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Anthropomorphic Artificial Intelligence Adoption and Its Determinants in Education: A Bibliometric Analysis and PRISMA

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ABSTRACT

Anthropomorphic artificial intelligence (AAIA) has recently emerged as a significant area of inquiry within educational technology, offering human-like interactions that aim to transform teaching and learning processes. This study undertakes a comprehensive bibliometric analysis to examine the trajectory, scope, and impact of AAIA in education. By systematically analyzing publication trends, citation networks, and thematic clusters, the research maps the intellectual development of this evolving field and highlights its interdisciplinary nature.

The analysis explores how AAIA has been conceptualized and applied in educational contexts, including intelligent tutoring systems, virtual teaching assistants, and emotionally responsive learning companions. These applications demonstrate the potential of AAIA to enhance learner engagement, personalization, and inclusivity, while simultaneously raising ethical concerns related to bias, dependency, and authenticity of human–AI interactions. The study also situates AAIA within broader debates on digital pedagogy, emphasizing how anthropomorphic design features—such as voice, facial expressions, and adaptive emotional responses—shape learner trust, motivation, and social presence.

Bibliometric mapping reveals emerging clusters of research around affective computing, human–AI collaboration, and culturally responsive AI design, underscoring the growing relevance of AAIA across disciplines. The findings clarify the technological, pedagogical, and socio-cultural factors influencing its development and application. By identifying knowledge gaps and future research horizons, this study contributes to shaping scholarly discourse and guiding responsible innovation in the field. Ultimately, the research provides a foundation for educators, policymakers, and researchers to critically assess the role of anthropomorphic AI in transforming educational practices and ensuring its ethical integration into learning environments.

Keywords: anthropomorphic artificial intelligence (AAIA), artificial intelligence in education, educational technology, technology adoption, human–ai interaction, trust in ai, higher education, research trends.

INTRODUCTION

The combination of state-of-the-art computational technologies and educational theory has given rise to a new paradigm: Anthropomorphic Artificial Intelligence (AAIA). Artificial Intelligence Systems with Human attributes (AIAS): AI systems that show human attributes like social responsiveness, natural language interaction, and emotional adaptation. The features are not only functional but also more socially involved in the education process, allowing for a more integrated and interactive learning experience (Unified Theory of Acceptance and Use of Technology, Technology Acceptance Model).

In recent times, more and more educational institutions have embraced the AAIA concept, ranging from K-12 schools and higher education institutions to training institutions. The development of intelligent tutoring systems, conversational agents, and teacher-bots (T-bots) has captured the attention of many countries worldwide,

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especially in the era of generative AI (Alhumaid et al., 2023; Ouyang et al., 2022). Despite increased interest, AAIA implementation has not been uniform or consistently accepted.

The concepts of perceived usefulness, trust in AI systems, ethical issues, and emotional connection form a complex web that traverses the landscape. These ideas of perceived usefulness, trust in AI systems, ethical considerations, and emotional involvement create a tangled web that navigates the landscape between students and educators (Chatterjee & Bhattacharjee, 2020; Mogaji et al., 2024). Previous studies have tackled this topic by employing a wide range of frameworks, including UTAUT and TAM, but a few studies have succeeded in integrating theories and context outside their own fields of research (Polyportis & Pahos, 2024)

Furthermore, previous research is usually limited to specific technological applications or contexts, which prevents cumulative synthesis in AAIA research in education from developing a complete picture of its intellectual structure. The fragmentation underscores the need for more appropriate analytical approaches to overcome the shortcomings of traditional narrative reviews or narrow bibliometric reviews (Ajis & Zakaria, 2022)

To address these shortcomings, this study has employed an integrated triple-method approach comprising bibliometric performance analysis, science mapping, and a systematic critical review, following the TCCM (Theory, context, characteristics, and methodology) framework. All analyses are based on a selected set of 524 documents collected from the Scopus database from 2014 to 2024.

Research Questions

The study is guided by the following research questions:
RQ1: What are the temporal trends and geographic distribution of AAIA research in education?
RQ2: What are the dominant intellectual structures, including key authors, journals, and collaboration networks?
RQ3: What are the key determinants influencing the adoption of AAIA in educational contexts?
RQ4: How are theoretical frameworks, contexts, characteristics, and methodologies represented and integrated within the existing literature (TCCM analysis)?
RQ5: What critical research gaps exist, and what future research agenda can be proposed for AAIA in education?

This study is different from previous ones based mainly on narrative synthesis or brief bibliometric snapshots, and, by combining performance analysis and conceptual synthesis, it tries to give a multi-dimensional view of the literature. Specifically, it makes contributions by outlining the development of themes (characteristics) of research, highlighting the presence of dominant and underutilized theories, and critically evaluating the methodological trends.

So, the study brings a holistic picture of the changing relationships between humans and AI in education and gives researchers, practitioners, and policymakers concrete insights for their action plans.

MATERIALS AND METHODOLOGY

The purpose of this research study is to analyze the research landscape of Anthropomorphic Artificial Intelligence (AAIA) in the field of education, and to derive factors that affect the adoption of this. To reach this goal, the study has adopted a hybrid method of analysis, a combination of bibliometric analysis and the systematic literature review method.

Initially, the study carried out a bibliometric analysis, which explores the field performance and the structure of the intellectual field by performing a science mapping and a performance analysis. The study then focused on the most relevant studies on AAIA adoption determinants and performed an in-depth qualitative analysis of these studies using clustering techniques. Advanced bibliometric analysis—with VOSviewer and Bibliometrix—was used to back up these analyses. Figure 1 shows the overall research framework that is used in this study.

Data Source & Collection

The bibliographic information was obtained from two widely used scientific search databases, namely Scopus and the Web of Science Core Collection, that are renowned for their reliability and comprehensiveness in bibliometric studies (Ajis & Zakaria, 2022; Ganji & Afshan, 2024).

The data collection was carried out in a systematic approach and followed several steps.

For the first stage, the study conducted a wide search based on the words “Anthropomorphism” and “Artificial Intelligence” to narrow down the scope of the study. Initially, the study considered a 20-year time frame (2000–2024). But the results showed that there is only a slight difference between the datasets of 10 years and 20 years. In more detail, the number of documents obtained in the Scopus database in the 10-year span (2014-2024) and 20-year span (1000–2014) was 999 and 1,035, respectively, with a difference of only 36 documents. In the same way, for the 20-year time period, the Web of Science database gave 363 records, and for the 10-year time period, it gave 364 records. Because of this small amount of variation, the analysis was carried out using the last 10 years of second-hand logging (2014 - 2024) to allow for a relevant, up-to-date analysis.

The second phase of the study refined the search term by incorporating Boolean operators for more precise and relevant search results: ("Anthropomorphism" OR "Human-like AI" OR "Chatbot" OR "Conversational Agent")

Education AND ("Artificial Intelligence")AND ("Adoption" OR "Acceptance" OR "Usage").

Data retrieval was done on 6th August 2024.

During the last phase, data were preprocessed. Duplication of records was done with Zotero and then double checked to ensure they are relevant to the AAIA domain by manual review. Following this tool, 524 papers were selected after applying the inclusion criteria (peer-reviewed journal articles, in the English language, and relevant to the field of education).

A wide range of bibliographic data, including author information, keywords, citations, and publication sources, was gathered, building the foundation for further analysis (Sang, 2024).

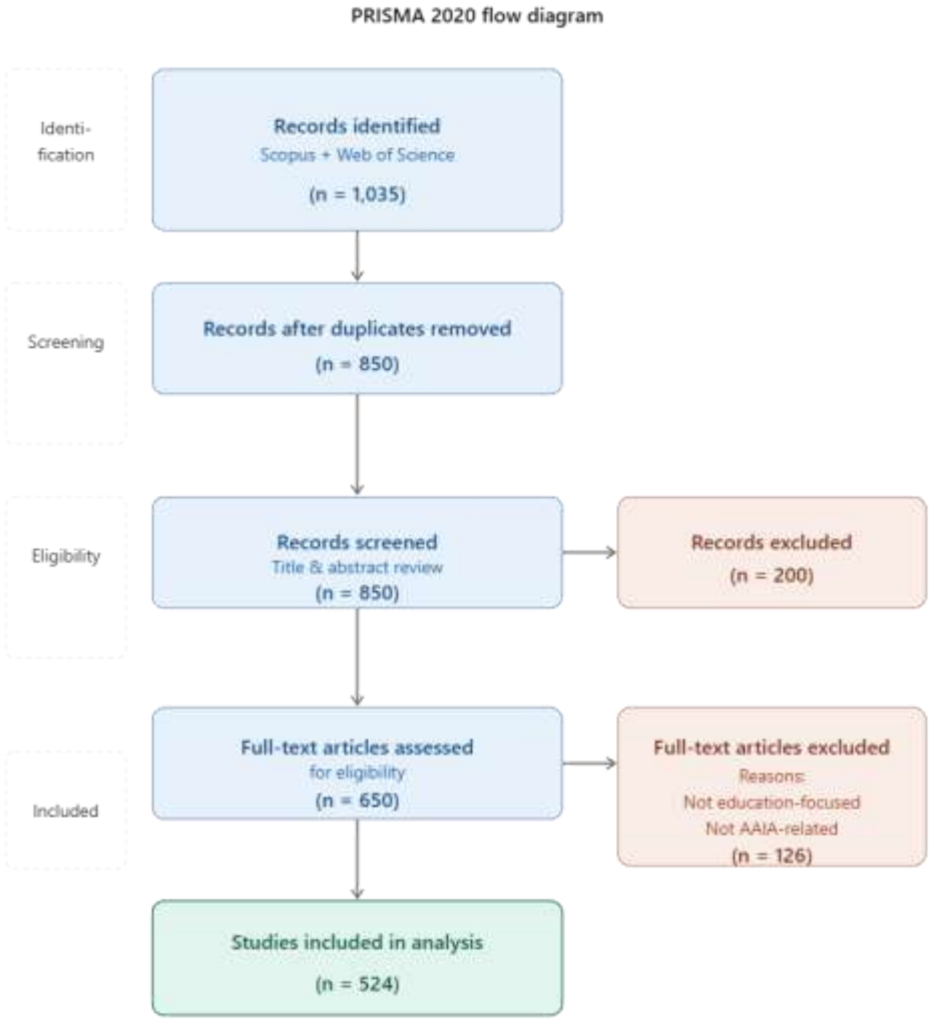

Figure 1: *The study selection process followed PRISMA guidelines to ensure transparency and reproducibility.*

Analysis Strategy

Data analysis is of vital importance in achieving the credibility and validity of research results. The quantitative bibliometric approach and qualitative synthesis method were adapted and applied to this study.

Scientific knowledge structures were mapped and visualized using the software VOSviewer and Bibliometrix, which are commonly used in bibliometric studies for mapping and visualizing scientific knowledge structures (Ajis & Zakaria, 2022; Watrianthos et al., 2023).

VOSviewer was used to build and visualize bibliometric networks, such as co-authorship networks, co-citation networks, keyword co-occurrence networks, etc. These analyses helped outline the types of collaboration, influential authors, and emerging research themes. On the other hand, the performance analysis was conducted using the application "Bibliometrix", which enabled us to examine the distribution of production characteristics, the impact of publications, and the role of sources (Figure 2).

The number of publications, the number of citations, and citations per publication were used as typical indicators of research productivity and influence. Moreover, science-mapping methods were employed to better understand the intellectual structure and thematic development of the AAIA research field (Ganji & Afshan, 2024; Sang, 2024).

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In addition, clustering analysis was conducted for grouping of related studies as well as identification of dominant research lines, and then mesh and synthesize them with the TCCM (Theory, Context, Characteristics, and Methodology) framework for further concept analysis.

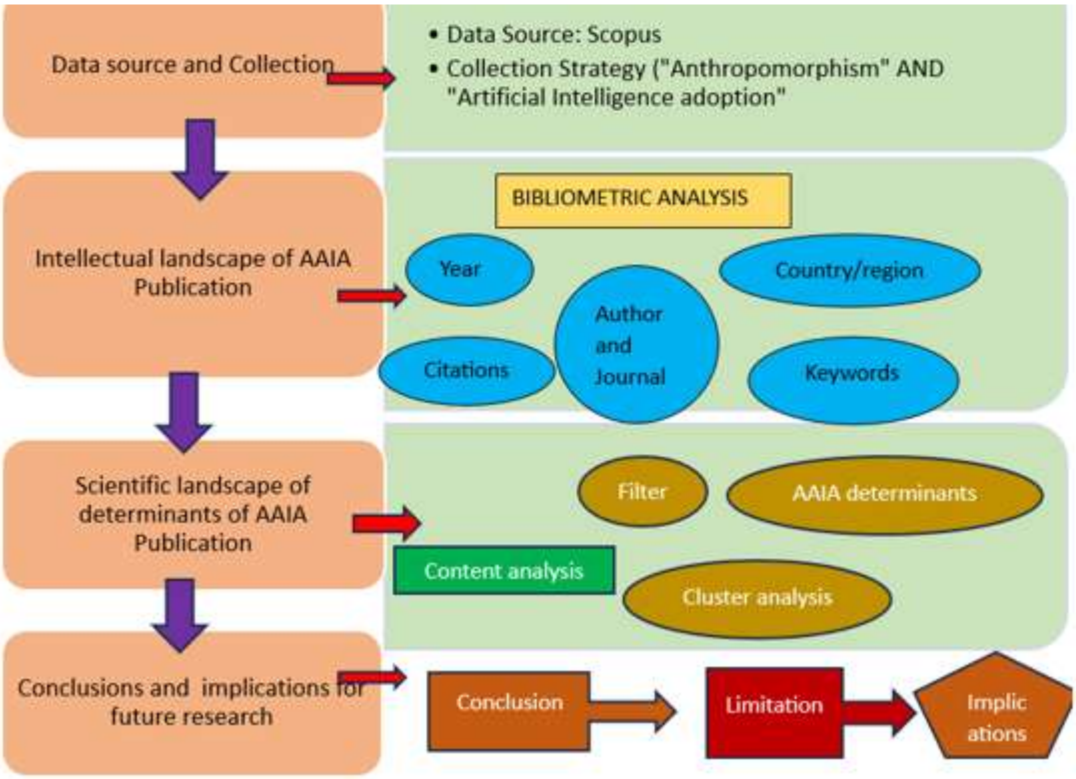

Figure 2: *The research framework of the methodology*

The approach used in this research is multi-faceted, designed to provide an overview of the intellectual landscape of the AAIA's publications. To build on the analytical strategies suggested by Han et al., we have followed three main steps: performance analysis, a science mapping exercise, and content analysis. The performance analysis adopted the conventional bibliometric method, which classifies publications based on total publications (TP), total citations (TC), and Average citations per publication (AC). The focus of this work is on answering the question of how successful the productivity and impact of AAIA are (TC/TP). These metrics provided a quantitative sense of the field, showing who the biggest and best producers are and noting patterns in research results. Science mapping techniques were used to gain a deeper understanding of the intellectual structure of AAIA. Three analytical approaches (co-authorship analysis, co-citation analysis, and knowledge domain forecast) were used to derive collaborative patterns, knowledge connections, and the development of research themes. This analysis was used to help visualize the field and identify trends and clusters of research that are influential (Watrianthos et al., 2023; Ganji & Afshan, 2024); Sang, 2024).

Furthermore, an extensive content analysis was conducted on a selected subset of AAIA publications, along with the bibliometric analysis. These documents were classified according to their thematic content using a clustering algorithm. This analysis enabled further understanding of the critical factors affecting the use of AAI in the education system.

This dual effort seeks to provide a fuller picture of the intellectual history of AAIA, both in terms of its development and the people and impetus that supported it. Results from this study will guide future research and the further development of effective strategies to integrate AAI into education.

Intellectual atmosphere of IA (AAIA) journal publications

This section describes a visualization of the intellectual landscape of the source code of Anthropomorphic Artificial Intelligence Adoption (AAIA) research. By conducting a detailed bibliometric study, various aspects of the publications, such as authorship, geographical distribution, citations, research themes, etc., are analyzed, and key insights are drawn. The analysis provides a more detailed picture of the ever-changing research landscape, identifies interests as well as emerging trends, and outlines the intellectual linkages between researchers in the AAIA community.

Examine the distinct features of AAIA publications in each year. Describe the unique characteristics of AAIA publications for each year.

From the figure (Fig. 2), there is a steady rise in the number of articles published from 2014 to 2023, which is indicative of increased interest in the field and research work. There is an apparent uptick in publications in 2024, which may be a breakthrough or research spotlight. The overall trend is one of upward growth, suggesting a thriving and expanding research community. Several factors could contribute to the observed trend, such as advancements in research tools and methodologies, which may have facilitated increased productivity. There is increased funding for research initiatives, and growing awareness could have stimulated more publications. There may have been more international collaboration among researchers, which contributed to an increased level of publications. (Chatterjee & Bhattacharjee, 2020) (Watrianthos et al., 2023) (Ouyang et al., 2022) (Jo, 2024) (Raman et al., 2024)

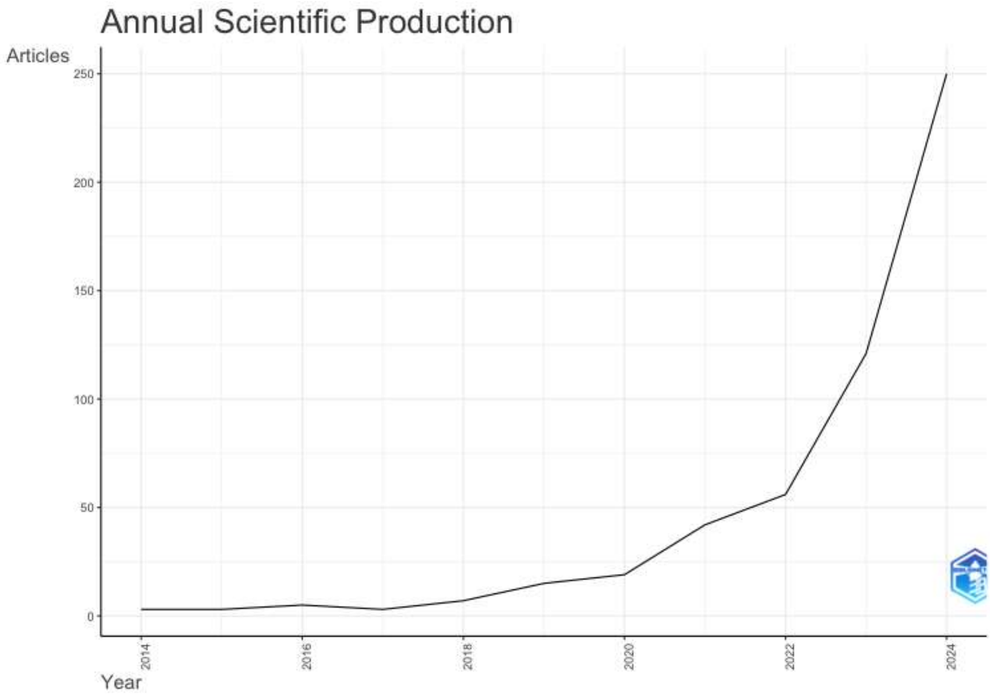

Figure 3. Annual Scientific production of AAIA publication

The table 1 displays the number of annual scientific publications on a certain scientific area between 2014 and 2024. The years are listed in the first column, and the number of articles in each year is indicated in the second column. The table illustrates a steady trend of rising published articles in this decade, indicating increasing interest and research efforts in the subject. The largest growth is between 2022 and 2024, which could be a sign of new research or an advancement in the field. (Watrianthos et al., 2023) (Ouyang et al., 2022) (Watrianthos et al., 2023

Fig. 3 illustrates the average number of citations received per year for a dataset of 524 documents. The x-axis represents the years from 2014 to 2024, while the y-axis indicates the average citations per year. The graph shows a steady increase in average citations from 2014 to 2018, suggesting growing interest and impact in the research area.

Table 1: Number of annual scientific publications between 2014 and 2024

Publication Year	**No. of Articles Published**

2014	3
2015	3
2016	5
2017	3
2018	7
2019	15
2020	19
2021	42
2022	56
2023	121
2024	250

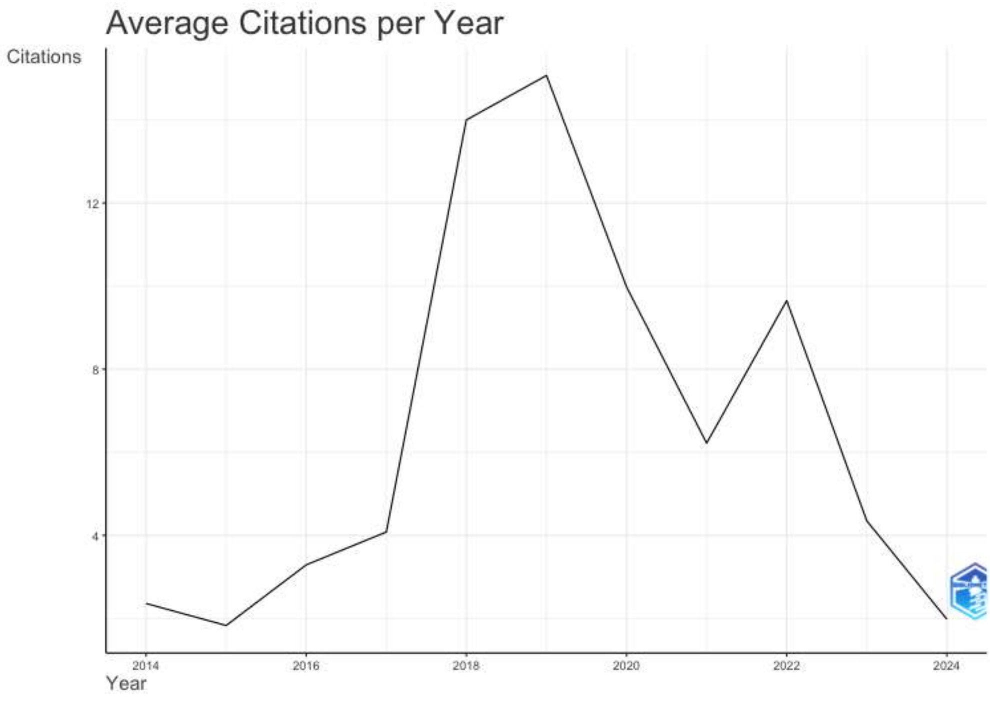

Figure. 4. The average citations per year for AAIA publications.

The year 2019 witnessed a significant peak in average citations, indicating a surge in scholarly attention and influence. Following this peak, the average citations declined from 2019 to 2022, before stabilizing at a relatively lower level in 2023 and 2024.

Characteristics of AAIA Publication by authors and journals

Collaborations among a variety of scholars are also expected to contribute to the establishment and development of any academic discipline. After performing a bibliography, 2160 authors with 524 documents contributing to this field are identified. In this field, contributors are illustrated by their collaboration networks (with the number of publications). The number of documents per author was thresholded at one, and the 1000 authors with the most links were chosen. Consequently, it produces a simplified co-authorship network as depicted in Fig.4 (a) that

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depicts the co-authorship information/relationship between the researchers working on Anthropomorphic Artificial Intelligence (AAI) in the education domain. The nodes are authors and the lines are the relationships between the authors. The size of the nodes could be related to productivity and the citation impact of a specific author, and the color of nodes could be related to theme and/or affiliation. Authors such as Gross, Seth, Repici, Alessandro, and Parasaravathi, Sravanti have central positions indicating that they are well influential in the field of education or are involved with the other involved authors of AAI. The network shows clear clusters, which may be used as evidence for a selection of research interest themes or for affiliation. Seth, for instance, may have a holistic interest in an aspect of AAI, such as a specific pedagogical and/or technical approach. Contributors from the 'periphery of the network', like Xu and Yue, may be venturing into new areas of research or publishing findings in a developing field of AAI in education. (Watrianthos et al., 2023) (Ganji & Afshan, 2024) (Sang, 2024).

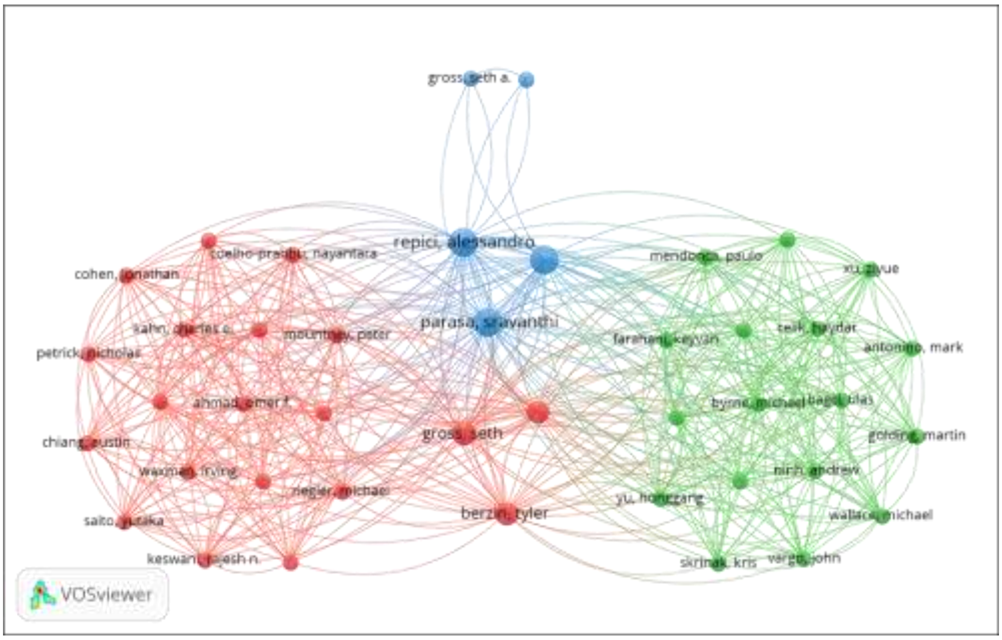

Figure. 4 (a)

The temporal overlay in Figure 4(b) gives a dynamic view of the evolution of the author collaborations in the research domain. By linking authors to their publications, this visualization allows tracking of influential authors over time. Darker nodes are authors who were important in earlier years; lighter nodes are authors who were more recent. This is the temporal overlay to help identify the trajectory of the research contributions of authors. The visualization shows three separate groups of researchers (2020, 2022, 2024). The leftmost cluster of years (2020 on average) has a higher density than the other clusters, and appears to indicate more cohesive collaboration within a group of authors. This could suggest a more renowned or powerful research team. The temporal overlay is useful, as demonstrated in the case of Sravanthi Parasaravathi. This author has 48 links and has an average publication year of 2022, indicating that they may be a prominent player in their field of study.

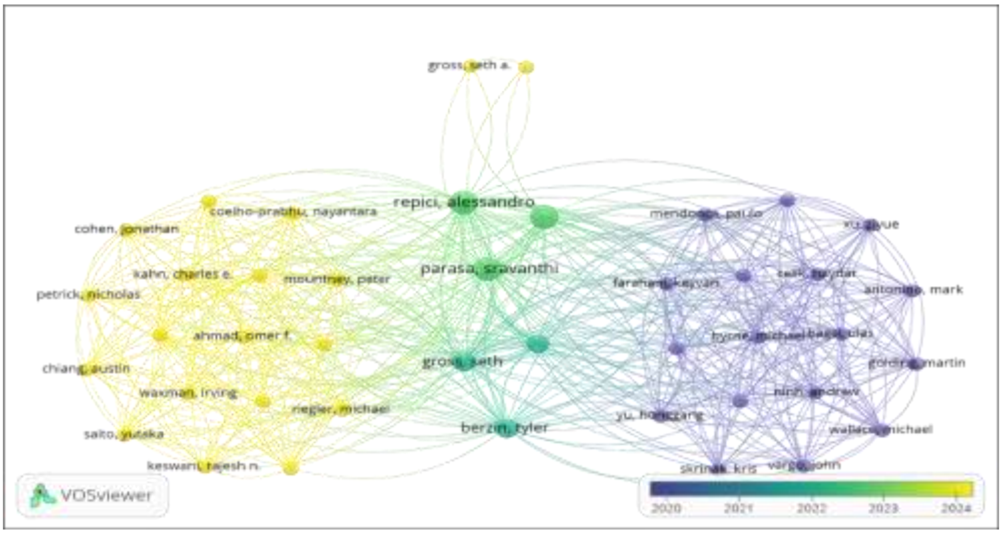

Figure. 4 (b)

***Figure. 4** AAIA publications by authors and author collaboration networks.*

Figure 5: Most relevant sources or Journals of AAIA publication

The following bar chart, Figure 5, shows the distribution of different sources in a particular research area. On the y-axis are the different sources, and on the x-axis are the number of documents linked to each source. The top sources cited are "Education and Information Technologies" and "IEEE Access", indicating their prominence in the field. The distribution of documents by source is fairly uneven, in that a few sources represent a large share of the documents. The diagram shows trends in the impact of education and other factors over time for some journals.

The 12 sources with the highest number of publications are ranked in Table 2. The two most important sources are "Education and Information Technologies" and "IEEE Access", indicating the key role of these sources in the field. The two sources with the most publications are shown, but there are other relevant journals that are not shown, indicating a diversity of research. The journals, such as "Computers and Education: Artificial Intelligence" and "Interactive Technology and Smart Education," reflect the particular emphasis on technology-driven learning and the use of AI in education.

Table 2: Sources with the highest number of publications

Sources	Articles
EDUCATION AND INFORMATION TECHNOLOGIES	15
IEEE ACCESS	10
INTERNATIONAL JOURNAL OF HUMAN-COMPUTER INTERACTION	8
COMPUTERS AND EDUCATION: ARTIFICIAL INTELLIGENCE	7
TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE	7
TECHNOLOGY IN SOCIETY	7
COGENT EDUCATION	6
COMPUTERS IN HUMAN BEHAVIOR	6
HELIYON	6
INTERACTIVE TECHNOLOGY AND SMART EDUCATION	6
INTERNATIONAL JOURNAL OF DATA AND NETWORK SCIENCE	6

1. ***Characteristics of AAIA Publication by countries/regions***

The map below illustrates the partnerships between countries and/or regions within the context of scientific research. Nodes represent countries/regions, and the lines between them indicate collaboration. partnerships. The thickness of lines could indicate the level of collaboration and/or its frequency (Watrianthos et al., 2023).

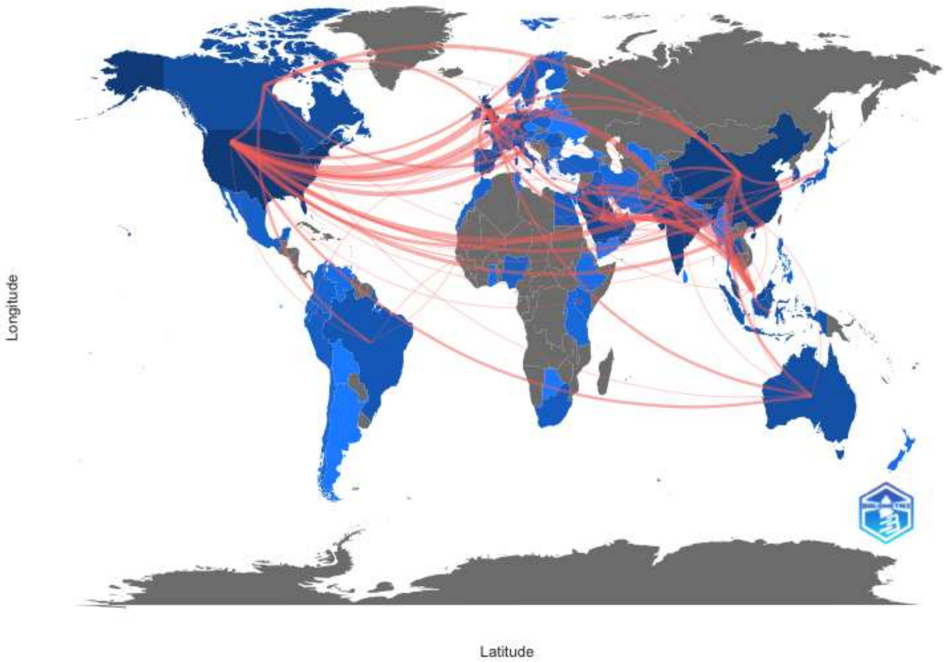

Figure 6: Map illustrates the partnerships between countries and/or regions

The map shows that many areas are considered significant international scientific cooperation hubs, such as North America, with a high concentration of connections to other areas, especially in the United States and Canada. Collaborative ties are also strong in several European countries, including the United Kingdom, Germany, and France. Increased involvement of countries in international collaborative efforts, such as China, Japan, and South Korea.

The map shows that there are certain countries that are grouped together, indicating possible regional networks or collaborations of research. In the example of collaborations, there seems to be a lot of concentration in Europe. The visualization also showcases new partnerships between regions that were not well-established before, like between Asia and Africa.

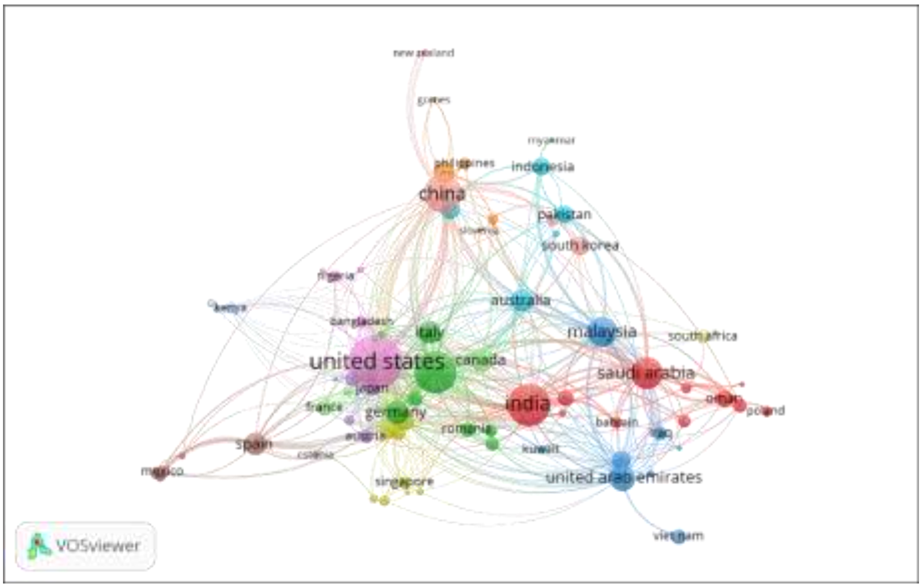

Figure 7 (a): visualization of the collaborative relationships between countries

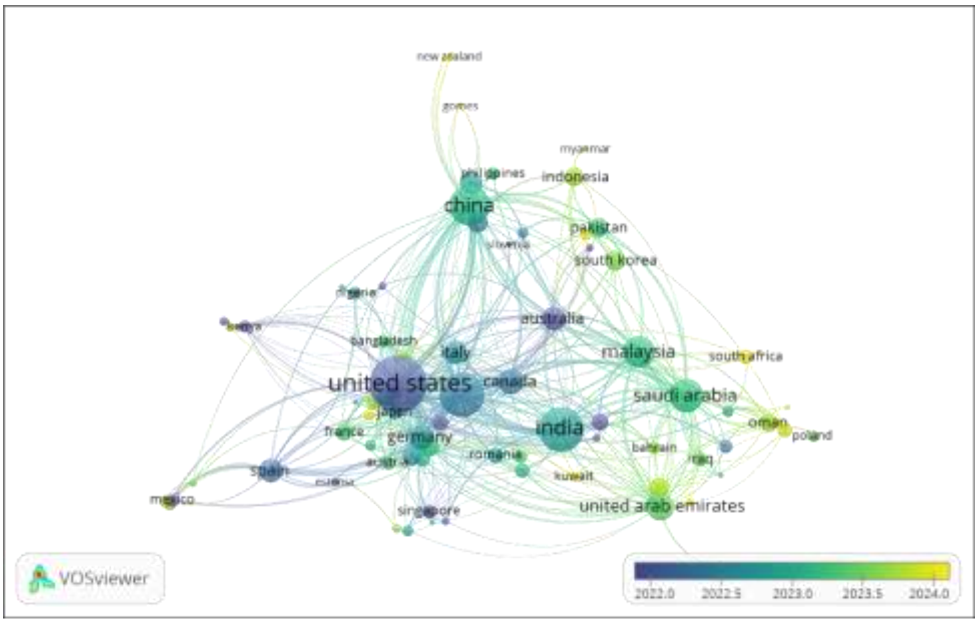

Figure 7 (b): The country/region collaboration network involves the clustering information

Network diagram Figure 6 (a) is a visualization of the collaborative relationships between countries based on scientific research. The nodes are countries, and the connections between countries are partnerships for collaboration. The nodes can be sized based on research output or impact, and the colors may indicate thematic clusters or affiliations. The United States, China, and India are found to be the key nodes in the network, indicating their commanding position in international research collaborations. The diagram shows that there are distinct groups of countries that are cooperating; these are the European cluster (France, Germany, Italy, Spain, United Kingdom) and the Asian cluster (China, Japan, South Korea, India). The visualization reveals new partnerships and connections between areas, especially between developed and developing countries. The network illustrates the interconnections of global research in which research collaborations are made between continents. Figure 6 (b) shows the overlay network of collaboration from 2022 to 2024 of 93 Countries (Ouyang et al., 2022;Chatterjee & Bhattacharjee, 2020).

Characteristics of AAIA Publication by citations

A bibliometric analysis of the intellectual structure of the AAIA research domain was conducted using Biblioshiny. Using this software, the citation network among publications was displayed, facilitating visualization of the connections and relationships between individual publications. The analysis enabled the identification of the evolution of the research themes, of citations, influential works, and of the overall knowledge structure in the field, by mapping these relationships.
The top 10 countries ranked by total citations (TC) and average citations per publication (Average) for AAIA research are shown in Table 3 and Fig. 7. The U.S. has the most citations (1002) and a relatively high average citations per publication (14.7). The United Kingdom, Germany, Sweden, Poland, and Ireland are in the top 10, suggesting robust research activity in Europe. India and China, which are behind the United States, have also contributed to the research, implying that they are gaining importance in the research community. The table shows that there are regional differences in citations. In particular, countries with high average citations per publication, such as Sweden and Ireland, might suggest that their research is of high impact.

Table 3: Most Cited Countries

Country	TC	Average Article Citations
USA	1002	14.7
United Kingdom	927	30.9
India	797	17.7
China	639	13.3
Germany	315	45
Malaysia	308	17.1
Sweden	266	53.2
Singapore	159	26.5
Poland	154	38.5
Australia	149	16.6

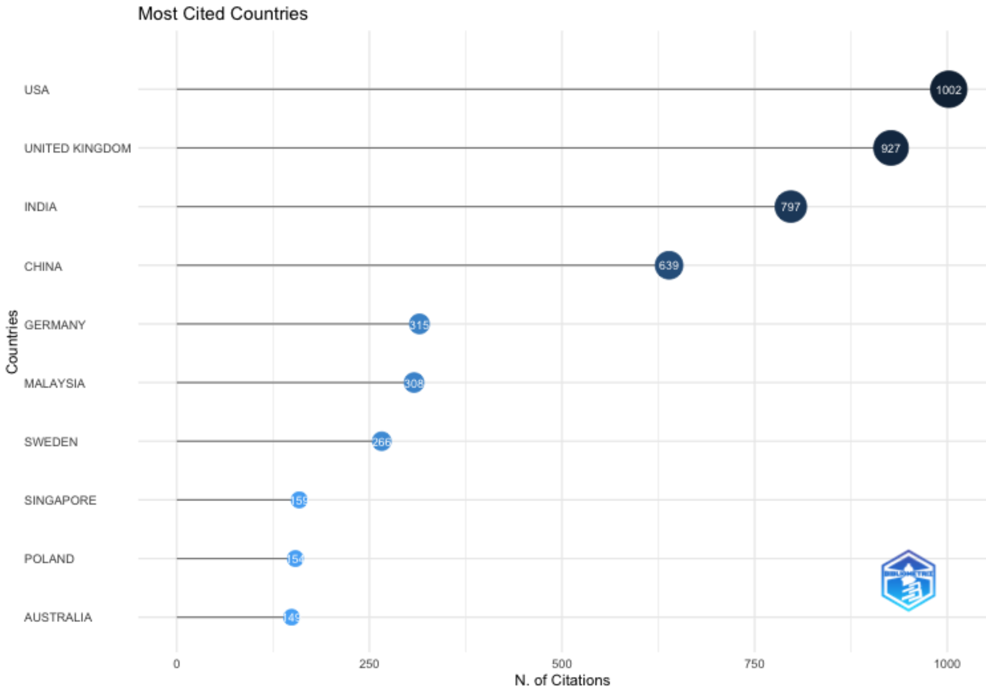

Figure 7: Most cited countries

Characteristics of AAIA Publication by keywords

The keyword co-occurrence network visualizes the relationships among terms in the fields of artificial intelligence and education (Watrianthos et al., 2023; Ganji & Afshan, 2024).

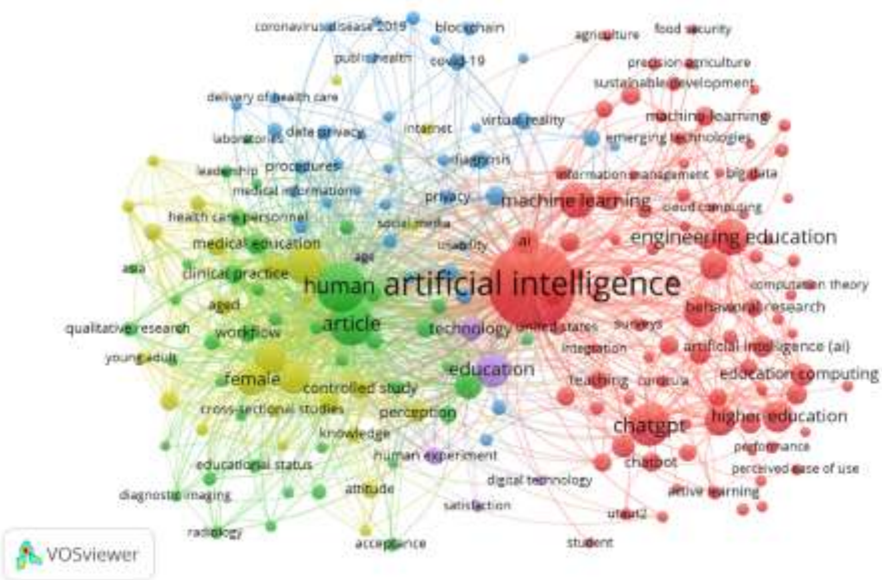

Figure 8: Keyword occurrence of AAIA Publication

When analyzing the co-occurrence network of all keywords (as shown in Figure 11), several key observations and characteristics emerge. Out of 1785 keywords, 71 keywords are in the top 5 occurrences. These keywords are also divided into six clusters, each given a color.

The first cluster (shown in red) contains 23 words, including ‘adoption,' ‘artificial intelligence,' and ‘decision making. The main focus of this cluster is on factors that affect the adoption of artificial intelligence. The second cluster (green) has 14 keywords, most notably being ‘education,' ‘technology acceptance model,' and ‘students.' It emphasizes research on the use of AI in education technology. The keywords in the blue third cluster are grouped: 10 keywords like ‘chatbots,’ ‘digital transformation,’ ‘e-learning,’ and ‘education. The fourth cluster (in yellow) includes nine keywords that revolve around the themes of ‘human’, ‘attitude’, ‘perception’, and ‘ethics’, focusing on perceptions of humans regarding the ethical use of artificial intelligence technology. The fifth cluster (purple) contains 8 keywords, such as ‘ChatGPT,' ‘generative AI,' ‘UTAUT2,' and ‘higher education institution. This cluster aims to examine the application of the UTAUT2 model in ChatGPT and Generative AI in Higher Education systems. Finally, the light blue group contains 7 keywords, including ‘behavioral intention,’ ‘perceived usefulness,’ and ‘trust.’ The focus of this cluster is primarily on behavioral intentions and trust factors related to the adoption of AI in the education sector.

Table 4: Top 10 keywords occurrence

No.	Keywords	Occurrence	Total link strength
1	Artificial intelligence	122	171
2	Education	86	161
3	ChatGPT	28	139
4	Higher education	33	127
5	Technology adoption	35	112
6	Machine learning	24	89
7	Technology	15	77
8	Education Computing	17	71
9	Adoption	16	70
10	Chatbots	19	69

interconnectivity of the keywords within the research domain. "Artificial intelligence" and "education" emerge as the most frequent keywords, reflecting the core focus of the research area. The table suggests potential keyword clusters related to specific research themes:

AI Technologies: "Machine learning," "deep learning," "neural networks."
Educational Applications: "Students," "learning," "teaching curriculum."
Technological Integration: "Technology adoption," "education computing," "higher education."

Keywords such as "ChatGPT" and "generative AI" appear with relatively high frequency, indicating their growing prominence in the field. The total link strength metric suggests the interconnectedness of keywords. Keywords with higher link strength are more closely related to other terms within the network.

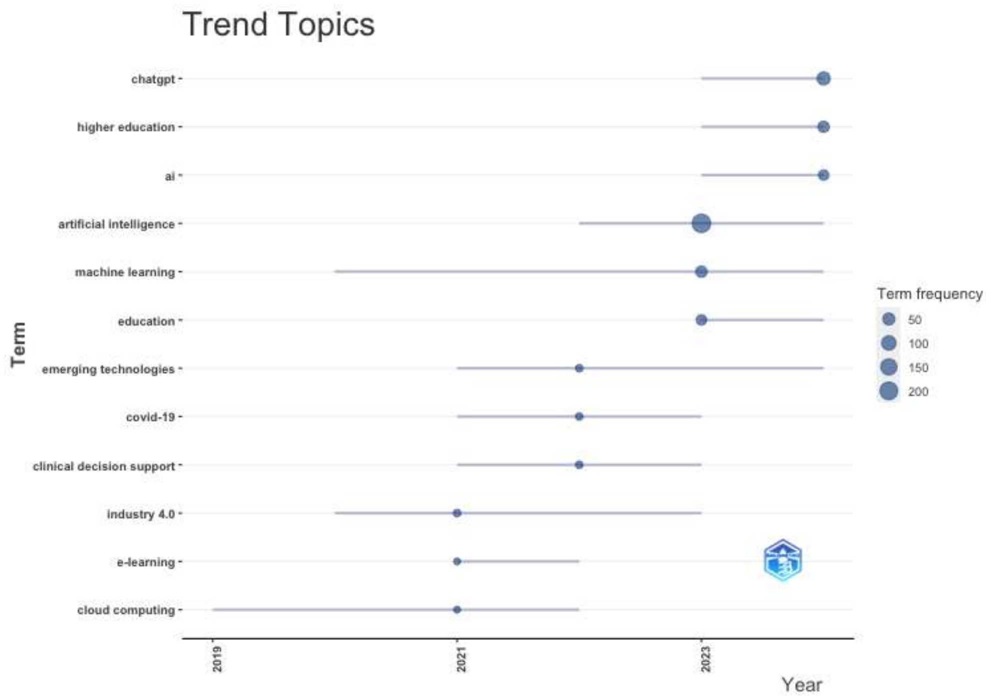

Figure 9: Trending topics of AAIA publication

The chart shows the trending topics in a particular domain, presumably a technology or research field. The x-axis shows the years 2019 to 2023, and the y-axis represents the frequency of terms, which is presumably the number of mentions or citations.

The term "ChatGPT" exhibits a sharp increase in frequency, suggesting its emergence as a prominent topic during the timeframe. Phrases such as "artificial intelligence," "education," and "higher education" have remained consistent over the period, suggesting continued interest in these topics. Words like "emerging technologies," "machine learning," and even "cloud computing" are indicative of a trend, as the technologies are adopted and developed. The words "COVID-19" highlight its impact on research topics throughout the pandemic. Other words, such as "clinical decision support," "industry 4.0," and "e-learning," also reveal a significant trend and are becoming increasingly relevant in the field. The use of terms such as AI and education indicates their continued relevance in education and research. (Jo, 2024; Watrianthos et al., 2023).

The table lists the key research areas in education for AAI (Table 5). The table lists keywords, the number of publications on topics involving Anthropomorphic Artificial Intelligence (AAI), and the frequency with which they appear. The occurrence and temporal distribution. The "year_q1," "year_median," and "year_q3" columns are for the first, 25th, 50th, and 75th percentiles of the year of publication, respectively. "Artificial intelligence," The key focus of the research area is revealed by the presence of the following most common terms: "machine learning" and "education. The terms "ChatGPT" and "higher education" are relatively common, indicating their relevance. New areas of potential interest in the field. The words "ChatGPT" and "higher education" are featured. The relatively high frequencies indicate relative areas of interest in the field.

Scientific landscape of determinants in AAIA

Anthropomorphic AI (AAI) has the potential to revolutionize education by providing personalized, engaging, and interactive learning experiences. However, its widespread adoption is contingent upon various factors, collectively referred to as determinants. These determinants can be broadly categorized into different themes based on the keyword occurrence. The fig 10 keyword map, likely generated with Biblioshiny, visually depicts the relationships among terms in the fields of artificial intelligence and education. The map is divided into four quadrants based on two dimensions: relevance degree (centrality) and development degree (density). (Alhumaid et al., 2023 ; Ouyang et al., 2022; Mogaji et al., 2024; Gansser & Reich, 2021; Ganji & Afshan, 2024).

Table 5: Temporal distribution of keywords in AAIA publication

Keywords	Frequency	Year (Q1)	Median Year	Year (Q3)
Industry 4.0	6	2020	2021	2023
Cloud computing	5	2019	2021	2022
E-learning	5	2021	2021	2022
Clinical decision support	6	2021	2022	2023
COVID-19	6	2021	2022	2023
Emerging technologies	6	2021	2022	2024
Artificial intelligence	227	2022	2023	2024
Machine learning	40	2020	2023	2024
Education	27	2023	2023	2024
ChatGPT	71	2023	2024	2024
Higher education	39	2023	2024	2024
AI	26	2023	2024	2024

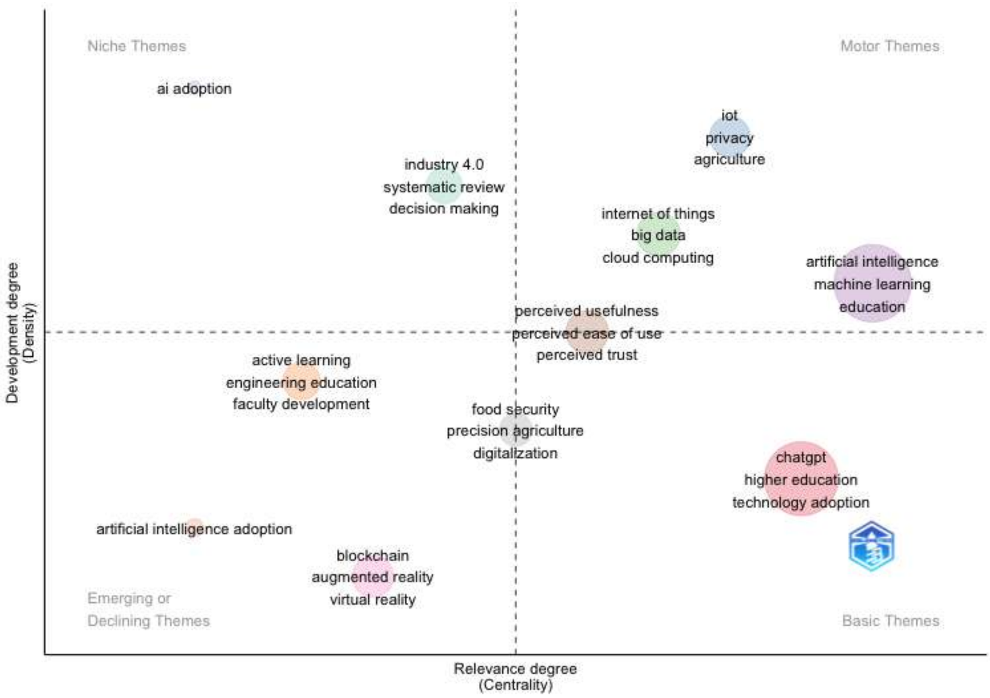

Figure 10: Thematic map of AAIA publication

The research domain keywords at the center of the map ("artificial intelligence," "education," and "machine learning") are likely central topics within the research domain. The niche themes (keywords in the top right quadrant) are emerging or less well-established research areas. Some examples are “blockchain,” “augmented reality," and "virtual reality." Lower left quadrant keywords ("Emerging or Declining Themes") may suggest research areas that are becoming less important or becoming niche. The terms in the bottom-right corner, labeled "Basic Themes," are likely general concepts or extensively researched topics in the field. This can include the Internet of Things, cloud computing, and big data. The map shows clear clusters of keywords, indicating themed areas. For example, AI technology terms (machine learning and deep learning) are grouped together, as are educational application terms (education, students, learning). (Ouyang et al., 2022; Luan et al., 2020).

THEORY: DOMINANT AND EMERGING FRAMEWORKS

The Technology Acceptance Model and Its Extensions

The most commonly used theory in the reviewed literature is the Technology Acceptance Model (TAM), which is based on the Theory of Reasoned Action (TRA). According to TAM, perceived usefulness (PU) and perceived ease of use (PEOU) are the two key factors influencing behavior towards technology. It is parsimony and cross-contextual applicability that have made it the default framework for the study of the adoption of educational AI, having been used as such in studies of the use of AI tools in accounting education, mobile cloud computing in higher education, and the use of chatbots in Dutch universities (Polyportis & Pahos, 2024). But the lack of capturing social, relational, and hedonic aspects of interactions with AI has motivated scholars to elaborate on the basic TAM model. The Extended TAM combines other constructs such as self-efficacy, subjective norms, technology readiness (TRI 2.0), and personal innovativeness. This is relevant since almost no literature cited in the reviewed TAM-based studies explicitly refers to anthropomorphism as a construct; a finding that is important in light of the fact that the anthropomorphic characteristics of many educational AI systems are key to their design rationale and user experience.

UTAUT and UTAUT2

The second most prevalent theoretical framework in the literature reviewed is the Unified Theory of Acceptance and Use of Technology (UTAUT) and its corresponding extension, the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). The 4 components of the UTAUT model, namely Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) have been applied to AI adoption in Indian higher education ChatGPT adoption among Malaysian University Students, Chatbot adoption in higher education institutions and Autonomous Vehicle Technology Acceptance (Adnan et al., 2018)The three other constructs of UTAUT2 — hedonic motivation, price value and habit — further broaden the scope of the model for explanations in the contexts of consumer and education. They are relevant to the adoption of ChatGPT in Polish higher education and are extended by constructs specific to AI products: health, convenience, sustainability, safety-security, and personal innovativeness, as demonstrated by Gansser & Reich (2021) based on a large-scale sample of 21,841 participants from Germany. The wide range of UTAUT2's uses demonstrates its prevalence, but its construct proliferation also suggests it could measure more variables than add depth to the theory behind different anthropomorphic uses of AI.

Anthropomorphism, CASA, and the Uncanny Valley

One group of frameworks that is theoretically under-represented but empirically significant is anthropomorphism, or making things human. The theoretical basis for the anthropomorphism phenomenon in AI-based technologies, drawn from the Computers Are Social Actors (CASA) paradigm and combined with Social Response Theory, serves as the framework for the systematic review of 35 empirical studies on anthropomorphism. Their analysis shows that social rules (such as politeness, reciprocity, and liking) are consistently applied to AI systems that exhibit human-like cues, even when they are not explicitly identified as non-human, suggesting that users do not require awareness of the AI's "non-human nature." Based on these observations, develop a structural model of conversational commerce adoption, showing a positive link between perceived anthropomorphism and perceived animacy with attitude and purchase intention, with trust in AI digital assistants as a mediating variable. This principle is applied to the context of educational AI, with Polyportis & Pahos (2024) demonstrating that anthropomorphism can markedly increase trust in ChatGPT, thus boosting intentions to adopt it. These are still scattered "islands" in a sea of TAM/UTAUT studies, indicating a great theoretical opportunity. However, as we mentioned before, there is a critical point in the relationship between human-likeness and positive affect that must not be overlooked, as AI systems that are close but not quite to the human look will be associated with eeriness and discomfort, not with warmth. This theoretical suggestion has yet to be tested in purely educational settings, highlighting an important lacuna.

Algorithm Aversion and Trust Frameworks

A fourth theoretical area focuses on the particular issue of user distrust in AI inputs – one that is pertinent in education settings where AI is applied as an evaluative, feedback, or decision-making tool. In a systematic review of 80 empirical studies, compile the Algorithm Aversion literature and find that the Perfect Automation Schema (PAS) – the desire for perfect automation – is one of the main factors contributing to aversion, occurring when AI commits even minor mistakes. This is backed up in the K-12 educational context by research that shows that confirmation bias and belief perseverance (which are two cognitive tendencies that can be partially reduced through professional development interventions) are empirically linked to algorithm aversion toward an AI grading tool. By using a lens of the Trust Disposition Model, analyze trust in ambient AI health systems, and they conclude that personal ability and control (PAC), empathetic cooperation, and social interaction are three key factors that should be considered when designing trustworthiness in AI systems that can be applied to the field of education.

Additional and Emerging Theoretical Frameworks

In addition to these dominant clusters, the literature reviewed draws upon a number of other theoretical frameworks that add to the diversity of theory. Use the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990) to complement individual-level TAM/UTAUT models to understand the adoption of AI in recruitment. The Uses and Gratification Theory (U&GT) provides the theoretical foundation for the study of the use of an AI voice assistant, which includes utilitarian, hedonic, and symbolic motives. The principles of cognitive load theory (Cognitive Load Theory) form the basis for educational principles and instructional design that may be useful for the development of effective educational AI interfaces. The theoretical contributions to the field that are least represented but potentially most relevant are critical and ethical frameworks, including Marxian Alienation Theory and practical ethics.

CONTEXT

Educational Level and Target Population

Educational Level and Target Population The context of the literature reviewed shows that there is a significant focus on the higher education level. The majority of the studies are about under- and post-graduates from universities in India, Malaysia, the Netherlands (Polyportis & Pahos, 2024), the United States and Poland. This focus is due to the availability of university student samples for survey-based studies and the increased presence of generative AI tools (such as ChatGPT) in tertiary education settings. The educator's perspective is central in K-12 education, investigating K-12 science teachers' trust in AI tools for grading and offering a critical humanistic analysis of the use of AI in smart classrooms for this age group. The student perspective in education contexts of K-12 is completely absent in the reviewed literature, which represents a significant practical and theoretical gap since, potentially, the dispositions toward human-machine collaboration acquired in these contexts may influence lifelong dispositions for life with AI systems.

Geographic and Cultural Context

The regional coverage of reviewed studies is quite wide-ranging, but with uneven geographic distribution. Most studies are in Asian settings with studies conducted in China, India, Malaysia, and Japan, followed by studies in European settings (UK, Germany, Netherlands, Poland) and Middle Eastern (Jordan) settings. The view from the developing world is largely represented by India, Malaysia and Nigeria, but there are no studies from other countries in Sub-Saharan Africa, Latin America and Southeast Asia beyond Malaysia. Theoretically, there are consequences to this geographic imbalance. Social influence and subjective norms are consistently more strongly associated with adoption intention than other cultural contexts (e.g., China, India, Malaysia), which might not hold true for more individualistic contexts. Contextual barriers, such as the limitations of AI tools in Jordan due to the Arabic language (as noted in the broader literature), are not reflected in technology-based adoption models.

Sectoral Diversity Beyond Education

There are several studies reviewed here that discuss the use of AI in other industries—such as healthcare, human resource management, autonomous vehicles (Adnan et al., 2018), consumer AI assistants, and marketing—that lend theory to the enhancement of but do not directly impact the discussion of the adoption of AI in education. A key strength of the TCCM analysis is its sectoral breadth, specifically the fact that results from trust research in healthcare informed by AI, and anthropomorphism research among consumers provide direct extensions to the theory that are relevant to the design of educational AI and which are not well integrated into the education-specific literature.

CHARACTERISTICS: CONSTRUCTS, PREDICTORS, AND OUTCOMES

Individual-Level Characteristics

Cognitive Utilitarian Factors

The TAM core (perceived ease of use and perceived usefulness) consistently appears as the strongest individual level determinants of the adoption of educational AI in the reviewed literature. They are the primary example in other populations, methods, and technologies. In addition to these canonical constructs, technology readiness, a dispositional variable that reflects the multidimensional nature of individual technological disposition including an individual's attitude toward new technologies, namely, technological optimism, innovativeness, discomfort, and technological insecurity, is important as an upstream predictor of both PU and PEOU.

Affective and Relational Factors

The major affective predictors identified in the literature reviewed are attitude, hedonic motivation, and trust in AI. Given the centrality of trust to anthropomorphic AI adoption, it is noteworthy that anthropomorphism increases the likelihood of a chatbot's adoption, which showed that algorithm aversion among teachers is fundamentally a matter of trust, and that trust in AI systems in the health care industry is heavily dependent on the ability of such systems to be empathetic and to interact socially —attributes by definition anthropomorphic. Operationalizing perceived anthropomorphism as a distinct construct, Polyportis & Pahos (2024) found a significant positive effect on attitude and adoption intention with this construct. The utilitarian-affective model is supplemented with an aesthetic-experiential component by novelty, which refers to the manner in which an AI presents itself in terms of interface and interaction, as noted by Polyportis & Pahos (2024).

Risk and Ethical Sensibilities

The social or psychological discomfort, privacy risks, and performance risks are all grouped under perceived risk, and it seems to be a key barrier to AI adoption in several studies. The hedonic motivation use-voice assistant relationship is significantly moderated by privacy risk. Perceived ethics is explicitly mentioned as a predictor of the adoption of chatbots in higher education. theorise the ethical challenges of the deployment of learning analytics as a multi-framework problem, while make the most radical critique that AI in education may lead to Marxian alienation, commodification of learner interactions and the endangerment of the ontological security of teachers.

Institutional and Organisational Characteristics

Technical infrastructure, institutional support, training availability and policy frameworks are aspects of facilitating conditions that hold significance across the studies grounded in UTAUT. This salience is especially interesting in an educational environment lacking adequate infrastructure and supportive resources, which means that the individual's motivation is insufficient to overcome the lack of infrastructure. This brings the institutional AI policy as a separate organisational-level predictor to the fore, as Polyportis & Pahos (2024) show that the existence of explicit university policies on the use of ChatGPT significantly affects the intention to use it by students, as it gives them legitimacy and lowers uncertainty. The TOE framework by also indicates that in Chinese HR contexts, organisational readiness and competitive environment are important factors influencing the uptake of AI, which are relevant to the context of educational institutions facing questions of governance.

Key Outcomes Measured

Most of the studies reviewed assessed behavioural intention (BI) as the main outcome based on the TAM/UTAUT tradition. A subset of these looks at actual use behavior, which is important as there has been consistent evidence of an intention-behavior gap with technology adoption. Very few studies investigate sustained or continued adoption, and this is a major limitation because adoption is a process, rather than a single point, and studies that look at initial intention may overestimate the success of adoption.

METHODOLOGY: PATTERNS, STRENGTHS, AND LIMITATIONS

Dominant Methodological Approaches

The analysis of the literature showed that structural equation modeling (SEM) was the predominant approach in quantitative survey research. The results of the literature analysis indicated that the most common method used in the literature analyzed is quantitative survey research, applied within the Structural Equation Modeling (SEM) paradigm, with Partial Least Squares (PLS) and Structural Equation Modeling (SEM). PLS-SEM is a method of choice in technology adoption research because it can handle small sample sizes, non-normal data, and exploratory model testing. A few studies illustrate this strategy, which surveyed several thousand students and educators across contexts in various parts of the world, including Sri Lanka, and in a variety of contexts in their respective countries.

Studies that test confirmatory hypotheses within pre-established theory-based models use a covariance-based SEM (CB-SEM). An important methodological development is the presentation of PLS-SEM fuzzy-set qualitative comparative analysis (fsQCA) and Artificial Neural Network (ANN) modeling, respectively, which are capable of identifying configurational pathways of adoption; linear regression-based methods are not.

Qualitative and Mixed-Methods Approaches

Based on the literature analysis, the dominant method is quantitative survey research, grounded in the Structural Equation Modeling (SEM) paradigm. The literature analysis showed that although less common, qualitative methods are of theoretical value. To systematically develop teacher trust in AI graders, we used a mixed-methods experimental design that included professional development interventions, discourse analysis, and interviews. Conducts in-depth interviews with stakeholders in the smart hospitality sector, highlighting the importance of qualitative research that is integrated with the context, and how this can provide insights that are absent from surveys and questionnaires. A critical philosophical approach (deconstructive analysis developed by Derrida) is shown, demonstrating the theoretical richness of non-positivist methods. The third type of documents in the reviewed corpus are systematic literature reviews (SLRs). A total of more than 300 primary studies have been synthesized using SLR methodologies. What they say together is a theoretically rich overview of the dynamics of AI adoption across domains – but at times their findings on education are lost in the scope of the story.

Methodological Gaps

There are three methodological gaps that should be addressed in particular. One is that there are virtually no longitudinal designs. Most cross-sectional surveys are just a 'snapshot' of adoption intention at a given moment in time and do not provide insights into the dynamics of continued use, habituation, disengagement, or fluctuating levels of trust. There is a pressing need to study AI over time, with the changing dynamics of the learner-AI relationship, to discern the long-term consequences of AI interactions on learning outcomes. Secondly, experimental designs are few. In addition to the studies mentioned above, none of the reviewed studies are based on an experimental or quasi-experimental design. This is an important limitation when making causal inferences, particularly in the anthropomorphism-trust-adoption pathway, where causal inferences can be made by experimenting with AI's human-likeness. Thirdly, there is limited sample diversity. The literature consists of a plethora of convenience samples of university students, and there is some reason to question the generalisability of this literature to K-12 students, mature learners, educators, and digitally underserved populations. Future studies should actively recruit marginalized and non-traditional learners in order to capture the diversity of educational actors in theories of adoption.

Tccm Summary Table

Table 6 presents a consolidated TCCM mapping of the primary theoretical frameworks, characteristics, contexts, and methodologies identified across the 30 reviewed studies.

Table 6: TCCM Analysis: Anthropomorphic AI Adoption in Education

Theory / Framework	Concept / Factor	Context	Method	Key Source(s)
TAM	Perceived Usefulness, Perceived Ease of Use, Attitude	HEI students, accounting, AI tools	SEM, PLS-SEM, Regression	Polyportis & Pahos (2024)
UTAUT / UTAUT2	Performance & Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation	Higher education, HRM, healthcare, and autonomous vehicles	SEM, PLS-SEM, fsQCA, ANN	Gansser & Reich (2021)
Anthropomorphism / CASA / Uncanny Valley	Perceived Anthropomorphism, Animacy, Trust, Design Novelty, Institutional Policy	Chatbots, AI digital assistants, conversational AI in HEIs	SEM with moderation	Polyportis & Pahos (2024)
Diffusion of Innovation (Rogers, 1962)	Relative Advantage, Compatibility, Complexity, Trialability, Observability	AI adoption in accounting, education, and HRM	Regression, Mediation (Hayes)	
Algorithm Aversion / Trust Models	Algorithm Aversion, Confirmation Bias, Trust Disposition, Belief Perseverance	K-12 teachers, healthcare AI, and autonomous systems	SLR, Experiment, Discourse Analysis	
TOE Framework / RBV	Technology, Organization, Environment; Resource-Based View	AI in HR recruitment, operations management	CFA, Moderation, SLR	
Ethical / Critical Frameworks (Marx, Deontology, Virtue Ethics)	Marxian Alienation, Practical Ethics, Privacy Risk, Academic Integrity	Smart classrooms, learning analytics, and AI voice assistants	Critical philosophy, Ex-post facto, SLR	
Cognitive Load Theory / Instructional Design	Schema Theory, Working Memory, Split-Attention Effect	Instructional design, science, maths, and programming education	Literature review, experimental synthesis	

Note. TAM = Technology Acceptance Model; UTAUT = Unified Theory of Acceptance and Use of Technology; CASA = Computers Are Social Actors; DOI = Diffusion of Innovation; TOE = Technology-Organization-Environment; SEM = Structural Equation Modeling; PLS = Partial Least Squares; fsQCA = Fuzzy-Set Qualitative Comparative Analysis; ANN = Artificial Neural Network; SLR = Systematic Literature Review.

RESEARCH GAPS AND FUTURE AGENDA

The TCCM analysis reveals five clusters of research gaps that define the frontier of the field:

Theoretical Gaps

The TAM and UTAUT have yielded an empirical and theoretical thin field. While there is evidence that the concept of anthropomorphism is important, especially in related disciplines such as psychology, it is not a dominant part of the education-specific literature and is not adequately theorized in the CASA paradigm, Uncanny Valley Theory, or the Theory of Mind. Prospective theoretical research should build on this and frame relations and sociality as features of anthropomorphic AI within broader frameworks of its adoption, rather than as features restricted to its utilitarian aspects.

Ethical theoretical frameworks as predictors (not background conditions) are nearly absent in adoption models. Perceived ethics should be introduced as an explicit variable, based on the work of in their work on Practical Ethics and that of in their critical humanistic study, as the learners' adoption decision is not only utilitarian but also morally reflexive.

Contextual Gaps

The reviewed corpus lacks perspectives on K-12 students, primary education, and the experiences of students in digitally underserved contexts (Sub-Saharan Africa, rural Asia, and indigenous learners). As a result, it is not an empirical extension, but a theoretical requirement to investigate the effects of exposure to anthropomorphic AI with younger learners, as it can impact basic epistemic dispositions. Likewise, cross-cultural studies are lacking to systematically test the moderating effects of cultural values (individualism-collectivism, uncertainty avoidance, power distance) on the adoption of anthropomorphic AI.

Construct and Measurement Gaps

The operationalization of anthropomorphism in educational AI research is heterogeneous and often borrowed uncritically from consumer or healthcare contexts. Domain-specific scales for educational anthropomorphism—capturing dimensions such as perceived pedagogical warmth, relational trust, epistemic authority, and social presence — are needed. The intention-behavior gap, consistently noted but rarely modeled, requires longitudinal and multi-wave measurement designs that can track the transition from adoption intention to actual use to sustained engagement.

Methodological Gaps

There is a strong need for experimental and quasi-experimental designs that allow causal links to be established between anthropomorphic design features and adoption outcomes. Triangulating survey research with qualitative research on learners' experiences of interaction with AI could deepen understanding of this field. The application of big data and learning analytics methodology, which can record real usage patterns at scale without requiring respondents to report their intentions, is yet to be fully explored in this area.

Ethical and Policy Gaps

The literature examined here does not consider ethics as a sine qua non of the study of adoption, but rather as a moderating factor. There are opportunities for future research into algorithmic fairness, data sovereignty, epistemic autonomy, and critical thinking in the context of AI-mediated assessment, as well as the long-term impact of anthropomorphic AI on learners' epistemic autonomy and critical thinking abilities. Evidence-based recommendations for the governance of anthropomorphic AI in education, including research into its adoption, are not yet geared towards providing policy guidance.

CONCLUSION

This overview of 30 studies on the use of AI in education demonstrates that the field of Educational Artificial Intelligence has undergone a theoretical consolidation around the theoretical frameworks of the TAM and UTAUT, that the methodology used is homogeneous (with a strong preference for cross-sectional PLS-SEM studies), that it has been conducted in higher education or developed world contexts, and that anthropomorphism is consistently overlooked in research as a theoretically separate and empirically relevant construct.

To further the field, the theoretical framework should be expanded and pluralistic research practices and research designs should be implemented, which is achieved by a combination of anthropomorphism-centered frameworks (CASA paradigm, Uncanny Valley Theory, Trust Disposition Models) and theoretical approaches in ethics and critical theory, in methodologically pluralistic and longitudinally strong research designs. The conversationally rich, emotionally responsive, and pedagogically responsive nature of emerging AI systems will only continue to grow, making the ways in which these systems embody human-like qualities and are treated as such and how learners trust these systems, engage with them, and develop a new kind of epistemic experience even more critical.

The TCCM has not only been applied in a bibliometric cataloging method in this paper, but also in a critical diagnostic method to illuminate not only what is known, but also what is unknown in the form of the unknown. The answers to the gaps identified here are not research programs, but the necessary initial steps to create knowledge to be used as an instrument to govern, design and deploy anthropomorphic AI in the education system responsibly.

Concluding remarks, Limitations, and recommendations for future research

This research aims to provide a comprehensive evaluation of the global research landscape in the field of Anthropomorphic Artificial Intelligence Adoption (AAIA). For this purpose, several knowledge-mapping tools are used, including VOSviewer and Bibliometrix. In this study, 524 scientific documents related to AAIA were thoroughly analyzed, and a literature survey was conducted to gather all published documents in the Scopus database. The study identifies determinants and trends in this field and provides insights into the current debate on the adoption of AAIA. (Alhumaid et al., 2023; Watrianthos et al., 2023; Ganji & Afshan, 2024; Ouyang et al., 2022; Mogaji et al., 2024).

The data provided is analyzed to provide an extensive overview of the intellectual landscape of Anthropomorphic AI in education. This knowledge of the main subjects, trends, and working groups will help researchers determine areas that may prove fruitful for further research—and effectively help design AAI applications in educational contexts.

Theoretical Contributions

The paper makes four main theoretical contributions to the AAIA in Education literature. First, it offers the first triple-method synthesis in the education field, combining bibliometric analysis, PRISMA-guided meta-analysis, and TCCM framework analysis (Figure 1). This methodological coupling allows both the macroscopical representation of the field's intellectual structure and the critical approach to its conceptual structure, which are possible only with bibliometric or systematic review approaches alone. Secondly, the TCCM analysis uncovers and theorizes the anthropomorphic gap in educational AI adoption literature. It provides a theoretically significant critique of TAM/UTAUT frameworks by showing that the relational, social, and human-like aspects of AAIA are crucial to their design rationale and user experience, but are neglected from the framework in a systematic way, thus proposing a concrete research agenda based on CASA theory, Uncanny Valley Theory, and Trust Disposition Models. Third, the empirical data derived from the bibliometric analysis create an innovative, empirical basis for the mapping of the intellectual structure of the AAIA in the field of education (including the identification of three research communities (2020, 2022, 2024), six keyword clusters, and a dominant journal landscape) that forms a data-driven basis for education research prioritization in the future. Fourth, and lastly, the paper offers a move towards the ethical and critical theorization of AAIA adoption, highlighting the practical ethics framework and the critical humanistic analysis as theoretical resources for adoption research that ought not to be sidelined as background conditions.

PRACTICAL IMPLICATIONS

For Educators and Academic Institutions.

The findings of Polyportis & Pahos (2024) that an explicit, transparent, pedagogically principled policy on the use of AAI has a direct impact on students' adoption intention, specifically enhancing it, have direct implications for university administrators. Teachers' algorithm aversion, identified as real and partially addressable, should be part of continuing education for teachers.

For Policymakers

Given the geographic and contextual nature of current research on the adoption of AAIA in higher education in Asia, Europe, and North America, and its virtual absence in K-12 and underrepresented contexts, policymakers should show heightened interest in investing in targeted research funding and data collection in these contexts. In the education sector, governance models that operate amid the growing use of AAIA systems should be grounded in the principles of practical ethics designed to safeguard algorithmic fairness, data sovereignty, and epistemic autonomy. New technologies, including AI, are transforming education. AI and other new technologies are changing education. Indeed, the significance of perceived anthropomorphism, design novelty, and trust in influencing the adoption intention for AAIA has practical design implications: AAIA systems designed for educational purposes should be engineered with appropriate anthropomorphic elements, such as natural language interaction, emotional response, and personalized feedback, while also being designed to avoid the Uncanny Valley effect which suggests that AI systems that are close to human appearance but not quite there can trigger a negative reaction. Operationalization, especially the different ways it has been handled across studies, is not standardized and calls for the standardization of measurement instruments.

For AI Developers and EdTech Designers

New technologies, including AI, are transforming education. AI and other new technologies are changing education. Indeed, the significance of perceived anthropomorphism, design novelty, and trust in influencing the adoption intention for AAIA has practical design implications: AAIA systems designed for educational purposes should be engineered with appropriate anthropomorphic elements, such as natural language interaction, emotional response, and personalized feedback, while also being designed to avoid the Uncanny Valley effect which suggests that AI systems that are close to human appearance but not quite there can trigger a negative reaction. Operationalization, especially the different ways it has been handled across studies, is not standardized and calls for the standardization of measurement instruments.

AUTHOR DECLARATIONS

CRediT Author Statement / Author Contributions

Preeti Sharma: Conceived the study, designed the research framework, collected and analyzed bibliometric data using relevant software, interpreted findings, prepared visualizations, and wrote the first draft of the manuscript.
Sna Farooqi: Provided methodological guidance, supervised the research process, reviewed the analysis, and critically revised the manuscript.
Mansoor Ahmad: Contributed to research design refinement, validated findings, provided scholarly feedback, and critically reviewed the manuscript.

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References

Adnan, N., Md Nordin, S., bin Bahruddin, M., & Ali, M. (2018). How trust can drive forward the user acceptance to the technology? In-vehicle technology for autonomous vehicle. *Transportation Research Part A: Policy and Practice*, *118*, 819-836. https://doi.org/10.1016/j.tra.2018.10.019

Ajis, A., & Zakaria, S. (2022). Trends of LIS education and practice in Asia and Oceania: A bibliometric analysis. *Library Trends*, *71*(2), 169-197. https://doi.org/10.1353/lib.2022.a922374

Alhumaid, K., Naqbi, S. A., Elsori, D., & Mansoori, M. A. (2023). The adoption of artificial intelligence applications in education. *International Journal of Data and Network Science*, *7*(1), 457-466. https://doi.org/10.5267/j.ijdns.2022.8.013

Andrews, J., Ward, H., & Yoon, J. (2021). UTAUT as a model for understanding intention to adopt AI and related technologies among librarians. *Journal of Academic Librarianship*, *47*(6), Article 102437. https://doi.org/10.1016/j.acalib.2021.102437

Chatterjee, S., & Bhattacharjee, K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies*, *25*(5), 3443-3463. https://doi.org/10.1007/s10639-020-10159-7

Dogru, T., Line, N., Hanks, L., Acikgoz, F., Abbott, J., Bakir, S., Berbekova, A., Bilgihan, A., Iskender, A., Kizildag, M., Lee, M., Lee, W., McGinley, S., Mody, M., Onder, I., Ozdemir, O., & Suess, C. (2023). The implications of generative artificial intelligence in academic research and higher education in tourism and hospitality. *Tourism Economics*. Advance online publication. https://doi.org/10.1177/13548166231204065

Du, L., & Lv, B. (2024). Factors influencing students' acceptance and use generative artificial intelligence in elementary education: An expansion of the UTAUT model. *Education and Information Technologies*. Advance online publication. https://doi.org/10.1007/s10639-024-12835-4

Fu, C., Silalahi, A., Huang, S., Phuong, D., Eunike, I., & Yu, Z. (2024). The (un)knowledgeable, the (un)skilled? Undertaking Chat-GPT users' benefit-risk-coping paradox in higher education focusing on an integrated, UTAUT and PMT. *International Journal of Human-Computer Interaction*. Advance online publication. https://doi.org/10.1080/10447318.2024.2365028

Ganji, K., & Afshan, N. (2024). A bibliometric review of Internet of Things (IoT) on cybersecurity issues. *Journal of Science and Technology Policy Management*. Advance online publication. https://doi.org/10.1108/JSTPM-05-2023-0071

Gansser, O., & Reich, C. (2021). A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technology in Society*, *65*, Article 101535. https://doi.org/10.1016/j.techsoc.2021.101535

García de Blanes Sebastián, M., Sarmiento Guede, J., & Antonovica, A. (2022). Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants. *Frontiers in Psychology*, *13*, Article 993935. https://doi.org/10.3389/fpsyg.2022.993935

Hasija, A., & Esper, T. (2022). In artificial intelligence (AI) we trust: A qualitative investigation of AI technology acceptance. *Journal of Business Logistics*, *43*(3), 388-412. https://doi.org/10.1111/jbl.12301

Hidayat, A., & Kahar, M. (2024). Investigating the adoption of AI in higher education: A study of public universities in Indonesia. *Cogent Education*, *11*(1), Article 2380175. https://doi.org/10.1080/2331186X.2024.2380175

Ivanov, S., Soliman, M., Tuomi, A., Alkathiri, N., & Al-Alawi, A. (2024). Drivers of generative AI adoption in higher education through the lens of the Theory of Planned Behaviour. *Technology in Society*, *77*, Article 102521. https://doi.org/10.1016/j.techsoc.2024.102521

Jo, H. (2024). From concerns to benefits: A comprehensive study of ChatGPT usage in education. *International Journal of Educational Technology in Higher Education*, *21*(1), Article 47. https://doi.org/10.1186/s41239-024-00471-4

Lemaignan, S., Newbutt, N., Rice, L., Daly, J., & Charisi, V. (2022). UNICEF guidance on AI for children: Application to the design of a social robot for and with autistic children. *arXiv*. https://doi.org/10.48550/arXiv.2108.12166*(Note: Originally registered as an archived preprint preprint in late 2021, indexed contextually in 2022).*

Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S., Ogata, H., Baltes, J., Guerra, R., Li, P., & Tsai, C. (2020). Challenges and future directions of big data and artificial intelligence in education. *Frontiers in Psychology*, *11*, Article 580820. https://doi.org/10.3389/fpsyg.2020.580820

Ma, H., Ismail, L., & Han, W. (2024). A bibliometric analysis of artificial intelligence in language teaching and learning (1990–2023): Evolution, trends and future directions. *Education and Information Technologies*. Advance online publication. https://doi.org/10.1007/s10639-024-12848-z

Malik, R., Sharma, E., Trivedi, S., & Mishra, R. (2021). Adoption of chatbots for learning among university students: Role of perceived convenience and enhanced performance. *International Journal of Emerging Technologies in Learning*, *16*(18), 200-212. https://doi.org/10.3991/ijet.v16i18.24315

Mogaji, E., Viglia, G., Srivastava, P., & Dwivedi, Y. (2024). Is it the end of the technology acceptance model in the era of generative artificial intelligence? *International Journal of Contemporary Hospitality Management*. Advance online publication. https://doi.org/10.1108/IJCHM-08-2023-1271

Ouyang, F., Zheng, L., & Jiao, P. (2022). Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020. *Education and Information Technologies*, *27*(6), 7893-7925. https://doi.org/10.1007/s10639-022-10925-9

Polyportis, A., & Pahos, N. (2024). Understanding students' adoption of the ChatGPT chatbot in higher education: The role of anthropomorphism, trust, design novelty and institutional policy. *Behaviour & Information Technology*. Advance online publication. https://doi.org/10.1080/0144929X.2024.2317364

Raman, R., Mandal, S., Das, P., Kaur, T., Sanjanasri, J., & Nedungadi, P. (2024). Exploring university students' adoption of ChatGPT using the Diffusion of Innovation Theory and sentiment analysis with gender dimension. *Human Behavior and Emerging Technologies*, *2024*, Article 3085910. https://doi.org/10.1155/2024/3085910

Saif, N., Khan, S., Shaheen, I., Alotaibi, A., Alnfiai, M., & Arif, M. (2024). Chat-GPT: Validating Technology Acceptance Model (TAM) in education sector via ubiquitous learning mechanism. *Computers in Human Behavior*, *154*, Article 108097. https://doi.org/10.1016/j.chb.2023.108097

Sang, N. (2024). Bibliometric insights into the evolution of digital marketing trends. *Innovative Marketing*, *20*(2), 1-14. https://doi.org/10.21511/im.20(2).2024.01

Tiwari, C., Bhat, M., Khan, S., Subramaniam, R., & Khan, M. (2024). What drives students toward ChatGPT? An investigation of the factors influencing adoption and usage of ChatGPT. *Interactive Technology and Smart Education*, *21*(3), 333-355. https://doi.org/10.1108/ITSE-04-2023-0061

Vorm, E., & Combs, D. (2022). Integrating transparency, trust, and acceptance: The Intelligent Systems Technology Acceptance Model (ISTAM). *International Journal of Human-Computer Interaction*, *38*(18-20), 1828-1845. https://doi.org/10.1080/10447318.2022.2070107

Watrianthos, R., Ahmad, S., & Muskhir, M. (2023). Charting the growth and structure of early ChatGPT-education research: A bibliometric study. *Journal of Information Technology Education: Innovations in Practice*, *22*, 235-253. https://doi.org/10.28945/5221

Yusuf, A., Pervin, N., & Román-González, M. (2024). Generative AI and the future of higher education: A threat to academic integrity or reformation? Evidence from multicultural perspectives. *International Journal of Educational Technology in Higher Education*, *21*(1), . https://doi.org/10.1186/s41239-024-00453-6