of

brain activity related to specific learning styles, which are then analysed using deep learning models [54], [55]. This approach provides an objective dimension in the identification of learning styles that previously relied on self-reports. In addition, multi-criteria decision-making methods such as ANP and DEMATEL [35] are used to address the complexity of the relationship between learning styles, cognitive characteristics, and learning objectives, thus allowing the system to prioritise adaptation more accurately.

Overall, the findings across RQ1–RQ4 provide an integrated view of the development and research landscape of style-based personalised learning, including its thematic evolution, research community, identification approaches, and AI/ML applications. Table X summarises the key findings for each research question and provides a brief synthesis of the study's key outcomes. Overall, the findings across RQ1–RQ4 provide an integrated view of the development and research landscape of style-based personalised learning, including its thematic evolution, research community, identification approaches, and AI/ML applications. Table 6 summarises the key findings for each research question and provides a brief synthesis of the study's key outcomes.

Table 6. Summary of key findings

RQ	Key Findings
RQ 1	The field has grown rapidly, with research themes extending from learning style identification to broader personalized learning oriented to AI, learning analytics, and technology.
RQ 2	Research production and collaboration are concentrated among a limited number of authors, countries, and publishing communities, with conference proceedings as the primary publication channel.
RQ 3	LMS interaction logs are the most frequently reported learning style identification approaches, while SVM, Neural Networks, and Random Forest receive the most AI/ML research attention.
RQ 4	AI/ML techniques primarily operationalize predefined learning style categories for learner identification and personalization, without validating the underlying learning style theory.

4. CONCLUSION

This study presents a systematic mapping of the development of learning style-based personalised learning through a bibliometric approach. The results show that this field has experienced significant growth, especially in recent years, which is accompanied by increasing research attention to the integration of artificial intelligence and machine learning. Conceptually, learning style models, particularly the Felder–Silverman Learning Style Model (FSLSM), remain visible in the research landscape, while thematic structures increasingly include data-driven personalisation, learning analytics, learner modelling, and intelligent learning systems. Methodologically, the literature reports a diverse range of AI/ML techniques for learning style identification. Random Forest is among the most frequently reported approaches in the dataset analysed. The findings of the study also show that AI primarily functions as a computational mechanism to operationalise predetermined learning style categories or learner profiles through learner data, classification, prediction, and adaptation processes. This study has several limitations. First, the analysis uses only publications indexed in Scopus, so relevant research not indexed in Scopus is not covered. Second, the dataset covers the period 2006–2026, but the 2026 publication is incomplete because data collection was carried out while 2026 is still ongoing. Third, the analysis is mainly based on bibliographic metadata, so it does not evaluate the methodological quality of each article, the validity of its empirical findings, or the educational effectiveness of the reported learning personalisation approach. Further research needs to complement this bibliometric mapping with a full-text systematic review and meta-analysis to evaluate the methodological quality, empirical evidence, and educational effectiveness of learning style-based personalisation. In addition, comparative research needs to be conducted to compare learning style-based personalisation with a broader learner modelling approach, which integrates various learner characteristics, such as behaviour, interaction, performance, and other learner data.

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