International Journal of Human–Computer Interaction

ISSN: 1044-7318 (Print) 1532-7590 (Online) Journal homepage: www.tandfonline.com/journals/hihc20

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To cite this article: Yigit Emrah Turgut, Seda Aktı Aslan, Tuba Kopuz, Alper Aslan, Jordan Allison & Özcan Özyurt (23 Apr 2026): Thematic Structure of Pedagogical Agent Studies: LDA Analysis for the Period 2020–2025, International Journal of Human–Computer Interaction, DOI: 10.1080/10447318.2026.2655931

To link to this article: https://doi.org/10.1080/10447318.2026.2655931

Published online: 23 Apr 2026.

INTERNATIONAL JOURNAL OF HUMAN–COMPUTER INTERACTION
https://doi.org/10.1080/10447318.2026.2655931

Thematic Structure of Pedagogical Agent Studies: LDA Analysis for the Period 2020–2025

Yigit Emrah Turgut[a], Seda Aktı Aslan[b], Tuba Kopuz[c], Alper Aslan[d], Jordan Allison[e] and Özcan Özyurt[f]

[a]Faculty of Arts and Sciences, Department of Information Systems and Technologies, Recep Tayyip Erdogan University, Rize, Türkiye; [b]Karakoçan Vocational School, Department of Child Care and Youth Services, Fırat University, Elazığ, Türkiye; [c]Republic of Türkiye Ministry of National Education, Rize, Türkiye; [d]Faculty of Engineering, Department of Computer Engineering, Munzur University, Tunceli, Türkiye; [e]School of Business, Computing and Social Sciences, University of Gloucestershire, Cheltenham, UK; [f]Faculty of Science, Department of Software Development, Karadeniz Teknik University, Trabzon, Türkiye

ABSTRACT

This study examines 2,360 pedagogical agent (PA) articles published between 2020 and 2025 to identify thematic structures, trends, and research gaps through bibliometric analysis and LDA-based topic modeling. The optimal model produced 10 themes ($c\_v = 0.4767$). The dominant themes—Learner Interaction with Virtual Assistants in Education, Student-Centred Learning and Individual Guidance, and NLP Foundations for Pedagogical Agents—account for 51.3% of publications. Trend analyses revealed consistent growth in both Artificial Intelligence and Pedagogical Design in Education and NLP Foundations for Pedagogical Agents, while Learner Interaction with Virtual Assistants in Education reached saturation. Interaction network results showed these themes at the conceptual core of the field, whereas AI-Driven Medical Chatbots, Knowledge-Based Learning Models, and Student Experiences in Intelligent Learning Environments emerged as future research areas. Overall, findings highlight a strong thematic shift toward artificial intelligence, natural language processing, and student-centered learning.

KEYWORDS

Pedagogical agents; LDA; latent Dirichlet allocation; topic modeling; bibliometric analysis

1. Introduction

Education has been profoundly shaped by technological advances throughout history, with teaching and learning methods evolving in parallel with these innovations. Digitalization has accelerated access to information, and learning environments have become increasingly flexible, personalizable, and interactive. In this context, innovations ranging from computer-assisted instruction to contemporary developments in artificial intelligence are redefining traditional learning approaches through educational technologies. Consequently, interactive interface elements have been systematically integrated into learning processes, and virtual characters that interact with students in digital learning environments, namely pedagogical agents, have begun to feature in educational environments.

Pedagogical agents (PAs) are defined as computer-controlled screen characters designed to facilitate teaching processes (Schroeder & Craig, 2021) and support learners' experiences of accessing and interacting with information in multimedia-based environments (Heidig & Clarebout, 2011). These agents are typically characters designed specifically for educational environments (Martha & Santoso, 2019) and engage in social interaction with users to facilitate learning (Sinatra et al., 2021). As emphasized across the literature, PAs are realistic and animated screen characters that support learning (Siegle et al., 2023) and are deployed in various educational technologies to enhance students' academic performance across multiple learning environments (Zhang et al., 2024). However, pedagogical agents may

CONTACT Tuba Kopuz tuba_kopuz23@erdogan.edu.tr Republic of Türkiye Ministry of National Education, Rize, Türkiye.

vary depending on the context in which they are deployed and may refer to different functional roles (Clarebout & Heidig, 2012).

PAs can take on the role of teacher, coach, student or peer in the learning process and can also provide emotional support (Sinatra et al., 2021). In digital interactive learning environments, they function as digital characters that assist teaching by providing coaching, feedback, and social and emotional support to students (Tao et al., 2022). In this context, PAs can be used not only to present information but also for interaction-based purposes such as increasing motivation, engaging in dialogue, and fostering collaborative activities (Schroeder & Craig, 2021). Particularly in collaborative learning processes, PAs enrich learning experiences by facilitating communication and guiding student collaboration. PAs support both group and individual performance, foster task and group awareness, and positively influence attitudes toward collaborative learning (Sikström et al., 2022). They also increase interaction by promoting more meaningful student participation and sustained engagement and have the potential to enhance learning environments (Craig & Schroeder, 2018). Furthermore, PAs support learning by providing messages, adaptive feedback, and contextual hints throughout the learning process (Sikström et al., 2022).

The most common expected outcome of integrating PAs is an improvement in learners' learning performance (Apoki et al., 2022). A meta-analysis has shown that learning with PAs yields more positive results compared to learning without these agents (Castro-Alonso et al., 2021). Pai et al. (2021) reported that PAs are as effective as human instructors. Furthermore, other studies have demonstrated that the use of PAs improves learning outcomes (Grivokostopoulou et al., 2020; Shalmani, 2021). Overall, PAs support learning performance (Beege & Schneider, 2023; Li et al., 2022; Zhang et al., 2024). Collectively, these findings highlight the substantial potential of PAs to enhance learning outcomes.

In recent years, the PA field has experienced significant growth (Zhang et al., 2024) and numerous literature review studies on PAs have been conducted in different contexts (Apoki et al., 2022; Dai et al., 2022; Pérez et al., 2020; Septiana et al., 2024; Sikström et al., 2022; Tao et al., 2022; Zhang et al., 2024). However, traditional literature reviews are constrained by subjectivity, limited scope, lack of reproducibility, and the potential to overlook important trends. Therefore, researchers advocate a Latent Dirichlet Allocation (LDA)-based approach to mitigate these limitations (Asmussen & Møller, 2019). LDA is an analysis technique that automatically identifies latent themes in documents and offers rapid and rigorous analysis of large datasets using variational inference techniques (Kherwa & Bansal, 2019). It also enables comprehensive, systematic, and replicable examination of extensive scholarly collections (Gurcan et al., 2021). LDA is widely recognized for its robustness and reliability (De Mauro et al., 2018). Accordingly, the aim of this study is to analyze academic articles published on pedagogical agents (PA) between 2020 and 2025 using the LDA-based topic modeling method:

1. To reveal the thematic structure of the field,
2. To examine the development and trends of themes over time,
3. To identify research gaps and potential areas for future work.

This will provide a comprehensive thematic map of studies on pedagogical agents, serving as a valuable resource for both researchers and practitioners. In this context, answers have been sought to the following research questions:

RQ1: What themes are prominent in articles published in the PA field between 2020 and 2025?

RQ2: How do the prominent themes in articles published in the PA field between 2020 and 2025 change over time?

RQ3: What structure do the relationships and interaction networks between the prominent themes in articles published in the PA field between 2020 and 2025 exhibit?

RQ4: What are the research gaps and emerging topics in the PA field during the 2020–2025 period?

2. Methodology

2.1. Research design and approach

This research was designed using a hybrid research methodology to reveal the thematic structure of academic articles published on PAs between 2020 and 2025. The method integrates two complementary analytical approaches:

1. Bibliometric analysis—This was applied to map the structure of the research field, determine publication volume, geographical distribution, and leading authors and journals. This stage provides a quantitative basis for understanding the field's publication ecosystem.
2. LDA-based topic modeling—This approach was used to uncover latent thematic patterns in the literature that are not explicitly stated, based on article titles, abstracts, and keywords. LDA models each document as a probabilistic composition of multiple themes, enabling semantic analysis that extends beyond superficial keyword matches.

The primary reason for favoring this hybrid approach is that bibliometric analyses are limited in capturing the semantic dimension of article content, while manual content analyses are inefficient in terms of time and resources when dealing with large datasets. LDA-based modeling enables the discovery of topic clusters in large-scale datasets in a repeatable, data-driven, and unbiased manner (Blei et al., 2003).

The methodological design of the study was inspired by the LDA-bibliometric integration previously effectively applied educational technology research, including augmented reality (AR), artificial intelligence-supported teaching systems, and journal-based thematic analyses (Aslan & Özyurt, 2026; Gurcan et al., 2021; Ozyurt & Ayaz, 2022). However, the original contribution of this study lies in its comprehensive thematic mapping of the PA literature and its focus on capturing current research trends by targeting the post-2020 period, during which rapid advances in generative AI technologies and conversational systems have substantially reshaped the conceptual and applied landscape of pedagogical agents. This design enables the results to present both a holistic view of the field and systematically identified priority areas for future research.

2.2. Data collection and corpus creation

The dataset for this study was obtained from the Scopus database, one of the most comprehensive and interdisciplinary academic publication indices internationally. The main reasons for choosing Scopus include:

i. its broad coverage across different disciplines,
ii. consistent metadata standards,
iii. advanced query filtering and targeted access capabilities (Mongeon & Paul-Hus, 2016).

Other databases were considered but excluded for methodological reasons. For instance, Google Scholar, while expansive, lacks transparent indexing criteria and provides limited control over metadata quality, duplication, and document type classification, which complicates large-scale automated analysis. PubMed, by contrast, is highly domain-specific and primarily oriented toward biomedical research, which could introduce disciplinary bias and reduce the comparability of the dataset with respect to the study's broader educational and computational focus. The use of a single, well-curated database therefore reflects a deliberate tradeoff between coverage breadth and analytical rigour.

During the data collection process, a set of key terms was identified to cover the literature in the PA field as comprehensively as possible. The selection of these terms was guided by three main considerations: (i) conceptual relevance to pedagogical agent research, (ii) frequent usage in the existing literature, and (iii) their capacity to accurately represent the core scope of the field. Terms that were overly broad, ambiguous, or likely to retrieve conceptually unrelated studies were deliberately excluded to maintain the precision of the dataset. For instance, highly generic concepts such as "artificial intelligence" or "intelligent system" were not included in the query, as they would substantially increase noise without necessarily referring to pedagogical agent research. This strategy ensured a balanced tradeoff between coverage and specificity. These terms were designed to include both technical concepts in the field (e.g., intelligent tutoring system, embodied agent) and commonly used application names (e.g., educational chatbot, AI tutor). The query was iteratively reviewed with the input of two domain experts and reached the following final form:

TITLE-ABS-KEY ("pedagogical agent" OR "intelligent tutoring system"

OR "AI tutor" OR "virtual learning agent" OR "embodied agent"

OR "conversational agent" OR "educational chatbot")

AND PUBYEAR $>$ 2019 AND PUBYEAR $<$ 2026

AND (LIMIT-TO (DOCTYPE, "ar"))

AND (LIMIT-TO (LANGUAGE, "English"))

2.2.1. Inclusion criteria

- Published between January 1, 2020, and August 1, 2025,
- Research articles published in peer-reviewed journals,
- Written in English,
- Publications containing terms directly related to pedagogical agents in their title, abstract or keywords.

2.2.2. Exclusion criteria

- Conference papers, book chapters, preprints, technical reports,
- Works that do not involve an educational context and focus solely on technical engineering applications.

To ensure consistency and comparability across the corpus, this study deliberately restricted its analysis to peer-reviewed journal articles. Journal publications provide relatively stable editorial standards, review practices, and metadata structures, which are essential for the reliable preparation of large-scale textual datasets used in LDA-based topic modeling. While peer-reviewed conference papers play a central role in computer science, particularly in human–computer interaction, their inclusion would introduce substantial heterogeneity arising from differences in submission formats, review rigour, publication length, and indexing practices across venues. Such variability poses significant challenges for systematic preprocessing and threatens the validity of any topic distributions that are derived. We therefore acknowledge that influential conference venues such as ACM CHI contribute meaningfully to education-related HCI research, but their exclusion reflects a methodological tradeoff rather than an assessment of scholarly value.

The data query was executed on August 1, 2025, and yielded a total of 2,360 articles. Each record was exported to include the title, abstract, keywords, publication year, author(s), country, source journal, and subject area information. The corpus created at this stage was prepared in a unique and standard format for use in both bibliometric analyses and the LDA-based topic modeling process.

2.3. Data Pre-processing process

The corpus created during the data collection phase underwent a multi-stage text pre-processing procedure to enhance both semantic accuracy and computational efficiency. This process is based on standard protocols widely used in the field of natural language processing (NLP) (Maier et al., 2018) and includes the following steps:

1. Text standardization:
   - All text was converted to lowercase.
   - Punctuation marks, numbers, and special characters were removed.
   - Non-English characters and symbols were removed.

2. Tokenization.
   - Texts were divided into word-based token units.
   - Sentence boundaries were not considered; context-based word sequences were preserved.
3. Lemmatization.
   - Words were reduced to their root or canonical forms.
   - Morphological variations such as "running" → "run" and "students" → "student" were merged.
   - This step aims to increase the model's thematic consistency by reducing word diversity.
4. Stop Words Cleaning
   - Common function words with no semantic contribution ("the," "is," "and," etc.) were removed.
   - Words that are not distinctive in the domain context but are excessively repeated in the corpus due to query terms were added to a special stop list. In this context, the word "agent", which appeared in more than 70% of all articles, was removed from the model.
5. Frequency-based filtering
   - High-frequency terms: Words such as "agent" mentioned above, which appeared in more than 70% of the documents, were excluded due to low discriminatory power between themes.
   - Low-frequency terms: Extremely specific and rare words that appear in less than one per thousand (0.1%) of the articles were excluded. As a result of this process, 9,404 words were eliminated.
6. Text merging
   - For each article, the title, abstract and keywords were combined into a single text field.
   - Thus, the input to the LDA model was transformed into a single, integrated text representing each document.

At the end of this pre-processing stage, a set of text that was cleaned, statistically robust, and analytically valuable was obtained. This set was used as the fundamental data input for the LDA-based topic modeling applied in the subsequent stage.

2.4. LDA-based topic modeling

The text corpus, which underwent pre-processing, was subjected to topic modeling analysis using the LDA algorithm. LDA is an unsupervised machine learning method that treats each document as a probabilistic mixture of multiple topics and represents each topic with specific word distributions (Blei et al., 2003). This approach facilitates the discovery of hidden thematic structures that are not explicitly stated in the texts.

2.4.1. Software and libraries used

The modeling process was carried out using the Python programming language and the Gensim library (Řehůřek & Sojka, 2010). Gensim's multi-core parallel processing feature was utilized to optimize processing time.

2.4.2. Hyperparameter settings

The settings recommended in the literature and successfully applied in previous similar studies were used as a basis (Goedecke, 2017):

- alpha: symmetric
- beta: symmetric
- passes: 15
- iterations: 100
- random_state: 42 (for repeatability)
- workers: 13 (number of parallel processes)

2.4.3. Determining the optimum number of topics

One of the most critical parameters affecting the model's success is the number of topics to be extracted (K). Therefore, models were created with topic counts ranging from K = 5 to K = 30, and the quality of each model was evaluated using the c_v coherence score (Röder et al., 2015), which measures the semantic coherence of the topics. The highest coherence score was obtained for K = 10 (c_v = 0.4767), and this model was selected as the final solution. Although this value reflects a moderate level of coherence, such scores are common in large and interdisciplinary bibliometric corpora. Moreover, the interpretive reliability of the model was strengthened through expert validation of theme labels and consistency across multiple analytical outputs (e.g., trend and network analyses).

2.5. Model output

The selected final LDA model produced two main outputs:

1. Topic-Document Matrix—Contains the probability distributions of each article in relation to the extracted themes.
2. Topic-Term List—A list of the 15 terms with the highest weight for each topic, which forms the basis for the subsequent theme interpretation process.

2.5.1. Theme interpretation and naming process

After running the LDA model, the top 15 terms with the highest weight for each topic were identified. These terms were not left as statistical outputs alone; they were reinterpreted while considering the comments of subject matter experts and conceptual equivalents in the literature.

The following steps were followed in the theme naming process:

1. Analysis of Representative Terms
   - High-weight terms associated with each topic were evaluated in terms of their semantic proximity and conceptual alignment.
   - For example, terms such as "student," "learning," "adaptive," and "feedback" indicate a specific pedagogical approach theme, while terms such as "dialogue," "NLP," and "LLM" indicate natural language processing-based systems.
2. Matching with the Conceptual Framework
   - The obtained term sets were matched with established concepts used in the pedagogical agent's literature.
   - At this stage, words with similar semantic fields were grouped and combined under a more inclusive concept name.
3. Revision with Expert Opinion
   - Two researchers experienced in the field of educational technologies and artificial intelligence-based teaching systems reviewed the proposed theme names and made the necessary adjustments in terms of conceptual clarity and alignment with the literature.
4. Concept Profile Creation
   - Finally, a brief description (theme profile) was prepared for each theme, formulated to clearly reflect the meaning and scope of that theme in the research field.
   - Thus, the topic clusters statistically determined by the LDA model were transformed into conceptual themes that correspond to the literature and can be easily interpreted by researchers.

This systematic process ensured the resulting themes accurately reflect current research trends and content clusters in pedagogical agents, rather than relying on purely statistical outputs.

3. Discussion, conclusions, and recommendations

3.1. Bibliometric profile

To understand the trends, scope, and position in the literature of studies conducted in the PA field, bibliometric data for the field were examined prior to thematic analysis. Figure 1 presents the bibliometric findings regarding subject area, country, journal, and author distribution of publications in the PA field between 2020 and 2025.

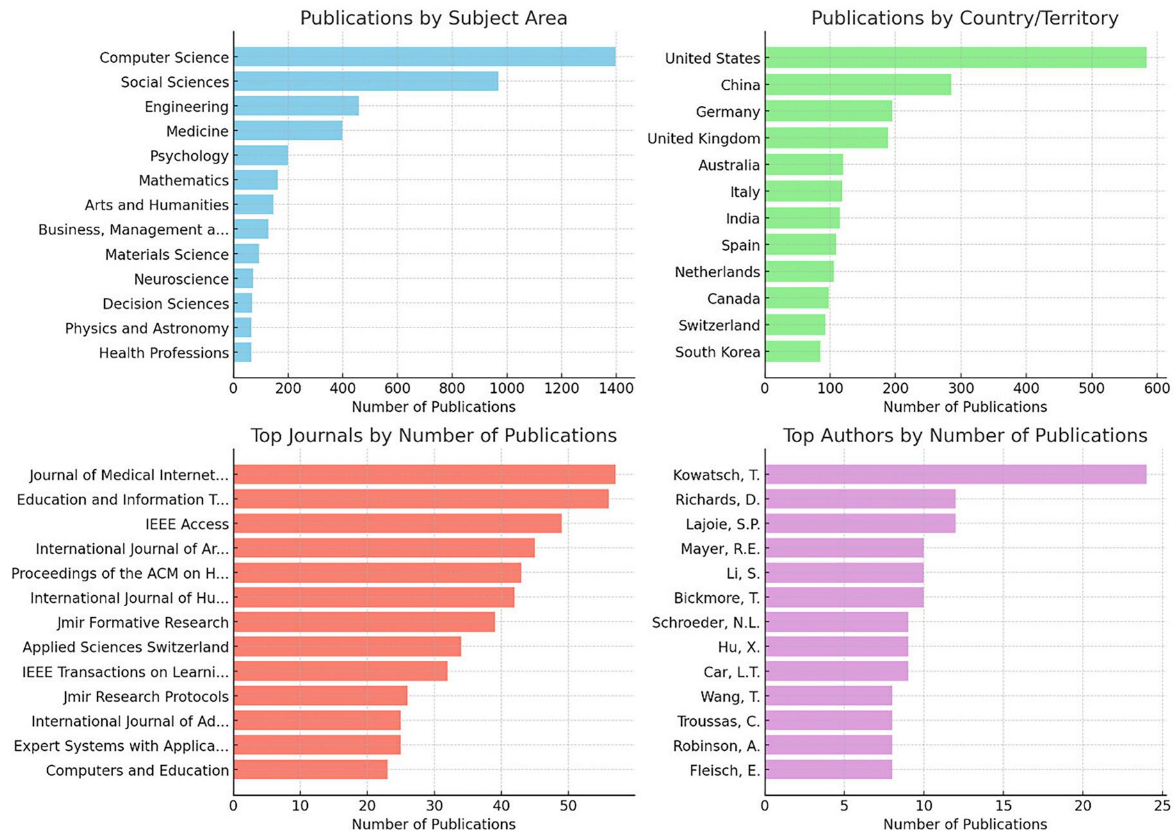

Figure 1. Bibliometric distribution of publications in the PA field by subject area, country, journal, and authors.

Upon examining Figure 1, it is evident that most publications are concentrated in the fields of "Computer Science" and "Social Sciences." In terms of country distribution, the United States is far ahead, followed by China, Germany, and the United Kingdom. In terms of journals, the "Journal of Medical Internet Research" and "Education and Information Technologies" have the highest number of publications. In terms of authors, "Kowatsch, T." has the highest number of publications, followed by "Richards, D." and "Lajoie, S.P."

3.2. Prominent themes in articles published in the PA field between 2020 and 2025 (RQ1)

The first research question of the study focuses on identifying the themes within academic articles published in the field of PA between 2020 and 2025. Themes that emerged from the topic modeling analysis were named considering the content context, and a conceptual profile was created for each theme. In naming these themes, attention was given to the frequency of key terms, their academic and disciplinary context, and their conceptual parallels in the existing literature. Consequently, the resulting themes are presented not merely as technical outcomes of the analysis, but as meaningful conceptual frameworks that capture and represent the core research directions within the field of pedagogical agents. Table 1 provides the name of each theme, a brief description (theme profile), the key terms that constitute that theme in the LDA analysis, and its percentage share (Pt %) within the total publication volume of the dataset. To enhance readability throughout the manuscript, an abbreviation was assigned to each theme, and these abbreviations are used consistently in the text and figures. The full list of theme names and their corresponding abbreviations is provided below.

- LIVAE—Learner Interaction with Virtual Assistants in Education
- SCLIG—Student-Centered Learning and Individual Guidance
- NLPPAG—NLP Foundations for Pedagogical Agents
- AIPDE—Artificial Intelligence and Pedagogical Design in Education

- HFPP—Health-Focused Pedagogical Practices
- SEILE—Student Experiences in Intelligent Learning Environments
- HCPS—Healthcare Chatbots for Patient Support
- KBLM—Knowledge-Based Learning Models
- AIMCDT—AI-Driven Medical Chatbots for Diagnosis and Treatment
- HCI—Human-Computer Interaction

Table 1 indicates that LIVAE ranks first in terms of publication volume, accounting for 18.0% of total publications. SCLIG ranks second with 17.3%, followed by NLPPAG with 16.0%. These three themes together account for 51.3% of the dataset, representing more than half of the total volume. AIPDE is also high in terms of publication volume, accounting for 14.3% of total publications. Among themes with medium publication volume, HFPP accounts for 7.7%, SEILE for 7.5%, HCPS for 5.2%, and KBLM also for 5.2%. Themes with lower publication volume are AIMCDT at 4.8% and HCI at 3.1%.

3.3. How did the prominent themes in articles published in the PA field between 2020 and 2025 change over time (RQ2)?

The second research question investigates the annual distribution and evolving trends in themes within the field of pedagogical agents between 2020 and 2024. In this context, the number of publications associated with each theme was calculated excluding data from 2025, since the year was still ongoing, and the trends were then visualized. Thus, the increasing or decreasing trends of the themes over time were analyzed comparatively to identify increases, declines, and periodic peaks of scholarly interest. The analyses aim to determine whether certain themes experience short-term surges in attention or display sustained, long-term development.

Figure 2 illustrates the annual distribution of publications for prominent themes in the PA field between 2020 and 2024. The graph depicts each theme's relative visibility during this period and highlights their comparative positions within the field. Data from 2025 were deliberately excluded from this figure due to their partial nature and the potential risk of distortion in year-based trend interpretation.

An examination of Figure 2 reveals that while some themes show a marked increase in the number of publications, others follow a more stable publication pattern. For example, the NLPPAG and AIPDE themes have shown a continuous upward trend since 2020. In contrast, themes such as SEILE and HCPS show fluctuations but remain relatively consistent in publication volume. Furthermore, the LIVAE and SCLIG themes maintain their important position in the field by demonstrating high and consistent visibility.

To explore these general trends in greater depth, further analyses were undertaken to examine thematic changes over time using two complementary quantitative approaches. The first analysis calculated the annual slope for each theme, applying linear regression to the annual publication counts between 2020 and 2024 (thereby estimating the average annual rate of increase in publications per theme). This makes it possible to identify which themes have expanded most rapidly in absolute publication volume.

The second analysis involved the calculation of the compound annual growth rate (CAGR). This measures the average annual percentage growth by assessing the proportional change in publication counts between the start and end of the study period for each theme. CAGR is particularly effective in identifying themes that develop rapidly despite having a low initial volume. Together, these two indicators capture thematic trends from distinct but complementary perspectives:

- The slope highlights the absolute increase produced over the period, revealing the sustainability of current dominant themes.
- CAGR focuses on proportional growth, indicating "emerging" themes that may gain more prominence in the literature in the future.

This dual analytical approach therefore enables a comprehensive assessment of both the current dynamics within the field and its potential trajectories of future development. In Figure 3, the results of

Table 1. Discovered themes, terms constituting the themes, and volume ratios.

Topic/abbreviation	Theme profile / theme terms	n	P_t (%)
Learner Interaction with Virtual Assistants in Education (LIVAE)	This theme examines the interactions students establish with virtual assistants in educational settings. It addresses their contribution to learning processes through elements such as conversational interfaces, user experience, trust, social presence, and interaction design. user-conversational-interaction-human-social-voice-virtual-design-experience-participant-research-technology-chatbot-chatbots-assistant-service-perception-trust-embodied-communication	425	18,0
Student Centered Learning and Individual Guidance (SCLIG)	This theme encompasses student-centered learning approaches and individual guidance practices. Elements such as intelligent teaching systems, adaptive learning models and personalized feedback mechanisms are at the forefront. learning-student-tutoring-intelligent-learner-model-adaptive-educational-problem-education-process-teacher-knowledge-research-personalized-skill-self-support-feedback-intelligence	409	17,3
NLP Foundations for Pedagogical Agents (NLPPAG)	This theme addresses the natural language processing (NLP)-based infrastructure of pedagogical agents and the use of these technologies in education. Speech analysis, dialogue management, task-based interaction, and learning environments integrated with large language models (LLMs) are examined. language-conversational-model-user-dialogue-natural-task-human-information-response-domain-conversation-data-question-large-llm-research-robot-chatbots-generation	378	16,0
Artificial Intelligence and Pedagogical Design in Education (AIPDE)	This theme examines the integration of artificial intelligence technologies into pedagogical design processes. It focuses on the design of educational tools, teaching strategies, virtual learning environments, and artificial intelligence-supported teaching applications. learning-education-student-research-technology-artificial-intelligence-pedagogical-educational-design-virtual-language-environment-teaching-tool-higher-academic-teacher-potential-university	337	14,3
Health-Focused Pedagogical Practices (HFPP)	This theme covers health-focused pedagogical practices and educational strategies. In particular, it addresses health education, chatbot-based support systems for elderly and adult groups, and technological solutions for social interaction and care processes. chatbot-health-chatbots-conversational-adult-participant-user-care-support-older-mental-intervention-usability-information-design-research-covid-social-experience-technology	182	7,7
Student Experiences in Intelligent Learning Environments (SEILE)	This theme examines students' experiences in smart learning environments. The effects of factors such as emotional state, cognitive performance, feedback mechanisms, game-based learning and facial recognition on the learning process are evaluated. student-emotion-learning-feedback-cognitive-performance-model-emotional-affective-task-intelligent-expression-tutoring-game-state-learner-data-test-facial-recognition	178	7,5
Healthcare Chatbots for Patient Support (HCPS)	This theme covers chatbot applications designed to support patients in healthcare services. It focuses on areas such as providing clinical information, assisting with care processes, improving the patient experience and enhancing the quality of interaction. chatbot-health-chatbots-conversational-adult-participant-user-care-support-older-mental-intervention-usability-information-design-research-covid-social-experience-technology	123	5,2
Knowledge-Based Learning Models (KBLM)	This theme addresses knowledge-based learning models and their application in technology-supported educational environments. It focuses on deep learning, network-based learning, monitoring systems and cognitive tasks. knowledge-learning-model-network-tracing-state-graph-deep-student-performance-navigation-neural-task-question-intelligent-exercise-memory-algorithm-data-embodied	123	5,2
AI-Driven Medical Chatbots for Diagnosis and Treatment (AIMCDT)	This theme examines the use of artificial intelligence-powered medical chatbots in diagnosis and treatment processes. It focuses on applications such as clinical decision support systems, patient assessment, symptom analysis, and health information management. patient-medical-health-chatgpt-care-information-conversational-question-clinical-artificial-intelligence-response-objective-chatbot-conclusion-disease-assessment-intervention-gpt-participant	113	4,8
Human-Computer Interaction (HCI)	This theme examines human-computer interaction and the design of pedagogical agents and user experience. Interaction frameworks, privacy, data security, design principles and decision-making processes are evaluated within this scope. human-digital-conversational-information-question-chatbot-physical-framework-design-development-decision-artificial-intelligence-machine-word-privacy-interaction-dat	74	3,1
	Total	2360	100

both measures are presented side by side, showing a comparative view of the absolute and proportional growth performance of the themes.

The findings presented in Figure 3 demonstrate that examining thematic developments in the PA field through two distinct growth indicators provides a robust framework for understanding the field's current dynamics and future directions. According to the slope-based analysis, the themes AIPDE, NLPPAG, and SCLIG display consistent and substantial publication growth across the study period. This growth highlights their status as some of the most actively investigated domains within PA research and underscores their pivotal role in shaping the field's ongoing development.

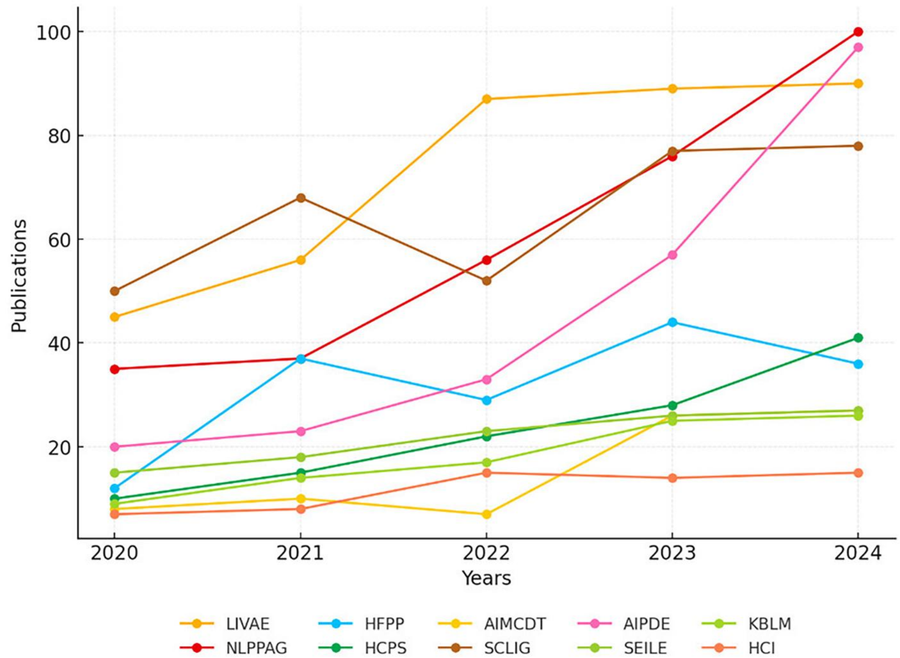

Figure 2. Annual publication numbers by theme in PA research.

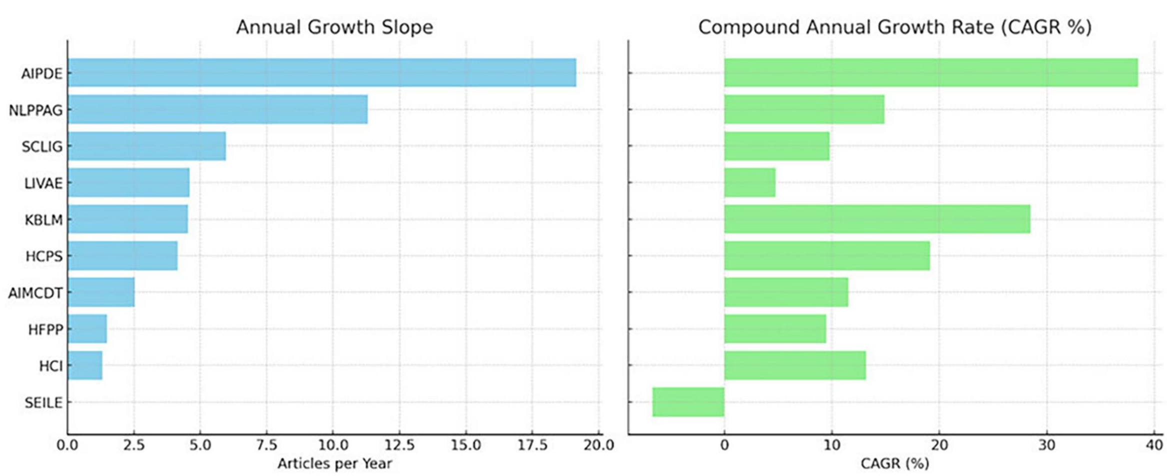

Figure 3. Comparison of annual growth and compound growth rates for PA themes in the 2020–2025 period.

In contrast, the compound annual growth rate (CAGR) analysis identifies themes exhibiting rapid proportional growth despite beginning with comparatively modest publication volumes. In particular, the themes KBLM and HCPS have the potential to become more dominant research areas in the coming years, given the strong momentum they have gained throughout the period. This finding emphasizes the importance of considering not only currently dominant topics but also rapidly emerging themes that may redefine the future research agenda.

The analyses conducted thus far have clarified current and potential research foci in the PA field by revealing the annual trends of themes in terms of both absolute (slope) and proportional (CAGR) growth metrics. However, to provide a more comprehensive visual interpretation of the perspectives derived from these two indicators, a comparative thematic heat map was constructed and is presented in Figure 4.

In this heat map, the publication volume of each theme between 2020 and 2025 is represented by varying color intensities, making it easy to see which themes achieved prominence in specific years. Darker colors indicate higher publication numbers, while lighter colors indicate lower levels of publication activity. This visualization facilitates a rapid comparison of annual differences in publication output while simultaneously illustrating the shifting prominence of themes over time.

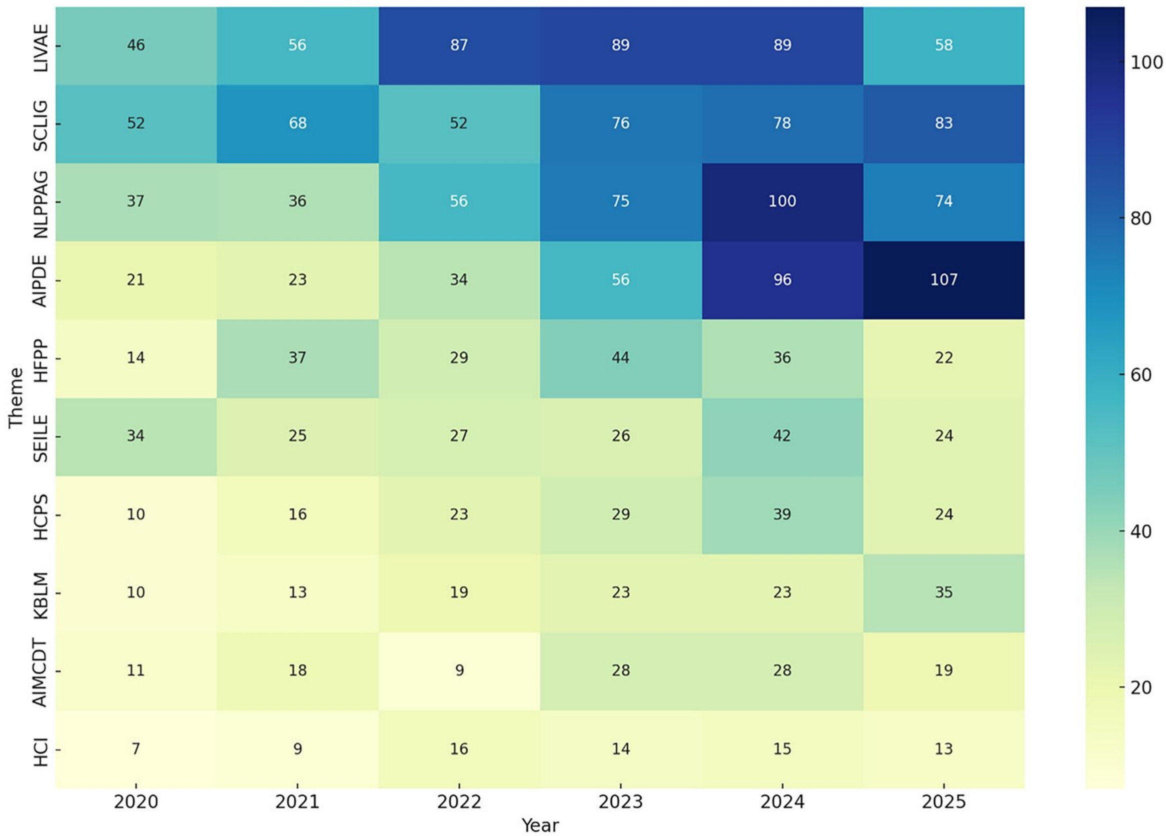

Figure 4. Comparative heat map of annual publication volume by theme.

An examination of Figure 4 reveals that certain themes are particularly prominent in specific years. It is evident from the dark color tones that the Student-Centred Learning and Individual Guidance (SCLIG) theme attained high publication volume from 2023 onwards. In the LIVAE theme, a noticeable darkening is observed from 2020 to 2023, while the lightening of the color in 2025 indicates a decline in volume. In the NLPPAG theme, the gradual darkening of the tone over the years visually demonstrates a steady upward trend, despite falling in 2025. However, it should be noted that a full inclusion of articles in 2025 was not possible at the time of writing as the year was not complete. In addition, themes such as HFPP and AIMCDT have remained relatively light in tone throughout the period, reflecting persistently low publication levels.

Following the visualization of annual publication volumes (RQ2), an additional analysis was conducted to evaluate the themes' positions within the period not only in terms of publication volume but also in terms of popularity rankings. Accordingly, all themes were ranked annually based on publication count, and their ranking trajectories were tracked from 2020 to 2025. The results are shown in Figure 5.

When examining Figure 5, it is evident that the popularity ranking has undergone significant changes over the years. Student-Centred Learning and Individual Guidance (SCLIG) and LIVAE generally occupied the top two positions during the 2020–2023 period, while AIPDE and NLPPAG ascended to leading positions in 2024–2025. KBLM and SEILE began in mid-level positions and demonstrated a gradual upward trend toward the end of the period. In contrast, themes such as HFPP, AIMCDT, and especially HCI have remained in the lower ranks and have not shown a significant upward trend throughout the period. This is consistent with the low number of publications observed in the total volume analyses for these themes.

3.4. Relationships and interaction networks between prominent themes in articles published in the PA field between 2020 and 2025 (RQ3)

The third research question explores the structure of relationships and interaction networks between prominent themes in the PA field between 2020 and 2025. Connections between themes were identified

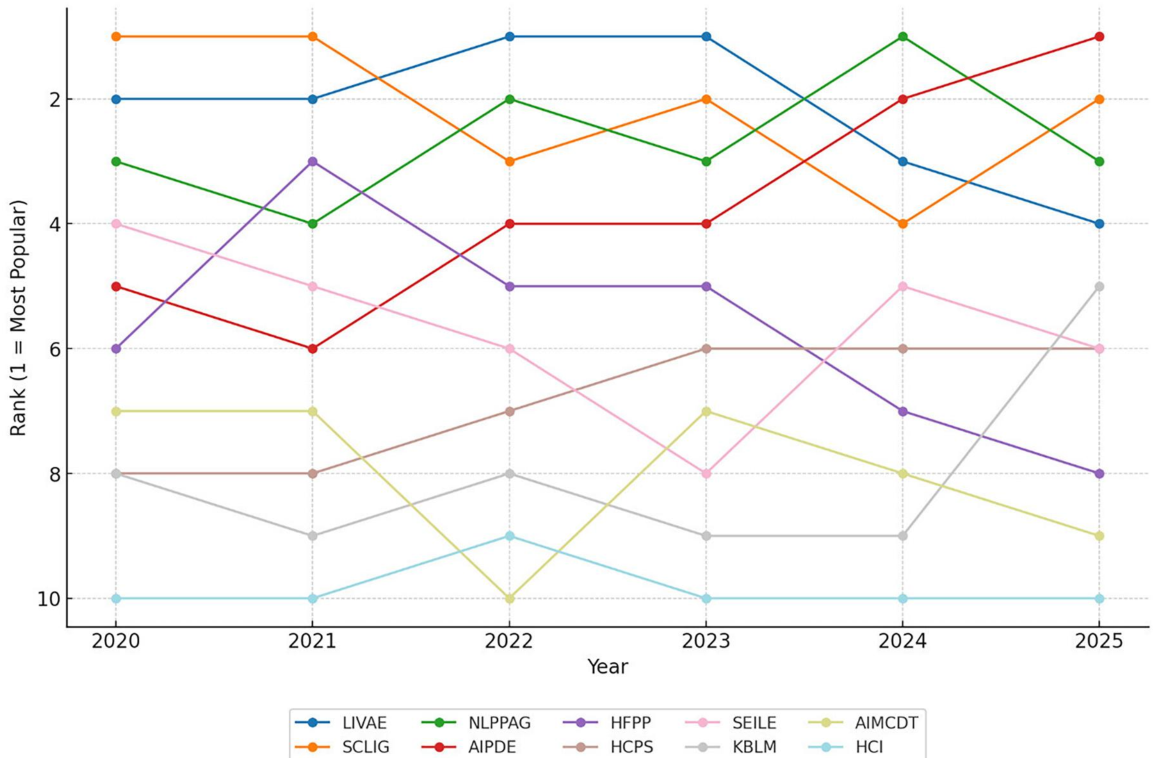

Figure 5. Change in the popularity ranking of themes (2020–2025).

using LDA analysis and the key terms that constitute these themes. Shared key terms between themes were interpreted as the indicators of conceptual proximity and potential interaction.

In this study, a bipartite network consisting of theme-term pairs was initially created, and subsequently, this network was reduced to theme nodes (projection) to obtain a theme-theme interaction network. The bipartite network was projected into a unipartite theme–theme network using a shared-term co-occurrence approach. Edge weights represent the number of shared terms between two themes. To improve interpretability and reduce visual noise, only connections based on at least two shared terms were retained in the final network. Edge (link) thicknesses were determined based on the number of common terms between two themes, while node sizes were scaled to reflect the theme's connection density (degree centrality) in the network. Furthermore, themes were represented using abbreviations to reduce visual complexity, and label colors were optimized only where necessary for visual readability.

This network structure provides valuable insight into which themes are conceptually related within the PA literature, and which remain more isolated. Themes with high centrality serve as conceptual bridges, linking their own subdomains with other thematic areas. Thus, the visualization highlights conceptual clusters within the field and potential interdisciplinary transitions. The results are presented in Figure 6.

Upon examining Figure 6, it is evident that the intensity of connections between themes varies considerably. Student-Centred Learning and Individual Guidance (SCLIG), LIVAE, and NLPPAG, located at the center, stand out as the nodes with the highest degree of centrality in the network; these themes share common terms with numerous other themes. This suggests that these themes not only exhibit high publication volumes but also maintain substantial conceptual links across subfields. In contrast, themes such as HCPS, HCI, and AIMCDT have a more limited number of connections and are located in the peripheral regions of the network. This indicates that these themes share relatively less content with other fields and focus on more niche topics within the research ecosystem.

When examining the edge thicknesses of the network, the connections between SCLIG–LIVAE, LIVAE–NLPPAG, and SCLIG–AIPDE are particularly strong. These strong ties indicate that there is common conceptual ground between the themes and that researchers frequently address these areas together in their work.

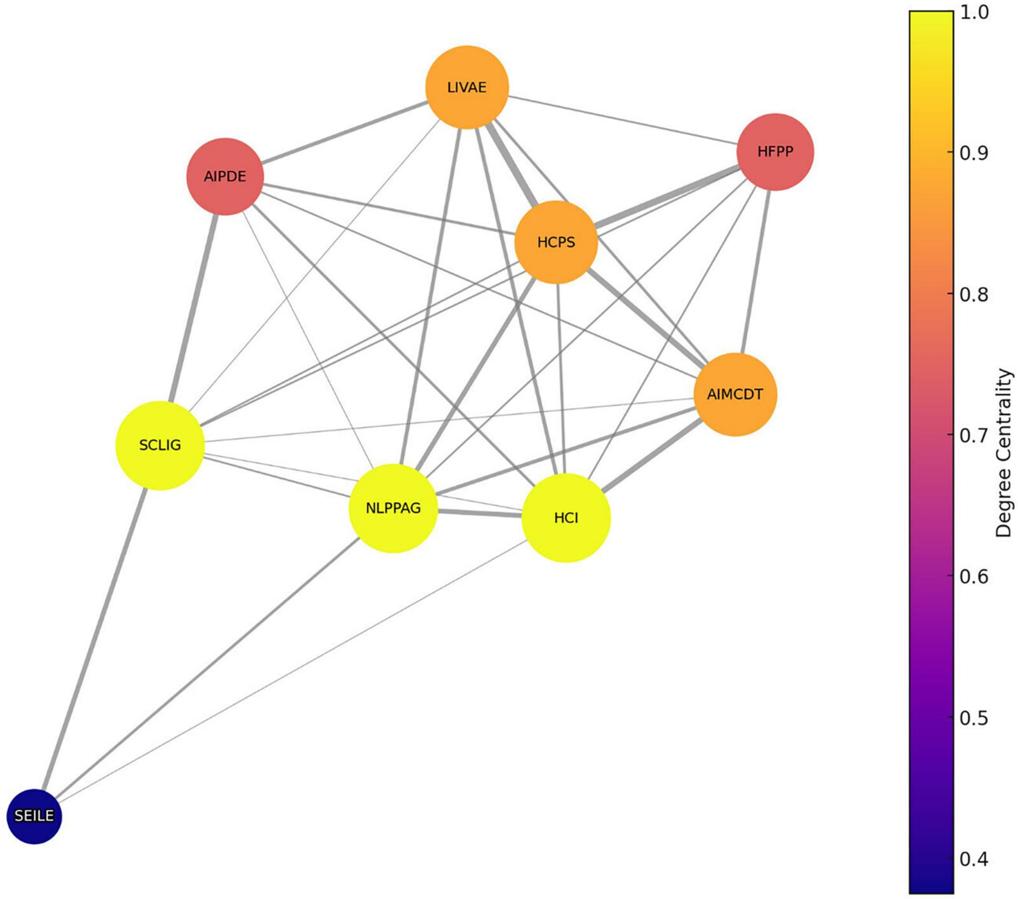

Figure 6. Theme–theme interaction network based on common terms.

3.5. Research gaps in the field of PA during the 2020–2025 period (RQ4)

The fourth research question examines all themes together in terms of both total publication volume and annual growth trend (Acc) to objectively identify research gaps in the PA field during the 2020–2025 period. The total publication volume represents the overall research intensity associated with a given theme, while the growth trend indicates the increase or stagnation in interest in this theme over time. Using these two indicators, the themes were classified into four categories based on average publication volume and mean slope values as reference thresholds. Thus, this method enables identification not only of currently dominant research areas but also of emerging themes with low publication volume but high potential for expansion.

Figure 7 presents a visual representation of this approach, with themes positioned in four research quadrants: (i) high volume–high growth (mature and accelerating areas), (ii) low volume–high growth (emerging/potential areas), (iii) high volume–low growth (maturing areas), and (iv) low volume–low growth (niche and lagging areas). This structure offers a comprehensive perspective on both current research patterns and potential future opportunities.

As shown in Figure 7, the themes SCLIG, NLPPAG, and AIPDE are classified as “mature and accelerating fields” due to their high publication volume and steep growth curve. This indicates that these themes have both a broad literature base and sustained interest. In contrast, the KBLM, SEILE, and AIMCDT themes stand out among the “emerging/potential areas” by exhibiting high growth rates despite low publication volumes. The position of KBLM, and SEILE, particularly in the context of education, indicates that insufficient work has been done in these areas and that there is therefore a clear research gap. The LIVAE theme, despite its high publication volume, falls into the “maturing field” category with a low growth trend, meaning that although the production volume in this field is high, the rate of increase remains limited. Finally, the themes HFPP, HCPS, and HCI themes are among the “niche and background fields” with both low publication volume and low growth trends.

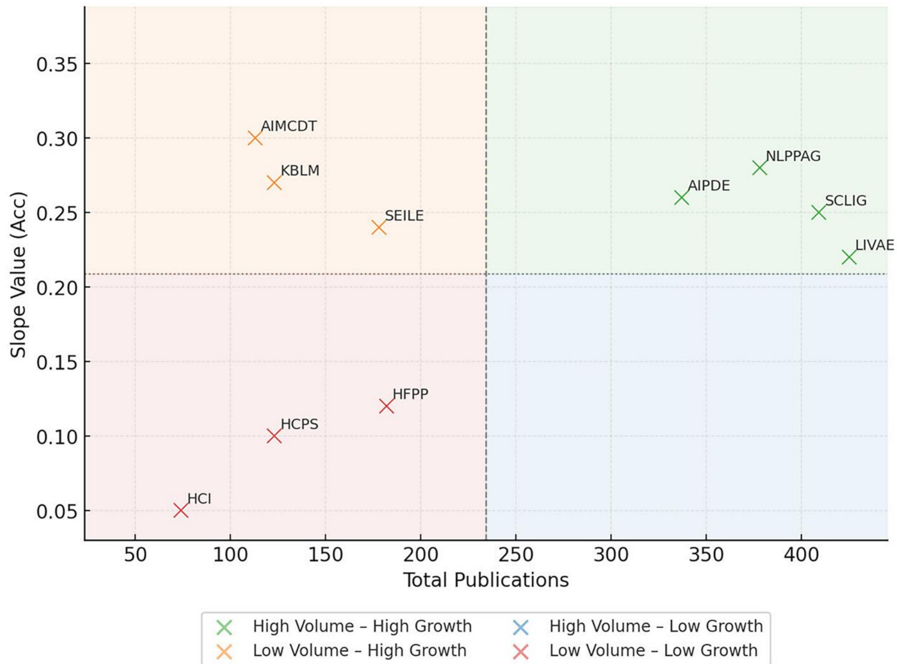

Figure 7. Four-region analysis based on the publication volume and growth trend of PA themes.

4. Discussion, conclusions, and recommendations

This study analyzed academic articles published in the field of PAs between 2020 and 2025 using an LDA-based topic modeling method and identified the thematic structure of the field, its development over time, interaction networks, and research gaps. The findings highlight both contemporary research directions and potential future priorities. It also reveals the theoretical axes toward which the PA field has evolved. The results are presented within the framework of the research questions.

4.1. Thematic trends in the PA field (RQ1)

Analysis of the 2,360 articles included in the topic modeling dataset revealed that learner-centered themes such as LIVAE, SCLIG, and NLPPAG were dominant in the literature. This result indicates that learner-centered technologies are becoming increasingly important in education. The prominence of these themes demonstrates that learning is being repositioned as not only a cognitive process but also a social and emotional one.

PAs significantly influence cognitive processes and learning outcomes through design and interaction strategies (Yusuf et al., 2025). Students perceive anthropomorphic or human-like computer behaviors as authentic social interactions, which supports learning (Schneider et al., 2022). In this regard, PAs function as interfaces that fill the "social presence" gap in digital environments. The decline in face-to-face interaction, particularly in the post-pandemic period, has increased the need for social presence in digital learning environments; this situation may have accelerated interest in pedagogical agents capable of human-like interaction. Lin and Yu (2025) found that that PAs positively affect learning through student-agent interaction. Conversational agents can be integrated into diverse pedagogical contexts, facilitating interaction between human learners and digital systems, and have thus gained broad acceptance in educational research and practice (Yusuf et al., 2025). Indeed, PAs generally aim to establish human-like natural interactions with their users (Dai et al., 2022). This is because learning is a social process and should be supported by interaction (Sikström et al., 2022).

The purpose of using PAs in digital systems is to provide interaction (Chiou et al., 2020). They deliver individualized assistance, motivational support, and facilitate collaborative learning processes within digital environments (Sikström et al., 2022). A meta-analysis examining the effectiveness of PAs in education found the strongest contribution in the functions of information provision, guidance, and motivational support (Sakellariou et al., 2024). Therefore, the obtained result aligns with existing studies. Previous findings also support the conclusions that interactions between students and PAs have positive effects on learning motivation and cognitive engagement.

Overall, emotionally intelligent PAs enhance students' positive emotions, motivation, and learning performance (Wang et al., 2023), and they also positively influence personalized language learning (Sinatra et al., 2021). PAs employ multimodal communication channels including verbal communication or non-verbal cues, such as gestures and facial expressions, to communicate and provide feedback in order to improve students' learning outcomes (Siegle et al., 2023). PAs utilize natural language processing technologies depending on the purpose served (Siegle et al., 2023). These findings show that PA research is not limited to the development of technological tools; it is integrated with learning theories, motivation models, and social cognition approaches. Therefore, it can be said that the field of PA is gaining increasing theoretical depth and is becoming part of the central debates in educational sciences.

Findings also reveal that the AIPDE theme has gained significant prominence in recent years. This finding is consistent with studies highlighting the role of artificial intelligence in creating personalized learning experiences (Holmes et al., 2019; Zawacki-Richter et al., 2019). However, health-focused pedagogical applications, including the themes HFPP, HCPS, and AIMCDT, have remained relatively low in volume. Therefore, health-focused studies represent promising avenues for future exploration.

4.2. The evolution of prominent themes in the PA field over time (RQ2)

Research findings demonstrate that thematic emphases surrounding artificial intelligence applications in education regarding PAs have evolved substantively over time. In particular, the themes of AIPDE and NLPPAG have emerged as focal points. This result aligns with broader trajectories observed in the field of Artificial Intelligence in Education (AIED) (Wang et al., 2024). As a result of rapid developments in artificial intelligence technology, the technical sophistication and pedagogical functionality of educational agents have increased significantly (Zhou, 2025).

The heat map data show that the two themes (AIPDE and NLPPAG) in particular have increased significantly from 2020 to 2025, while interaction/student-centered themes such as LIVAE and SCLIG, despite being studied with high intensity at the outset, have experienced a relative decline in 2025. This trend is also consistent with the changes in the ranking graph. AIPDE has risen to become the most popular theme in 2025. NLPPAG, on the other hand, approached second place in 2024 and 2025. In contrast, LIVAE, once dominant in earlier years, declined in relative importance.

These patterns indicate a disciplinary shift from user-experience and interaction-oriented investigations toward pedagogical design and NLP-driven agent architectures. In other words, there is a shift from the LIVAE theme toward the AIPDE and NLPPAG themes. This result shows that the thematic structures addressed in PA research have changed over time. Therefore, the findings collectively suggest that a paradigm shift has occurred. Indeed, increases in publication intensity and ranking prominence jointly validate this transformation.

The literature also increasingly emphasizes pedagogical integration, NLP agents, and ethical issues (Wang et al., 2024; Yusuf et al., 2025). While the heat map provides thematic intensity changes, the ranking graph shows the relative perceived importance of these themes within the research community. This dual-analytical approach thus provides a nuanced understanding of both absolute and relative thematic trends. However, although themes such as HCI, HCPS, AIMCDT, and KBLM remain present, they lag behind the dominant themes. Future investigations should therefore consider transition analyses tracing inter-theme evolution and finer-grained sub-theme mapping.

4.3. Interrelationships and interaction networks between themes in the PA field (RQ3)

In the interaction network graph, nodes represent themes, while edges represent the frequency of co-occurrence or conceptual relationship intensity between these themes. According to the results obtained from the analysis, the themes in the PA field have a highly interconnected structure. Accordingly, it has been concluded that articles published in the PA field during the 2020–2025 period show strong interactions between themes. This indicates that the field is undergoing intellectual maturation, characterized not by thematic fragmentation but by the emergence of a dense knowledge-sharing network. Therefore, it can be said that PA studies are shaped through multi-interactive structures and interdisciplinary bridges. Such dense network structures can be interpreted as an indication that a research field is beginning to integrate around common theoretical frameworks. The consolidation of interaction networks in the field of PA indicates that pedagogical agents are no longer considered as individual applications; rather, they have become a core research area positioned at the intersection of disciplines such as learning theories, HCI, artificial intelligence, and instructional design.

The themes NLPPAG, HCI, and SCLIG emerged as the prominent central nodes in the network. This result implies that these themes have strong relationships with all other themes. Therefore, it can be said that the themes NLPPAG, HCI, and SCLIG serve as bridges and integration points in the PA literature. The fact that the NLPPAG theme is connected to almost all other themes shows that natural language processing capabilities are integrated into every theme in pedagogical agent studies. This is also supported in the literature. Dai et al. (2022) state that pedagogical agent studies are increasingly shifting toward dialogue-based learning approaches. This central position demonstrates that natural language processing technologies have evolved beyond being merely a feature to become the backbone of PA designs. With the proliferation of large language models, the pedagogical functions of agents are being structured directly through language; feedback, guidance, and motivation processes are becoming speech-based. This situation may support PA research being addressed more robustly through cognitive load theory, constructivist learning, and dialogue-based teaching approaches. It was concluded that the SCLIG theme shows strong interactions with HCI, LIVAE, and NLPPAG. This result indicates that student-centered pedagogical principles continue to underpin personalization and individual guidance mechanisms within AI-enhanced agents (Chiu et al., 2023; Yusuf et al., 2025). Therefore, the future of PA research may be shaped more by how this technological capacity is integrated with learning theories than by the increase in technological capacity itself.

4.4. Research gaps and emerging issues in the PA field (RQ4)

When examining the total publication volume and annual growth trend of themes in the PA field during the 2020–2025 period, it was concluded that the AIPDE, NLPPAG, and SCLIG themes are mature themes with both high production volume and sustained growth. Therefore, it can be said that these themes form the “mature but vibrant” axis of the PA literature.

Artificial intelligence-supported instructional design has one of the highest growth potentials. Studies supporting this result exist in the literature (Beege & Schneider, 2023; Dai et al., 2022; Mustafa et al., 2024). The rise of natural language processing-based agents parallels the integration of large language models into education systems (Yusuf et al., 2025). Indeed, advanced technologies such as artificial intelligence and natural language processing can help establish better communication with agents (Guzman, 2020). Student-centered learning approaches continue to expand, particularly when artificial intelligence systems are combined with individual guidance and learning (Dever et al., 2023). This result indicates that the future research agenda in the field of PA will be shaped around the quality of pedagogical integration rather than purely technological advancement.

Novel research gaps are evident at the convergence of these thematic domains. Accordingly, future studies should examine student-centered learning mediated by AI-supported PAs and design interaction models grounded in LLM capabilities. Themes such as AIMCDT, KBLM, and SEILE remain less explored but exhibit rapid growth trajectories. Therefore, it can be inferred that future research opportunities lie predominantly within these emerging areas. AIMCDT, in particular, has not been sufficiently addressed in the educational sciences literature (Feigerlova et al., 2025). Hence, future investigations should focus on integrating knowledge-based systems into medical education and modeling student experiences through AI-based frameworks.

In conclusion, the comprehensive topic modeling and bibliometric analyses conducted in this study offer a holistic view of the intellectual structure and evolution of research on PAs between 2020 and 2025. The findings reveal a dynamic field characterized by the convergence of learner-centered pedagogies and artificial intelligence-driven instructional design. Meanwhile, the interaction network analysis underscores an increasingly interconnected research ecosystem, where conceptual overlaps between HCI, learner guidance, and natural language processing foster interdisciplinary integration. Taken together, these results point toward a paradigmatic transition in PA research, from technology-centered experimentation toward pedagogically informed, ethically grounded, and learner-responsive intelligent systems.

Limitations

Despite its contributions, this study has several methodological limitations that should be acknowledged. First, the LDA approach is based on the bag-of-words assumption, which does not account for word order or contextual meaning and may limit the depth of semantic representation. Second, topic modeling outcomes are sensitive to preprocessing choices such as stop-word removal, lemmatization, and frequency thresholds, which may influence the resulting thematic structure. Third, although theme naming was supported by expert review and alignment with existing literature, it inevitably involves a degree of subjective interpretation.

The selected model yielded a moderate c_v coherence value (0.4767). While such values are commonly observed in large and interdisciplinary corpora, this indicates that topic coherence is not perfect and should be interpreted with caution. To address this, the interpretive reliability of the findings was strengthened through complementary validation strategies, including expert review of theme labels and consistency across multiple analytical outputs. Moreover, CAGR values may be sensitive to small initial publication counts, which can lead to disproportionately high growth rates for themes with low baseline values. Therefore, CAGR results were interpreted cautiously and always in conjunction with absolute publication volumes.

Author contributions

CRediT: **Yigit Emrah Turgut**: Conceptualization, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing; **Seda Aktı Aslan**: Conceptualization, Resources, Validation, Visualization, Writing – review & editing; **Tuba Kopuz**: Investigation, Project administration, Writing – original draft; **Alper Aslan**: Data curation, Formal analysis, Methodology, Visualization; **Jordan Allison**: Investigation, Resources, Writing – review & editing; **Özcan Özyurt**: Data curation, Formal analysis, Validation.

Disclosure statement

The authors declare no potential conflicts of interest.

Generative AI disclosure

In the preparation of this manuscript, ChatGPT (OpenAI, GPT-4o) was used for language editing, literature searching, and figure generation. DeepL (DeepL SE) was used for translation purposes. All AI-assisted outputs were reviewed and verified by the authors, who take full responsibility for the integrity of the manuscript.

Funding

No funding was received for this study.

ORCID

Yigit Emrah Turgut http://orcid.org/0000-0002-6306-4090
Seda Aktı Aslan http://orcid.org/0000-0001-9345-6194
Tuba Kopuz http://orcid.org/0000-0001-6418-4580
Alper Aslan http://orcid.org/0000-0003-2970-6114
Jordan Allison http://orcid.org/0000-0001-8513-4646
Özcan Özyurt http://orcid.org/0000-0002-0047-6813

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About the authors

Yiğit Emrah Turgut is an Associate Professor at the Department of Information Systems and Technologies, Faculty of Arts and Sciences, Recep Tayyip Erdogan University, Rize, Türkiye. His research interests focus on safe internet use, open and distance learning, digital media research, topic modeling, and AI in education.

Seda Aktı Aslan is an Associate Professor at Karakoçan Vocational School, Fırat University, Elazığ, Türkiye. Her research interests include media literacy, educational technologies, curriculum development, virtual learning environments, Web 2.0 technologies, and instructional design.

Tuba Kopuz is a PhD candidate in the Department of Computer Education and Instructional Technology at Recep Tayyip Erdoğan University, Türkiye. She also serves as a specialist teacher at the Ministry of National Education of Türkiye. Her research interests include social media, media theories, and online safety.

Alper Aslan is an Associate Professor at the Department of Computer Engineering, Munzur University, Tunceli, Türkiye. His research interests include instructional design, secure internet, big data, and topic modeling.

Jordan Allison is a Senior Lecturer in Computer Science in the School of Business, Computing and Social Sciences at the University of Gloucestershire, United Kingdom, where he is the Academic Course Leader for the MSc Computer Science. His research interests include educational technologies, simulation-based learning, and research methodologies.

Özcan Özyurt is a Professor at the Department of Software Development, Faculty of Science, Karadeniz Technical University, Trabzon, Türkiye. His research interests include AI in education, software engineering, data mining, big data analytics, and topic modeling.