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Exploring Elementary Preservice Teachers' Nature Investigations

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Abstract

The shift to online instruction during the COVID-19 pandemic posed significant challenges for engaging preservice teachers in authentic, inquiry-based science learning. To address these challenges, place-based and inquiry-driven investigations emerged as promising strategies for supporting meaningful scientific engagement in remote settings.This study aims to explore elementary preservice teachers' (PTs) inquiry-based nature investigations and their reflections on their perceptions of the experience. The participants of the study included 38 PTs in the context of a science laboratory course in an elementary education program at a public university in Turkey. Data sources included PTs' inquiry reports and reflections and were analyzed for inquiry coherence and their perceptions of the nature experience. Findings showed varying levels of inquiry engagements, from fully coherent investigations with clear research questions and explanations to minimal engagement with purely descriptive observations lacking inquiry focus. In addition, PTs reflected on the advantages of nature investigation, including increased biodiversity knowledge, awareness, and a deeper connection to the environment, as well as the affordances of mobile applications. Based on the findings, implications for teacher education are discussed.

Introduction

The global shift to online instruction caused by the COVID-19 pandemic created many challenges in maintaining practical and interactive science education (Avsar - Erumit et al., 2021; Bakioğlu & Çevik, 2020; Barton, 2020; Sahu, 2020; Ünal & Bulunuz, 2020). During this time, elementary preservice teachers (PTs) also struggled to engage in scientific inquiry (Avsar- Erumit et al., 2021). For PTs to improve their science teaching practices, their own engagement in inquiry-based learning as students is crucial (Windschitl, 2003).

In addition to inquiry skills, biodiversity knowledge is important for effective science teaching. Many PTs enter teacher education programs with limited experience with species identification (Kassas, 2002; Saunders, 2003), a gap compounded by a lack of biodiversity topics in standard teacher education programs (Bebbington, 2005; Hooykaas et al., 2019). Addressing this gap is important, especially in the elementary science curriculum, which emphasizes understanding living and non-living organisms. Using place-based learning became difficult to implement in online settings despite its reputation for fostering environmental awareness and confidence in teaching science (Carrier, 2009; Trauth-Nare, 2015). Enhancing PTs' biodiversity content knowledge could help them teach these concepts more effectively in their future classrooms. However, few studies explored how mobile applications in place-based learning can bridge this gap in remote teacher education contexts.

Mobile applications provide a unique opportunity for nature investigations, enabling PTs to explore biodiversity independently through real-time access to databases and visual resources (Chen et al., 2008). While previous studies have explored place-based and inquiry-based learning separately, few have examined how mobile applications can mediate place-based biodiversity investigations in an online teacher education context. This study addresses this gap by integrating mobile technology into online learning to enhance PTs' inquiry skills, local biodiversity knowledge, and environmental awareness. Improving PTs' biodiversity knowledge and inquiry skills is crucial not only for their own academic development but also for their future role as educators who can foster environmental literacy among elementary students. This study aims to contribute to this goal by examining how mobile application-facilitated nature investigations support PTs in developing coherent inquiry investigations and what their perceptions of this experience are in an online context. Specifically, it addresses the following research questions:

1. To what extent did PTs develop coherent inquiry-based nature investigations?
2. How did PTs reflect on their observations, noticings, and use of mobile applications during the nature investigation process in an online setting?

Conceptual Framework: Place-Based and Inquiry-Based Learning

This study is guided by place-based and inquiry-based learning approaches. Place-based education leverages local environments for learning, encouraging students to engage with their surroundings as sites of investigation (Sobel, 2004). By grounding learning in local contexts, place-based education enhances relevance, engagement, and cross-disciplinary understanding, supporting academic success (Semken & Freeman, 2008; Sobel, 2005). This approach centers on students' questions and interests, connecting their curiosities to their daily experiences to make learning more meaningful. In this study, PTs examined their local environments and developed research questions for investigation. Research shows that place-based education promotes experiential, participatory learning, improving understanding and academic outcomes (Ballantyne & Packer, 2009; Semken & Freeman, 2008). It emphasizes spatial, embodied, and contextual learning, allowing students to gain hands-on experience with natural or human-made environments (Semken et al., 2017). Through direct engagement with local sites, students apply skills and concepts in real-world contexts, deepening their understanding of environmental processes and their impacts (Sobel, 2004).

Inquiry-based learning involves engaging students in scientific investigations to make predictions, collect and analyze data, and develop evidence-based explanations (NRC, 2000). Engaging PTs in inquiry-based learning fosters essential skills as learners of science (Stuchlikova et al., 2013; Weld & Funk, 2005). Local environments provide authentic contexts for inquiry, aligning place-based pedagogy with inquiry-based learning to create meaningful and relevant investigations (Anderson, 2011; Brown, 2021). Research supports the efficacy of place-based education in teaching environmental education (Buxton, 2010; Meichtry & Smith, 2007; Semken, 2005; Sobel, 2005).

Many PTs enter teacher education programs with limited exposure to inquiry-based learning (Windschitl, 2003). Given these gaps, place-based education offers an ideal approach for addressing PTs' limited biodiversity knowledge by immersing them in local ecosystems, fostering direct interaction with diverse species and ecological processes. In this study, place-based learning provided the contextual foundation for PTs to engage with their local environments, while inquiry-based learning guided the process of formulating questions, collecting data, and analyzing findings. Mobile applications functioned as a mediating tool for species identification and supporting data collection and analysis. This study integrates place-based and inquiry-based approaches to provide PTs with meaningful investigations, fostering scientific skills and content knowledge in an online learning environment.

Background to the Problem

Challenges and Urgency in Biodiversity Education

Human activities such as greenhouse gas emissions, pollution, and habitat destruction have caused a biodiversity crisis, with up to one million species at risk of extinction (Hooper et al., 2005; IPBES, 2019). Thus, this situation requires teachers to equip future generations with knowledge of biodiversity and conservation. Biodiversity literacy is, therefore, a foundational element of environmental education and aligns with the United Nations' 2030 Agenda for Sustainable Development, especially Goal 15 (SDG 15), which focuses on halting biodiversity loss and promoting sustainable ecosystems (UN General Assembly, 2015).

Schools can play an important role in biodiversity learning through experiential and place-based learning opportunities. Observing species or conducting nature-based investigations can facilitate deep connections for students to their surrounding ecosystem (Bögeholz, 2006; Louv, 2006). Nature investigations are known to encourage positive attitudes toward conservation (Nelson et al., 2016) and to enhance overall well-being (Chawla, 2015; Gill, 2014). However, research shows that children are spending less time in nature (Louv, 2016; Soga & Gaston, 2016), leaving teachers with an increased responsibility to reconnect them with their environment. In this context, to develop students' environmental awareness, teachers need strong biodiversity knowledge and a positive attitude towards nature (Skarstein & Skarstein, 2020; Wolff & Skarstein, 2020).

Challenges in Species Identification

Research shows that PTs have difficulty in identifying species due to limited experience, insufficient training, and difficulty accessing accurate resources (Melis et al., 2021; Kurniawan, Tapilow, & Hidayat, 2017). For example, Kurniawan et al. (2017) found that limited online resources hindered the identification of bird species during field trips. Moreover, although PTs have positive attitudes toward biodiversity, their knowledge and confidence are often insufficient (Harman & Yenikalayci, 2020; Ozdemir, 2020; Melis et al., 2021).

Research shows that strengthening PTs' species identification skills increases their ability to effectively teach biodiversity (Kaasinen, 2019; Lindemann-Matthies et al., 2011; Palmberg et al., 2015). For example, Palmberg et al. (2015) found that while PTs recognize species knowledge as essential for sustainable development, they often focus on pragmatic properties (e.g., edibility or toxicity) rather than the ecological importance of the species. Kvammen and Munkebye (2018) demonstrated that targeted training improved PTs' identification skills but highlighted the need for sustained approaches to retain this knowledge in teacher education.

Research advocates for integrating biodiversity education into core curricula (Bulut & Beşoluk, 2019; Yüce & Doğru, 2018). One way to incorporate this into the curriculum would be to combine inquiry-based and place-based approaches to address these gaps in teacher education. For example, Skarstein and Skarstein (2020) found that inquiry-based species identification activities improved PTs' knowledge and confidence and helped them apply this knowledge during their teaching practice. However, the implementation of place-based inquiry investigations in online learning contexts remains challenging.

Potential of Mobile Applications in Environmental Education

Previous research has shown that mobile technologies, including smartphones and tablets, offer flexible, interactive tools for biodiversity education, enabling real-time data collection and species identification (Huang, Lin, & Cheng, 2010; Rogers et al., 2005; Sung, Chang, & Liu, 2016). In biodiversity education, traditionally, tools like dichotomous keys and printed guides have been used for species identification (Andic et al., 2019; Stagg & Donkin, 2013), but mobile applications provide enhanced functionality by integrating multimedia resources and taxonomic databases (Chen et al., 2008).

Mobile applications allow users to identify organisms using automated software, expert feedback, and extensive databases (Nugent, 2018; Zydney & Warner, 2016). For example, the iNaturalist app was used in identifying marine organisms (Michonneau & Paulay, 2015), birds (Thomas & Fellowes, 2017), reptiles (Whittmann et al., 2019) and mammals (Fraser et al., 2019). These applications bridge gaps in PTs' species identification skills (Nugent, 2018; France et al., 2016).

This study integrates mobile applications to address the challenges of remote, place-based, inquiry-based science learning during the COVID-19 pandemic. PTs were introduced to applications such as Google Lens, Inaturalist, Plantnet, and Plantsnap to conduct nature investigations in their local environments. By leveraging mobile technologies, this study aims to enhance PTs' biodiversity knowledge, inquiry skills, and environmental awareness within a remote learning environment.

Method

Research Methods and Context

This qualitative study used a naturalistic inquiry approach (Lincoln & Guba, 1985) to explore preservice elementary teachers' (PTs) engagement with nature investigations in an online learning environment. Naturalistic inquiry was used as it allowed for an in-depth exploration of PTs' experiences and reflections in the learning environment, focusing on how they engaged with nature investigation in their chosen places. The context of the study is a sophomore-level science laboratory course within the elementary education program. In this program, PTs complete two science content courses (general science and environmental science) in their first year, a science laboratory course in their second year, and a science teaching methods course in their third year. The science laboratory course, central to this study, is a mandatory, hands-on course taught over 15 weeks, with two hours of weekly instruction. PTs engaged in inquiry-based investigations using scientific practices coupled with theoretical knowledge. Instruction followed constructivist models such as the 5E Instructional Model (Bybee, 2015), the Predict-Observe-Explain (POE) model, and argumentation techniques, with PTs documenting their work in science notebooks.

Traditionally taught in person, the course shifted to an online format due to pandemic restrictions, necessitating adjustments to the main interactive and practical learning. PTs engaged in various inquiry-based investigations, documenting their observations and reflections in digital science notebooks, supported by Google Classroom. The course emphasized authentic scientific practices, requiring PTs to design experiments, make predictions, collect data, and construct evidence-based explanations. The nature investigation became a crucial component of the course, providing PTs with opportunities for field-based learning despite the online format. The nature investigation conducted post-midterm lasted three weeks: two weeks for observations and one week for report writing and presentations. Other investigations during the course covered diverse topics, including simple circuits, states of matter, seed germination, and nature observations. While most investigations spanned one week (e.g., electrical circuits), some (e.g., seed investigation) extended over multiple weeks. The course was taught synchronously online.

Participants

This qualitative study involved 38 (27 Female, 11 Male) elementary PTs from a public university in southwestern Türkiye, selected through convenience sampling. The class included 50 PTs, of whom 38 submitted reflection and inquiry reports; these 38 PTs formed the study's participant data set. Written informed consent was obtained from all participants, and the study received institutional review board approval before collecting data from Aydin Adnan Menderes University Educational Research Ethics Committee, with the decision dated August 6, 2021 (Session No: 18, Decision No: III). To ensure confidentiality, pseudonyms were used for all participant names in the data and reporting.

Data Collection Tools

Data consisted of 38 digital inquiry investigation reports and 38 written reflections. The reports included investigation questions, a description of data collection sites, collected data through photographs and videos, and evidence-based explanations of observations. For reflections, PTs were prompted with the following open-ended questions: "What were your thoughts on nature observation? What were the advantages and disadvantages of this experience for you? What did you notice during this process? Which mobile applications did you use, and how was your experience using them?" In the nature investigation, we discussed how scientists classify living organisms and the importance of PTs' understanding of the characteristics of living and nonliving things, as emphasized in the human and environmental unit of the primary school curriculum (MoNE, 2018). PTs were guided to develop observational skills and prepare to address future students' questions about species and nature.

Due to the pandemic, PTs conducted observations in their local environments. I guided PTs through modeling a nature investigation activity with children in a nearby park, sharing our experiences and observations of plants, trees, and animals with photos. A YouTube video (The Wonder of Science, 2018) was used to demonstrate techniques for exploring microhabitats to see species under logs, emphasizing respect for nature and small animals. Then, PTs were introduced to mobile identification apps, including iNaturalist (https://www.inaturalist.org), PlantSnap (https://www.plantsnap.com/), PlantNet (https://apps.apple.com/us/app/plantnet/id600547573), and Google Lens (https://lens.google/), which offer real-time identification and user-contributed databases. These tools were demonstrated to discuss species and illustrate how technology can support observation and inquiry. Then, I shared the types of questions children asked during our nature observations to illustrate how nature observations can spark curiosity and inquiry. I emphasized the importance of questioning as a scientific practice and that all inquiry investigations begin with a research question.

PTs were encouraged to choose local environments (e.g., parks, forests, fields, gardens) for observations, documenting findings through videos or photos. While identification targets were not specified, PTs were asked to freely observe and identify plants, animals, and other natural elements. Videos were recommended for richer accounts and easy sharing during synchronous online sessions. Some PTs faced challenges during the first week due to COVID-related restrictions, so an additional week was provided. After two weeks of observations, PTs submitted digital reports, including videos, photographs, and descriptions. The following week, PTs presented their findings using the collected media in the online class.

Data Analysis

The reports were analyzed using content analysis, guided by a rubric adapted from Plummer and Tanis Ozcelik (2015), originally designed to analyze PTs' lesson plans in astronomy inquiry investigations. The adapted rubric is used to evaluate the coherence of PTs' investigations using four key criteria, as shown in Table 1: the presence of an investigation question, the data collection process, the connection between the collected data and the investigation question, and the quality of evidence-based explanations. Each report was categorized into one of the four levels, as shown in Table 1.

Table 1. Rubric for analyzing inquiry reports

Level of Coherence in Inquiry	Level 1	Level 2	Level 3	Level 4
Is there an investigation question?	There is a clearly stated, and focused investigation question.	There is a clearly stated, and focused investigation question.	There is an investigation question.	There is no investigation question or statement.
Is there a data collection process?	Observational data is collected and presented through videos or photographs.	Observational data is collected and presented through videos or photographs.	Observational data is collected and presented through videos or photographs.	Observational data is collected and presented through videos or photographs.
Is Data and the investigation question connected?	The collected data is directly connected/aligned to the investigation question.	The collected data is connected to the investigation.	The collected data is not connected to the investigation question or there is limited connection due to the question being broad.	Not applicable, as there is no question.
Is there an explanation?	The explanation is evidence-based and connected, and directly answers investigation question.	The explanation is present, but the connection between evidence and explanation is implied, or limited in detail.	The explanation is not in response to the question. Or there is only a description of observations.	There is no explanation, only observational notes, or descriptions of what they did are provided.

The rubric was adapted to reflect the context of this study. The original rubric featured four levels (Levels 1, 2, 3, and 4). I used the same levels but slightly changed the level 3 description. Levels 1, 2, and 4 remained the same as the original rubric. In the original Level 3, there was an investigation question and data collection in response, but no explanation aligned with the question. In the adapted version, level 3 includes an investigation question, with observational data collected. However, either the data and research question were not connected, or the question was too broad, leading to an unfocused investigation. Thus, the collected data is not connected to the investigation question, or the explanation does not address the question. Reports were systematically assessed across these levels, allowing for a structured evaluation of coherence in PTs' inquiry practices. While Level 1 reports demonstrated the highest level of coherence in inquiry engagement, Level 4 reports showed minimal coherence.

Reflections were analyzed using thematic analysis (Braun & Clarke, 2006). Responses to the first three prompts were combined due to overlapping themes, while the last prompt was analyzed separately. I began by reading through all the reflections to gain an initial sense of the content. Next, I conducted open coding to identify emergent codes directly from the data without predetermined categories. Iterative, open coding is followed by grouping similar codes into broader categories. The coding framework is provided in the Supplementary material. Two researchers independently coded a subset of reflections to ensure consistency, resolving discrepancies through discussion. Final coding schemes were applied to all data.

Results

Results from Written Reports

The analysis of PTs' written reports revealed a variety of nature investigations conducted in diverse settings, including gardens, jogging tracks, and community parks in urban areas, as well as fields and gardens in rural areas, depending on where PTs resided. All reports included observational data supported by photographs or videos, though not all contained investigation questions or detailed explanations. In their videos, PTs often examined insects under logs, plants, trees, and animals, frequently expressing uncertainty about species names and resorting to general terms like “flowers,” “trees,” and “insects.” However, in their written reports, many PTs identified local plant names and often provided species and family names, indicating additional research on specific organisms.

Among the 38 reports analyzed, PTs showed varying degrees of inquiry engagement. Reports were classified into four coherence levels, ranging from fully integrated inquiry process (level 1) to minimal inquiry engagement (level 4). The majority of PTs’ reports (58 %, 22 PTs) were classified as Level 1, which included a clear investigation question, data collection aligned with the question, and connected evidence-based explanations. For example, Dilek posed the research question, “What are the names of the plants in my environment and which family do they belong to?” She documented her observations through videos and included screenshots from the inaturalist app (Figure 1), identifying species such as castor oil plant, Nerium oleander, and Clovers.

Figure 1. Dilek’s data shows a screenshot of the inaturalist app she put in her report

She explained: “The castor oil plant (Ricinus communis) is a species from the Euphorbiaceae family, native to India. It grows naturally or is cultivated in regions with a Mediterranean climate. The seeds contain a toxic substance called ricin.”

Level 2 reports (11%, 4 PTs) included a clear investigation question and connected data but offered limited or implied explanations. For instance, Furkan asked, is it possible for us to observe any underground organisms that live near the surface in our local environment? What can we see as the structures that animals use as nests? as research questions. He added a video showing ants and beetles under logs, along with observational notes The place where I conducted my observation was our garden. There are trees and many types of animals typically found in natural environments. During my observation, I came across ants and two beetles of the same species but in different colors. I also observed an ants’ nest in the area where the ants were active.

Figure 2. Screenshot from furkan’s video data showing animals under the logs

His explanation included: “Overall, we observed animals, their habitats, plants around us, and a form of life that isn’t easily noticed. After examining these, we researched the names of the animals we saw and found that one was called the Golden Beetle.” While his observation was linked to the research question, his explanation lacked depth and a clear connection to the research question.

Level 3 reports (13%, 4 PTs) featured an investigation question and collected data but lacked a strong connection between the two or posed overly broad questions, leading to an unfocused investigation. For example, Tuana posed, “Why do trees shed their leaves as the seasons change?” Her report included descriptive observations like leaves on the ground, tree colors, and the presence of animals. These observations were largely descriptive and focused on general surroundings but failed to directly address the research question.

Figure 3. Tuana's photographs in her data

Her explanation highlighted her observations:

The ground was covered with fallen leaves. The leaves on the trees were shades of orange. The surroundings were quiet. The animals were hungry and came close to us for food. The weather was beautiful. The clouds were scattered, but the view was extraordinarily beautiful. Some of her observations were connected to her posed question, however, the observations were descriptive. The question required a causal explanation rather than observational data, further limiting the coherence of her investigation. Level 4 (21%, 8 PTs) reports demonstrated minimal inquiry engagement, lacking an investigation question and formal explanations. For example, Ruya provided rich observational descriptions but no investigation question or explanation. She wrote:

The coexistence of plants and animals to beautify nature was wonderful to see. I observed how worms aerate the soil underground to sustain life and how fallen leaves decompose, enriching the soil. I also saw decaying fruits on the ground used as food by animals; here, I observed a quince fruit. I noticed how other animals fed on the body of a pigeon after it had fallen to the ground. Worms especially caught my interest; they create channels to allow air and water to reach deep into the soil, which is beneficial for plant roots. Ivy-like plants wrap around the nearest plant to reach sunlight. The ivy I observed was the bottle gourd plant. It has a hard outer shell with a unique liquid inside and is used for decoration or storing and serving food. The fact that the olive tree didn't shed its leaves, even in winter, shows it is an evergreen tree. Other trees like mulberry, walnut, and fig had their leaves turn yellow and fall. I couldn't identify the plant in the second image, but I observed that it had hair-like thorns, possibly to protect itself from the cold.

Figure 4. Ruya's photographs in her data

While her observations (e.g., interactions among plants and animals, seasonal changes in vegetation, and environmental features, the role of worms in aerating soil, or the ivy climbing for sunlight) were rich and detailed, the report included no guiding questions or explanation, leaving the report observational rather than inquiry based. These findings reflect a spectrum of inquiry engagement among PTs, ranging from a fully coherent inquiry process to observational descriptions without inquiry focus. While many PTs successfully structured their reports with clear research questions and evidence-based explanations (Levels 1 and 2), others struggled to connect observations to their questions or lacked a guiding question entirely (Levels 3 and 4).

Reflections on Nature Investigation

The analysis of PTs' reflections on their nature investigation revealed eight themes represented in Figure 5: science and technological knowledge gain, improved awareness about biodiversity and ecological changes, opportunities for investigation and detailed observations, positive ideas, awareness about attentiveness and knowledge levels, fear-related concerns, environmental and physical discomfort, and holistic well-being.

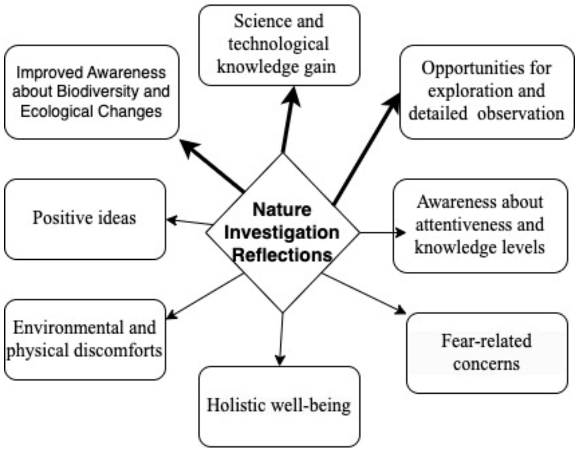

Figure 5. PTs' reflections on nature investigation

The first theme, science and technological knowledge gain, highlighted PTs' increased understanding of plant and animal species and their habitats. Many PTs noted that the investigation allowed them to learn about species' characteristics and their benefits to nature and humanity. For instance, Yener shared: "I learned that plant species from various regions can grow in different geographies. For example, Washingtonia robusta, native to Mexico, is also found in parks in Aydın [in Turkey]". Similarly, Melek wrote:

"I learned about living things that never caught my attention in nature. I discovered which group they belong to, where they grow, and their benefits. These observations showed me the transformations and formations in nature. I realized that many overlooked organisms have remarkable properties".

In addition to increased conceptual knowledge, PTs reported enhanced technological skills using mobile applications. Attila noted, "We can learn the names of almost all plant species quickly through mobile applications." These reflections emphasize how the nature investigation improved PTs' science and technological knowledge.

The second theme includes PTs' developing awareness of biodiversity, ecological changes, and the richness of their local environments. They reflected on the habitats, benefits, and interconnectedness of living organisms, as well as seasonal shifts. Sena observed, "I realized that the plants we see in our daily life are very important. For example, I learned that the sycamore tree absorbs polluted air." Seasonal changes also stood out to PTs. Atlas remarked, "Pine trees remain the same in summer and winter, and even in winter, they give cones. I observed maple trees shedding leaves at different rates and acacia seeds varying between trees." PTs expressed surprise at the diversity in their local environments. Zehra appreciated unique plants in the Aegean Region, while Melis shared, "The chicken varieties I saw surprised me. I never thought there was such a variety of animals on Earth." Melek noted a shift in perspective, saying, "Plants plucked and thrown away as harmful or useless in our garden have many benefits and are consumed in other cities. I now better understand the biodiversity value of my city." These reflections focused on the effect of nature investigation on raising environmental awareness among PTs.

The third theme, opportunities for exploration and detailed observation, emphasized how the activity encouraged PTs to make detailed observations and explore their surroundings. For example, Yasmin noted, "Nature investigation has made me observe nature better. I learned what lives with us, where, and how they live". Havin added, "This experience allowed us to see plant and animal species that we cannot see without examining them." Several PTs also reflected on the lasting value of this experience, suggesting it sparked ongoing interest: "I'm thinking of observing my surroundings more carefully and keeping a notebook for it" (Ferhan). Kevser also shared, "From now on, I will look around more carefully, research organisms that I do not know, and share this knowledge with others or my future students." These reflections demonstrate how nature investigation fosters a deeper connection to the environment, promoting curiosity and continuous inquiry.

The fourth theme, positive experiences, reflected the beneficial nature of the investigation. PTs described it as fun, motivating, and engaging. For example, Mehtap noted, "Being aware of the organisms around us was a beneficial experience," while Ilayda highlighted, "In this quarantine period and after the exam week, it was very motivating to discover the garden in nature. It was a nice, fun, and useful experience". These reflections suggest that such activities can enhance learning engagement even during challenging times like the pandemic.

The fifth theme, awareness about attentiveness and knowledge levels, showed PTs' developing self-awareness regarding their attentiveness to nature, knowledge gaps, and environmental responsibilities. Many reflected on how often they overlook their surroundings. Sena noted, "I realized how many plants and animals there are in nature that we do not pay attention to." Several PTs reflected on the decline of curiosity over time. Kevser shared, "As children, we wonder about everything around us and ask questions. As we grow older, we lose that curiosity. I realized I hadn't examined plants or my environment in such detail for a long time." Some participants acknowledged their limited knowledge about nature. Suna admitted, "I realized I had never had such deep knowledge about living things." Similarly, Zehra reflected, "I realized I did not know the names of many plants—I used to just say 'Flower.' Today, I learned the names of the plants I observed." A few PTs also expressed an increased sense of environmental responsibility. Zehra noted, "I realized once again that as humans, instead of protecting plants and animals, we pollute the environment and harm them in this way." These reflections highlighted not only heightened awareness and curiosity but also a recognition of knowledge gaps and a deeper sense of responsibility toward the environment.

Despite the positive outcomes, some PTs also wrote fear-related concerns and environmental discomfort, reflecting challenges they encountered during the activity. For example, Yasmin noted, "The disadvantage was examining the stink bug, the insect I feared the most." Similarly, Ipek added, "It is a disadvantage for me to carry out environmental research in a limited area due to the current pandemic and my fear of insects." Others faced difficulties with weather, muddy conditions, sticky substances, allergies, or seasonal limitations. For example, Havin wrote, "I had some difficulty entering muddy places and discovering organisms living there." Similarly, Sevgi stated, "The weather was very cold, and the ground was moist because of the rain. I couldn't explore much because of the virus." These reactions reveal logistical and personal challenges PTs faced during nature investigation.

The final theme, holistic well-being, showed how nature investigation supported PTs' self-care, stress relief, and motivation, particularly during the COVID-19 lockdowns. For example, Nil shared, "It [the experience] was both educational and enjoyable. We were able to devote a few hours of our day to ourselves and focus on good things." Tuba noted, "Going for a walk in nature relieves stress. At that moment, I only focused on the new organisms and plants I noticed, examining their movements. This was very beautiful." These reflections show the effects of incorporating nature-based activities into educational programs for their potential to enhance emotional well-being.

Reflections on the Use of Mobile Applications

PTs' reflections on the use of mobile applications to identify organisms during their nature investigation, categorized in Figure 6, highlighted three main themes: the used mobile applications, the affordances of mobile applications, and their shortcomings. Their responses revealed diverse usage patterns: some PTs used a single application, others used two simultaneously, and a few opted not to use any application but rather sought help from knowledgeable individuals. Among the 38 PTs, the majority (20 PTs) used Google Lens. Other applications included iNaturalist (10 PTs), PlantSnap (9 PTs), and PlantNet (9 PTs). Additionally, four PTs consulted knowledgeable individuals instead of apps. For example, Ata used the PlantNet: "I used the PlantNet mobile app. I realized that the application analyzes not only leaves but also flowers and stems of the plant." Melih combined Google Lens and PlantSnap: "I used Plantsnap and Google Lens applications. Google Lens was an application I used before, but I used Plantsnap for the first time". Some PTs relied on personal networks for identification. For example, Sena wrote, "I asked my friend, who is a landscape architect. I did not use any application, but I did a Google search to confirm its accuracy". Similarly, Fazilet explained, "I did not use any application; I asked my mother for the names of the plants, then after verifying it on the internet, I continued to search by the plant name."

Most PTs emphasized the benefits of using mobile applications, describing them as quick, accessible, and effective tools for learning. Buse noted the simplicity of learning with PlantSnap: "The Plantsnap app makes it easy to learn about plants. I always believed that it is very difficult to know the types of trees and plants. This app makes it easy. I will always use it." Selim appreciated Google Lens for its practicality: "I used the Google Lens application.

When I took a photo of the plant, it helped me find the information practically. It allowed me to access information quickly".

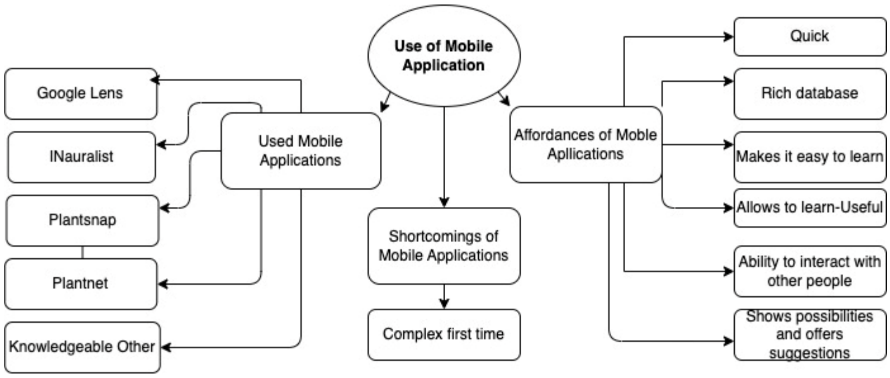

Figure 6. PTs' use of mobile applications

Other PTs valued the richness and interactive features of iNaturalist. Dilek shared, "I did my research with the iNaturalist app. The app gave more than what I was looking for. It was a nice feature that people can interact and comment within the app." Ipek added, "I used the iNaturalist mobile application. It shows similar results quickly, contains many species, and offers suggestions." Havin emphasized iNaturalist's social features: "It was a different feeling for me to get different views and have different audiences see the pictures I took. The app gave suggestions for the plant family and detailed characteristics of the plants".

While most PTs found the applications beneficial, a few noted initial challenges or confusion. For example, Sena found iNaturalist somewhat challenging: "iNaturalist was a bit confusing at first, but I solved the application by asking my friends for help." Overall, PTs found mobile applications to be valuable tools for identifying and learning about organisms, praising their ease of use, speed, and interactive features.

Discussion

The inquiry report results indicate a broad spectrum of PTs' inquiry engagement, ranging from coherent inquiry processes to limited inquiry engagement. While many PTs' reports were structured with clear research questions and evidence-based explanations (Levels 1 and 2), some were not structured to represent the links between observations and questions or presented solely descriptive observations in the absence of an inquiry focus (Levels 3 and 4). These results support the importance of engaging PTs in inquiry-based science learning as learners of science (Stuchlikova et al., 2013; Weld & Funk, 2005). Similar findings in other research indicated that the PTs have challenges in setting researchable and specific questions (Cruz-Guzmán et al., 2017, 2020) and had difficulty in designing inquiry investigations (Plummer & Tanis - Ozcelik, 2015). This variation in the coherence of inquiry points to the need for further instructional support to help PTs integrate inquiry elements together meaningfully within investigations. Specifically, there is a need for explicit guidance in framing research questions, as they provide a foundation for effective inquiry-based learning.

In this study, PTs engaged in nature investigation after electricity investigations, where they posed research questions and conducted controlled experiments. However, findings indicate that it takes more experience to build research questions based on different contexts, relate data to questions, and provide clear explanations on various inquiry topics. This was consistent with the previous studies that indicated an explicit need for guidance during various phases of inquiry (García-Carmona, 2016, 2017). Scaffolding can play an integral role in assisting PTs in properly structuring coherent inquiry investigations with a deeper understanding of inquiry-based science learning.

The reflections portrayed the multifaceted nature of PTs' perception of nature investigation, including enhanced scientific and technological knowledge, a fostered connection to nature, and increased awareness of biodiversity. PTs reflected on their awareness of adaptations, habitats, and ecological changes. The findings suggest that nature investigation fosters deeper connections to the environment and sparks curiosity and responsibility for the environment, consistent with the place-based education framework (Semken - Freeman, 2008; Sobel, 2005). In addition, it aligns with the research in highlighting the influence of outdoor education in fostering environmental awareness and commitment to it (Chawla, 2015; Soga & Gaston, 2016; Trautmann, 2013; Wals et al., 2014). Reflections also point to their acknowledgment of knowledge gaps and a lack of prior attention to local biodiversity, emphasizing the value of localized, inquiry-based education beneficial for ecological and self-awareness in teacher preparation.

PTs described the experience as fun, motivating, and beneficial, suggesting that place-based learning can increase engagement and enjoyment in learning. The findings also showed that nature investigation contributed to PTs' holistic well-being, offering stress relief and motivation during the lockdown period. This is particularly important in the COVID-19 pandemic, where maintaining motivation and engagement in virtual or socially distanced environments has been a challenge (Avsar - Erumit et al., 2021). These reflections emphasize the broader benefits of nature-based investigations, not only for their educational value but also for their ability to support mental and emotional well-being. The connection between nature and well-being is well-documented (Gill, 2014; Louv, 2016), and this study highlights the importance of integrating such experiences into educational programs, particularly during times of heightened stress, such as the COVID-19 pandemic.

While most PTs had positive experiences, some expressed fear-related concerns about animals and discomfort related to environmental factors or the limitations imposed by the pandemic. Fear-related concerns, especially with invertebrates, were also reported in previous studies (Melis et al., 2021; Prado et al., 2020). During the introduction of the nature activity, PTs viewed a video about microhabitats, which elicited negative emotions in some participants, particularly regarding investigating insects. We discussed their role as adult models in future classrooms, emphasizing the importance of avoiding the transfer of biophobic attitudes to their students. Despite this guidance, a few PTs' reflections still showed fears related to insects. These concerns are important to address in future nature-based investigations, as they can act as barriers to full engagement. Providing clearer guidance, better preparation, and choosing accessible and comfortable environments could help mitigate these issues and ensure that all participants can participate without fear or discomfort.

PTs considered mobile applications effective for identifying and learning about organisms, highlighting their ease of use, speed, and accessibility. The varied experiences of PTs with these applications show the potential value of applications in supporting their observations and science learning. Most PTs found mobile apps helpful in quickly identifying organisms and gaining information, aligning with existing research on the benefits of mobile technologies in science education (Van Praag & Sanchez, 2014). These digital tools facilitated real-time identification and knowledge acquisition, reflecting the growing importance of digital literacy in science education (Sung et al., 2016). They particularly appreciated the practicality, rich data, and interactive features of the tools, which made learning quick and engaging. These positive perceptions align with findings by Echeverria et al. (2021), who reported that students found iNaturalist enjoyable and easy to use and expressed interest in future use, emphasizing its pedagogical benefits. The pedagogical advantages of mobile devices include increased motivation, enhanced content delivery (Sung, Chang, & Liu, 2016), greater authenticity in learning experiences, and improved student autonomy (Van Praag & Sanchez, 2014). Integrating mobile technologies into nature-based activities provides a powerful combination of traditional observation and modern technological support, enhancing content knowledge, engagement, and interest (Unger et al., 2020).

Despite these advantages, a few PTs encountered challenges in the apps, highlighting the importance of user-friendliness and additional support to maximize their effectiveness. For example, some PTs faced initial difficulties due to a lack of on-site instructor support, emphasizing the need for clear instructions and structured guidance, which were later provided during synchronous classes. Language barriers with iNaturalist, which defaults to English, also posed difficulties for some PTs. Peer feedback during class discussions helped resolve these issues, but the challenges emphasize the importance of scaffolding and modelling the use of mobile tools in educational settings. These findings suggest that mobile applications can be effective tools for scaffolding observation and classification skills and supporting inquiry-based environmental education by bridging digital and field-based learning experiences.

Limitations

While these findings should be considered in the context of certain limitations, they still provide valuable insights into PTs' engagement with inquiry-based place-based learning. The online nature of the course, necessitated by the COVID-19 pandemic, may have influenced PTs' engagement and the overall quality of observations. The absence of in-person guidance and supervision during the observations might have limited the depth of observations compared to a traditional field-based setting. Additionally, variations in PTs' access to resources, such as reliable internet and conducive natural environments, could have affected the observation experience. Differences between urban and rural environments likely influenced the depth and scope of nature observations, highlighting an area for future research to explore how different settings influence PTs' learning experiences and outcomes in nature-based investigations. The three-week duration of the nature investigation, while practical within the course schedule, may have constrained opportunities for PTs to further develop their inquiry skills and ecological awareness. Despite these challenges, the study emphasizes the potential of mobile-supported, place-based investigations in enhancing PTs' inquiry skills and biodiversity knowledge, even in remote learning contexts.

Conclusion

This study highlights the potential of combining place-based education, mobile technologies, and inquiry-based learning for PTs' development of scientific knowledge, inquiry skills, and ecological awareness. By engaging PTs in local nature investigations supported by digital tools, the study fostered both cognitive and effective outcomes, enhancing PTs' scientific knowledge, curiosity, and connection to their surroundings. The findings highlight the importance of scaffolding inquiry processes and addressing challenges such as fear or discomfort to ensure inclusive and meaningful engagement in nature-based learning.

Recommendations

Given the varying levels of PTs' inquiry coherence, there is a clear need for explicit instructional guidance in framing research questions, designing investigations, and making evidence-based connections between observations and explanations. Scaffolding strategies should be emphasized in teacher education to help PTs develop stronger inquiry practices. Additionally, mobile applications provide valuable support for nature-based learning, yet their effectiveness can be enhanced through structured integration and instructor facilitation.

Future research should explore the long-term impact of such inquiry-based experiences on PTs' teaching practices and their ability to facilitate similar learning experiences for their students. Investigating the influence of extended engagement in nature investigations and the role of different environmental settings (urban vs. rural) on PTs' learning can further inform best practices in science teacher education. The findings from this study contribute to the growing body of literature on nature-based learning and emphasize the importance of fostering inquiry, environmental awareness, and digital literacy in teacher preparation programs.

Scientific Ethics Declaration

* The author declares that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the author.

* IRB approval was received from Aydin Adnan Menderes University Educational Research Ethics Committee, with the decision dated August 6, 2021 (Session No: 18, Decision No: III).

Conflict of Interest

* The authors declare that they have no conflicts of interest

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Digitizing Early Childhood Environmental Education: A Bibliometric Study

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Abstract

The integration of digital tools in education has gained attention for enhancing engagement and interactivity, particularly in fostering environmental awareness in early childhood. Early exposure to ecological concepts can nurture environmentally conscious individuals equipped to address climate challenges. This study analyzes research trends on digitizing environmental education in early childhood from 1968 to 2023. Using the Dimensions database, 443 relevant publications were identified from 9214 documents, and a bibliometric analysis was conducted via VOSviewer 1.6.20. Findings indicate that research in this field remains nascent. Although digital technology was first mentioned in 1968, significant scholarly interest only surged in 2023, with a record 1,503 publications. Vietnam, Thailand, and South Africa lead in publications, while top institutions include the University of Johannesburg, Mahidol University, and Ho Chi Minh University of Social Sciences and Humanities. The study also identifies key journals, prolific researchers, and highly cited works. Keyword co-occurrence analysis provides deeper research insights. These findings emphasize the rising role of digital tools in early childhood environmental education. Integrating technology enhances ecological understanding and fosters environmental responsibility. Additionally, this study offers a comprehensive literature overview, guiding future research on digitizing environmental education.

Introduction

The urgency of addressing global environmental challenges, such as the rise in global temperatures by approximately 1.2 degrees Celsius since pre-industrial times (Noor et al., 2021), has intensified the need for robust environmental education. Integrating such education into early childhood education (ECE) curricula is essential for fostering sustainable development and supporting the goals of quality education and climate action (Sanginova, 2024). This priority is reinforced by the academic community, which highlights the vital role of education in raising awareness and understanding of climate change (Priatna & Khan, 2024). In this context, the digitization of environmental education has emerged as a promising approach to enhance engagement, interactivity, and personalized learning among young learners (Pegrum, 2016).

To clarify this concept, "digitized environmental education in early childhood" refers to the intentional use of digital technologies to support environmental learning among young children (Mantilla & Edwards, 2019). This includes applications, videos, games, and interactive tools that teach concepts such as recycling, biodiversity, climate change, and sustainability in developmentally appropriate ways. Unlike general educational technology use, which may focus on literacy, numeracy, or entertainment, digitized environmental education specifically targets environmental awareness and action. It combines digital engagement with ecological themes to foster early environmental consciousness and responsibility (Hajj-Hassan et al., 2024).

Despite its potential, the implementation of digitized environmental education faces notable challenges. Only 38% of children worldwide have a fundamental understanding of climate change issues, indicating that environmental awareness among children remains shockingly low (Rulli et al., 2024; Biber et al., 2023). Digital technology is increasingly viewed as a key enabler for addressing this gap (Buchanan et al., 2018). However, significant infrastructural barriers persist, only about 53% of schools worldwide have internet access, which hampers the effective integration of digital tools into teaching and learning (Gupta & Hayath, 2022). This lack of connectivity poses a substantial obstacle to utilizing digital resources for environmental education in early childhood settings (Selwyn, 2011).

Consequently, the issue of digitizing environmental education in early childhood education is increasingly vital, and it has become a significant focus of educational innovation and policy development worldwide (Higgins et al., 2012). Early childhood is a crucial period for shaping children's understanding and attitudes towards the environment (Madden & Liang, 2017). The use of digitizing tools in ECE can significantly enhance the learning experience and effectiveness of environmental education (Alper, 2016). Researchers from various fields have explored the impact of digital tools on young children's learning, demonstrating that high-quality digitizing tool integration can foster better engagement and comprehension of environmental concepts (Siraj-Blatchford & Siraj-Blatchford, 2006).

Moreover, from cognitive and developmental perspectives, digitizing tools have been found to support the development of essential skills such as critical thinking and problem-solving, which are vital for understanding environmental issues. There is evidence that the use of digital tools in teaching can bridge the gap in environmental knowledge among children from different socio-economic backgrounds, thereby promoting equity in educational outcomes (Erstad & Voogt, 2018). This is particularly relevant for disadvantaged children who might otherwise have limited access to quality environmental education. A child's cognitive and social-emotional skills can be significantly enriched through digitizing tool-enhanced environmental education. Consequently, it is logical to assume that digital tools can provide a feasible solution to compensate for deficiencies in environmental knowledge and skills that children might not acquire at home. Therefore, the effective use of digitizing tools in ECE can contribute to a country's overall human capital by fostering a generation that is more knowledgeable and conscious about environmental issues (Yetti, 2024).

At the same time, efforts have been made globally to integrate digital tools into the educational system, including early childhood education, to enhance learning experiences and outcomes (Johnson et al., 2020). Despite challenges such as limited access to digital resources and infrastructure, various initiatives by governments and non-governmental organizations have aimed to promote the use of digital tools in classrooms worldwide. For example, projects like BridgeIT, which uses mobile technology to deliver educational content, have shown promising results in improving teaching and learning processes, including environmental education in different parts of the world (Wennersten et al., 2015). These efforts underline the growing recognition of digital pedagogy as a vital component of inclusive and equitable education in the 21st century.

In light of this, environmental statistics emphasize the urgent need for effective environmental education. Recent research by Le Quere et al. (2021) indicates that atmospheric carbon dioxide (CO_2) levels reached 413 parts per million (ppm) in 2021, a substantial increase from pre-industrial levels. Keenan et al. (2015) highlight alarming deforestation rates, estimating a loss of 10 million hectares of forest annually from 2015 to 2020. These findings emphasize the critical importance of integrating robust environmental education into early childhood education to address global environmental challenges effectively.

Accordingly, scholars advocate for the integration of digital tools in educational settings, particularly in ECE. This approach aligns with Sustainable Development Goal 4 (SDG 4), which emphasizes inclusive and equitable quality education (Elfert, 2019). However, disparities persist in global access to digital tools, especially impacting children in developing regions like sub-Saharan Africa (Selwyn, 2010). Efforts to bridge these gaps are essential to ensuring that all children benefit from innovative digital tools in their educational journey.

To this end, equitable access to digital tools in ECE is crucial, supporting high-quality environmental education that nurtures holistic child development. Ongoing research is vital to understand the evolving integration of digital tools in education. Voogt et al. (2013) stress the need for investigating the epistemology and intellectual structure of digitizing tools to fully comprehend their evolving impact. For instance, Pegrum (2016) discusses how educational software and interactive apps enhance the teaching and learning of environmental concepts in ECE, promoting engagement and critical thinking skills among young learners. Despite these advancements, there remains a gap in understanding how these tools specifically impact environmental education in ECE (Kim et al., 2023). This study addresses this gap by employing bibliometric analysis to investigate longitudinal trends in publications related to the digitization of environmental education within ECE. By examining the evolution and patterns of scholarly output, this study aims to identify key authors, primary sources, and influential academic affiliations contributing to this research domain (Donthu et al., 2021). Additionally, it seeks to uncover co-authorship dynamics and thematic associations through keyword co-occurrence analysis, thereby providing a comprehensive overview of collaborative networks and emerging trends in this field (Lozano et al., 2019).

Ultimately, understanding current publication trends, identifying prolific authors and institutions, and analyzing keyword co-occurrence are essential steps in advancing research on digitized environmental education in early childhood education (Van Eck & Waltman, 2010). The findings from this bibliometric study will shed light on the leading countries, institutions, and collaborative efforts driving this field (Moed, 2005). This comprehensive overview will provide valuable insights into the global research contexts, offering a clearer picture of how digital tools are being integrated into ECE to enhance environmental education.

Therefore, this study fills a critical gap in the literature by specifically examining how digital tools impact environmental education in ECE through a bibliometric analysis. While previous research has focused broadly on digital tools in education (Kucirkova & Falloon, 2016; Edwards, 2013), few studies have investigated their application to environmental education in early childhood settings (Cutter-Mackenzie et al., 2014). By mapping longitudinal research trends, identifying key contributors, and analyzing collaborative networks, this study offers new insights into the role of digital tools in fostering environmental awareness among young learners. The findings will not only inform future research directions but also support educational strategies and policy development aimed at integrating digital innovations more effectively in environmental education, thereby enhancing learning outcomes and promoting sustainability from an early age. To achieve this aim, the study seeks to answer the following research questions:

1. What are the annual publication trends related to the digitization of environmental education in early childhood curriculum?
2. Which journals have made the most significant contributions to the field related to the digitization of environmental education in early childhood curriculum?
3. Which authors are most cited and influential in the study related to the digitization of environmental education in early childhood curriculum?
4. What are the leading organizations contributing to research related to the digitization of environmental education in early childhood curriculum?
5. Which countries are at the forefront of publishing research on digitization of environmental education in early childhood curriculum?
6. What is the key keywords co-occurrence within the field of digitization of environmental education in early childhood curriculum?

Methodology

This study employs bibliometric analysis to provide an analytical overview of the scholarly context surrounding the digitization of environmental education in early childhood curricula. Bibliometric analysis is a quantitative method that investigates publication patterns, authorship, citation networks, and thematic trends to evaluate the structure and development of scientific knowledge (Aria & Cuccurullo, 2017; Donthu et al., 2021). This approach is particularly effective for tracing the evolution of research domains, identifying influential works, and uncovering emerging topics. By applying bibliometric tools, this study aims to map the key contributors, thematic clusters, and intellectual structure of this interdisciplinary field, offering insights that guide future research and policy development.

Data Source

Publications related to the digitalization of environmental education in ECE were retrieved from the Dimensions database, covering the period from 1968 to 2023. The Dimensions database was selected for its extensive and integrated research coverage, particularly in education and social sciences. It offers a large volume of open-access content and detailed citation data without subscription barriers. Compared to traditional databases like Scopus and Web of Science, Dimensions is recognized for its broader disciplinary scope and more inclusive representation of global scholarship, especially from underrepresented regions and non-elite institutions (Herzog et al., 2020). Its selection aligns with the aim of the study that is to capture a comprehensive and globally inclusive perspective on digital environmental education in early childhood.

Despite its advantages, Dimensions also present certain limitations. While its coverage is extensive, it may not be as exhaustive as Scopus or Web of Science, potentially omitting some relevant literature. The inclusion or exclusion of grey literature and publications from lesser-known journals can influence the completeness and diversity of the dataset, which is particularly significant in interdisciplinary fields like environmental education in ECE (Herzog et al., 2020). Therefore, while the Dimensions database serves as a valuable source for this study, these limitations are acknowledged to avoid overgeneralizing findings and to support a balanced interpretation of the results.

Data Collection Period

An extensive search was conducted on Wednesday, October 9th, 2024, to collect relevant literature. The time frame for the data collection spanned from 1968 to 2023, allowing the study to capture a broad historical and longitudinal perspective on the integration of digital tools into environmental education in ECE (Green, 2015). The starting point, 1968, aligns with the global rise of environmental consciousness that gained momentum in the late 1960s. This period laid the foundation for modern environmental education frameworks. It was notably catalyzed by events such as the 1972 UN Conference on the Human Environment and early policy initiatives on sustainability (Handl, 2012). The end point, 2023, ensures inclusion of the most current research developments, reflecting the ongoing expansion of digital pedagogy and environmental literacy in early childhood contexts (Hook et al., 2018).

Inclusion and Exclusion Criteria

The inclusion criteria focused on peer-reviewed publications addressing the intersection of digital technology, environmental education, and early childhood education. Eligible sources included journal articles, book chapters, edited books, and conference proceedings published in English. To ensure thematic relevance, publications were screened through title and abstract review, with documents unrelated to the scope of study excluded. Grey literature and non-open-access materials were also excluded to maintain quality and analytical consistency (Langham-Putrow et al., 2021).

From the initial 9,214 documents retrieved, 2,124 duplicates were removed, and 6,647 records were screened for relevance. A total of 3,469 grey literature and 3,178 non-open-access publications were excluded during the selection process. After applying all exclusion parameters, a final sample of 443 documents was retained for analysis. These documents represented thematically appropriate and high-quality literature for bibliometric study. The step-by-step data cleaning and keyword selection process is summarized in Table 1.

Table 1. Data cleaning and keyword selection process

S/n	Steps	Description
1.	Initial retrieval	9214 articles identified using search string in Dimensions
2.	Duplicate removal	2124 duplicates removed
3.	Screening	Titles and abstracts screened for relevance to both “digital technology” “environmental education” and “early childhood education”
4.	Exclusion	3469 grey literature and 3178 non-open-access items excluded
5.	Final inclusion	443 documents retained based on peer-review, language, and thematic focus
6.	Keyword refinement	Synonyms consolidated “digital technology” “environmental education”, “early childhood education”

Search Strategy and Article Selection Process

The search was conducted on May 8th, 2024, using the Dimensions database, employing a comprehensive string of keywords related to digitalization, environmental education, and early childhood education. Search terms included “Digital Technology,” “Educational Technology,” “E-learning,” “Environmental Education,” “Sustainability Education,” and “Early Childhood Education,” among others. These keywords were strategically combined using Boolean operators and applied in the TITLE-ABS-KEY fields to ensure precision. Filters were also applied to limit the results to English-language publications from 1968 to 2023.

Following the database query, a total of 7,090 documents were initially retrieved. A systematic review process involving title and abstract screening, followed by exclusion based on relevance, accessibility, and publication type, was implemented. Articles that did not meet the thematic, linguistic, or accessibility criteria were excluded from the final sample. The resulting 443 documents were deemed relevant and were prepared for further bibliometric analysis. The full process of data selection and preparation for analysis is summarized in Figure 1.

While Figure 1 outlines the overall methodological workflow adopted in this bibliometric study from keyword selection to data visualization, the next step involves a more detailed breakdown of the publication screening and eligibility process. To ensure methodological transparency and replicability, the inclusion and exclusion stages were systematically conducted following PRISMA guidelines (Page et al., 2021). Figure 2 illustrates this process, showing the progression from initial identification to the final selection of documents analyzed.

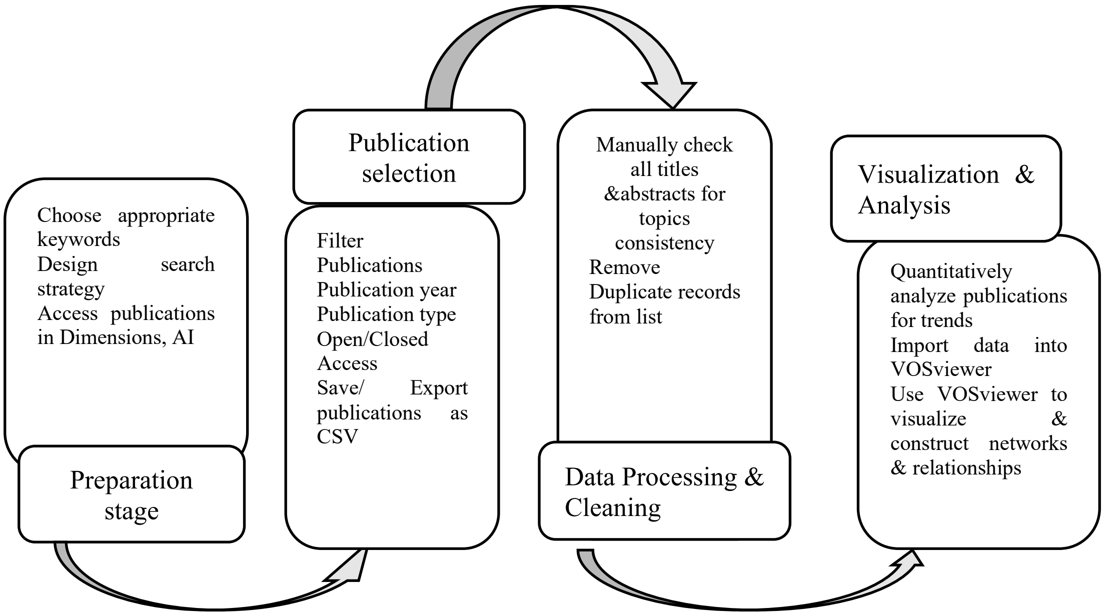

Figure 1. Bibliometric conceptual framework for the study. Adapted from Baako and Abroampa (2023)

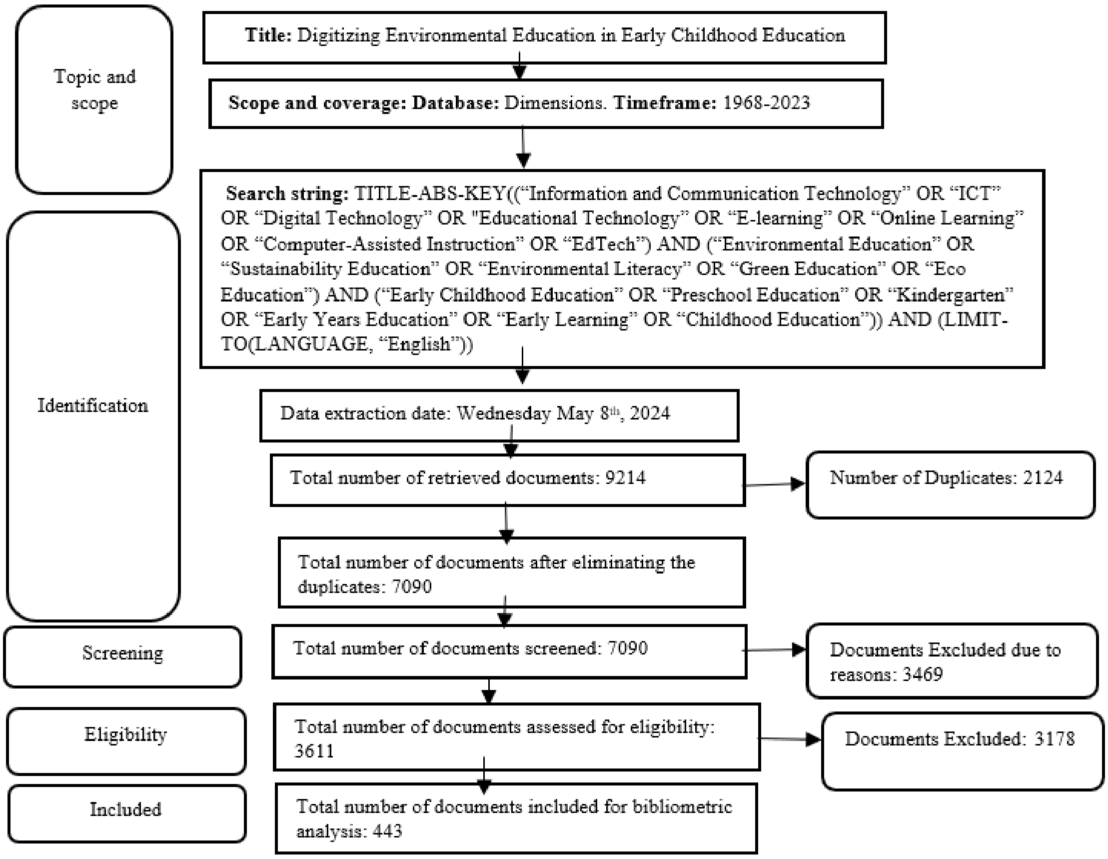

Figure 2. Flow chart illustrating the systematic review according to the PRISMA guidelines

Data Processing and Analysis

The selected documents were exported as a CSV file from the Dimensions database for processing and analysis. The data were cleaned to remove inconsistencies and ensure that only records directly related to the themes of the study were retained. Keyword harmonization was performed to consolidate synonyms and enhance the clarity of co-occurrence analysis. This ensured a focused and accurate representation of the scholarly discourse in the dataset.

VOSviewer version 1.6.20 was used to conduct the bibliometric analysis, generating network and overlay visualizations. (Van Eck & Waltman, 2010). These visual tools identified patterns of co-authorship, country collaboration, institutional contributions, and keyword co-occurrences. The analysis revealed influential authors, thematic clusters, and emerging research areas in digital environmental education within early childhood contexts. This method provided a robust and visual overview of the intellectual structure of the field (Khodabandelou et al., 2018).

Results

This section presents the key findings from the bibliometric analysis of literature on digitizing environmental education in early childhood curricula. Drawing on data from 443 selected publications, the analysis explores publication trends, influential authors, core journals, collaborative networks, and thematic clusters. The results offer insights into the intellectual structure and emerging directions within this interdisciplinary field.

Publication Trends

Figure 3 presents a bar graph depicting the distribution of annual publications from 1968 to 2023 in the field of digitizing environmental education in early childhood education. The earliest publication recorded was in 1968, with only one publication. For five consecutive years from 1969 to 1973, there were no publications, indicating a period of inactivity. In 1974, a single publication was made, marking a minor resurgence of interest. A significant increase occurred in 1996, with 810 publications, highlighting a substantial growth in scholarly activity. The year 2020 saw the second-largest number of publications, totaling 1,293, likely influenced by the shift to remote learning during the COVID-19 pandemic. The peak year was 2023, with 1,503 publications, demonstrating a continued and growing interest in this research area.

The cumulative frequency graph illustrates the growth pattern of publications over the years. The curve is concave upwards, indicating an accelerating trend in publication activity. Before 1996, publication numbers were minimal, but post-1996, there was a noticeable increase. The slope became significantly steeper from 1996 onwards, particularly between 2019 and 2023, reflecting a rapid growth in research output. This trend underlines the mushrooming importance and recognition of integrating digital tools in environmental education for young children.

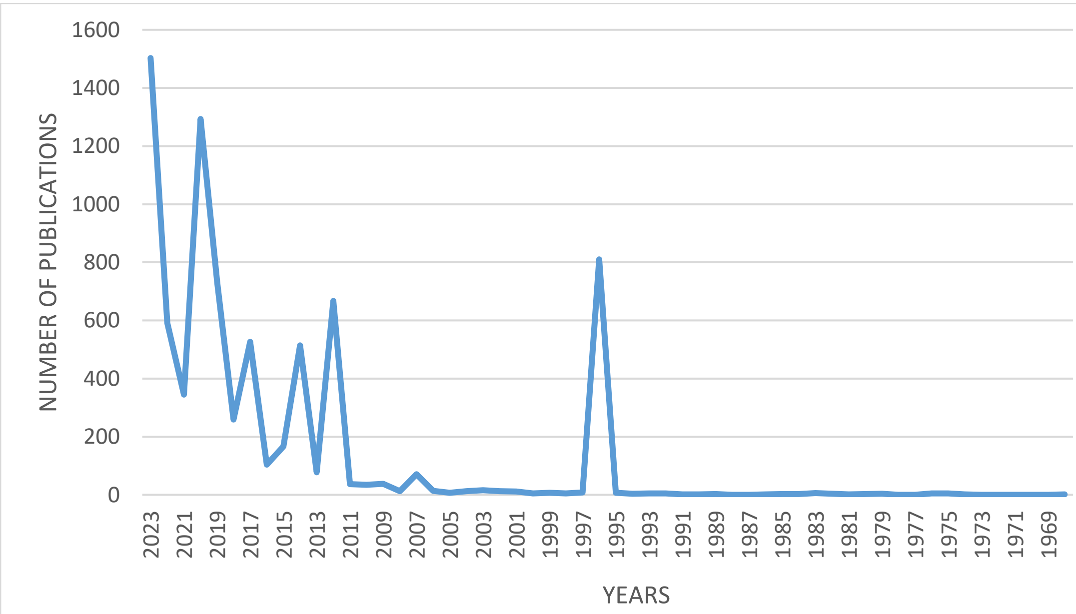

Figure 3. Distribution of publications by years

Most Productive Sources

The bibliometric analysis focused on identifying and visualizing sources that have contributed significantly to the literature on digitizing environmental education in early childhood education. Sources such as *Perspectives in Teacher Education and Development, Springer International Handbook of Education, Journal of Qualitative Research in Education* and *World Sustainability Series* appear prominently, reflecting strong productivity and frequent referencing by scholars. Figure 4 provides an overlay visualization of these sources, showing their relative productivity, influence, and temporal trends in publication. These findings suggest that these sources are highly influential in shaping research in this area. In contrast, sources like Perspectives on Teacher Education, although prolific in output, have received comparatively few citations.

This suggests that although “Perspectives on Teacher Education” produces many documents, they may not be widely cited, indicating potentially limited impact or relevance within the academic community. Therefore, it is reasonable to conclude that sources with higher citation scores tend to attract more manuscript submissions, solidifying their impact on advancing the digitization of environmental education in ECE. The citation network visualization stresses the importance of influential sources in shaping research directions and fostering academic discourse. Consequently, these highly cited sources play a crucial role in the ongoing development and dissemination of knowledge in this field.

The lack of interconnection between different sources in the figure may indicate that the cited sources are distinct and focused on specific aspects of the digitization of environmental education in early childhood education. This suggests that the research field might be diverse, with various studies contributing unique perspectives or findings rather than building directly on each other. It could also imply that these sources are influential within their specific subtopics, leading to isolated clusters of citations rather than a highly interconnected network. Figure 4 describes productive sources.

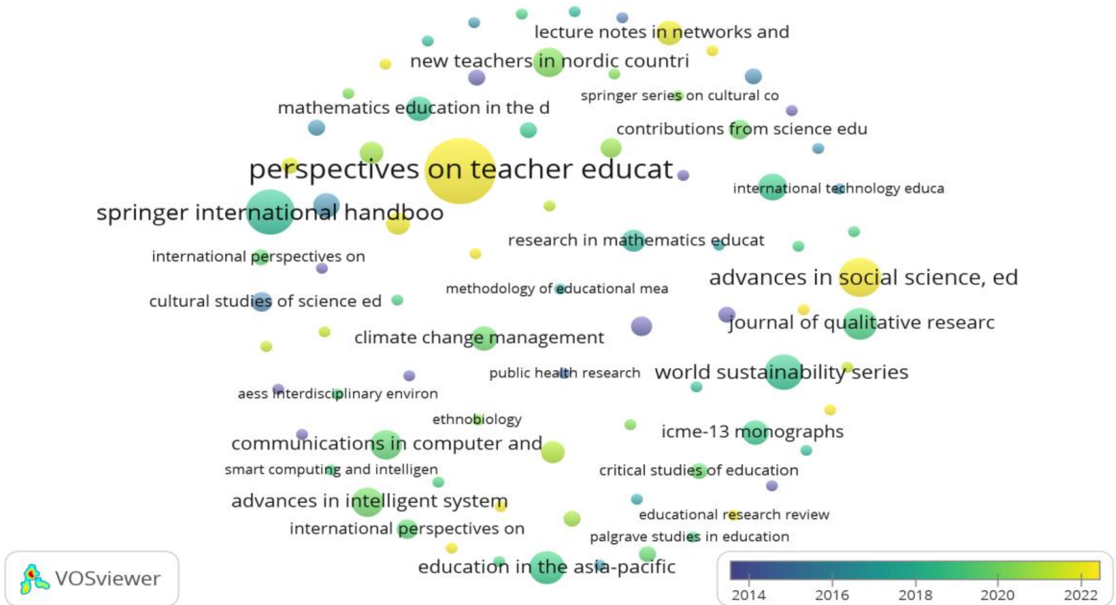

Figure 4. Overlay visualization of most productive sources

Productivity of Authors and Collaborations

Further bibliometric analysis was made to identify authors with the highest citations and collaborations with other authors in publishing in areas related to digitizing environmental education in early childhood education. Figure 5 indicates the patterns of most cited authors and collaboration with other authors in publishing in the area related to digitizing environmental education in early childhood education. Figure 5 indicates that Hallinger Philip, Nguyen-Vien-thong were the most cited authors in this area with 65 citations each. On the other hand, Avery Helen, Hallinger Philip, Nguyen-Vien-thong and Norden Birgitta were the authors with highest links in terms of collaboration. However, the total link strength among each of these scholars was only 2 which signify that the level of collaboration is very minimal. One good thing about collaboration is that it has brought together scholars from three different continents, Africa, Asia and Europe.

Figure 5. Productivity of authors and collaborations

Most Productive Institutions

The bibliometric analysis also identified the most productive institutions in terms of citations and collaborations within the field of digital environmental education in ECE. Among the top institutions are the University of Johannesburg in South Africa, Mahidol University in Thailand, and Ho Chi Minh City University of Science and Humanities in Vietnam. These universities have made significant contributions to the research context, as indicated by their high citation counts. Their active involvement in this field highlights the global nature of research efforts, with key institutions from Africa, Asia, and Southeast Asia leading the way in advancing the digital integration of environmental education in ECE. When it comes to institutional collaborations, other universities such as the Malmo university, Lund university and Linnaeus university add up to the former institutions as illustrated in the figure 6.

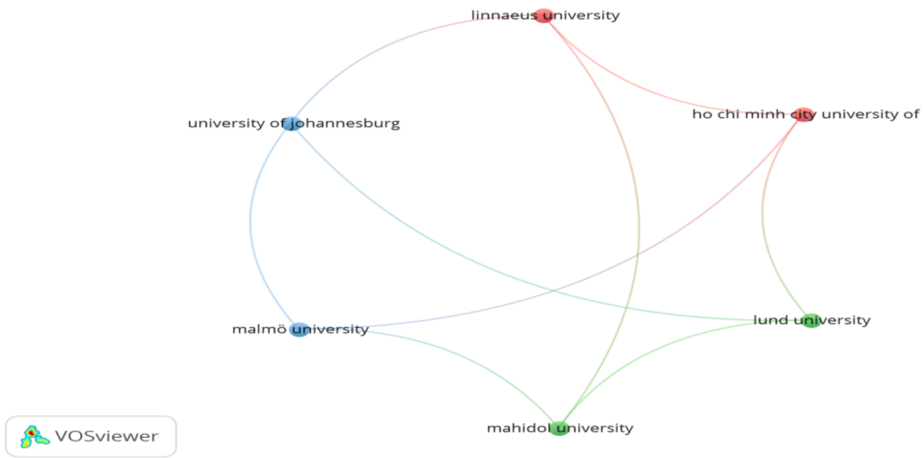

Figure 6. Most productive institutions

Author Co-citation

The co-citation analysis was conducted to identify authors who are commonly referenced in the field of digital environmental education in ECE. With a minimum threshold of two citations per author, the analysis revealed that out of 4580 sources, 400 authors met the criteria. Among these, Rapleye Jeremy and Mohar David emerged as the leading co-cited authors. This highlights their significant influence and the regular referencing of their work alongside other prominent authors in the field. Interestingly, some authors had no co-citations, indicating either a niche focus or emerging research areas that have not yet established strong connections within the broader academic network. The strong presence of Rapleye Jeremy and Mohar David in co-citation networks highlights their key role in shaping research trends and contributing to the academic discourse on digital environmental education. See figure 7.

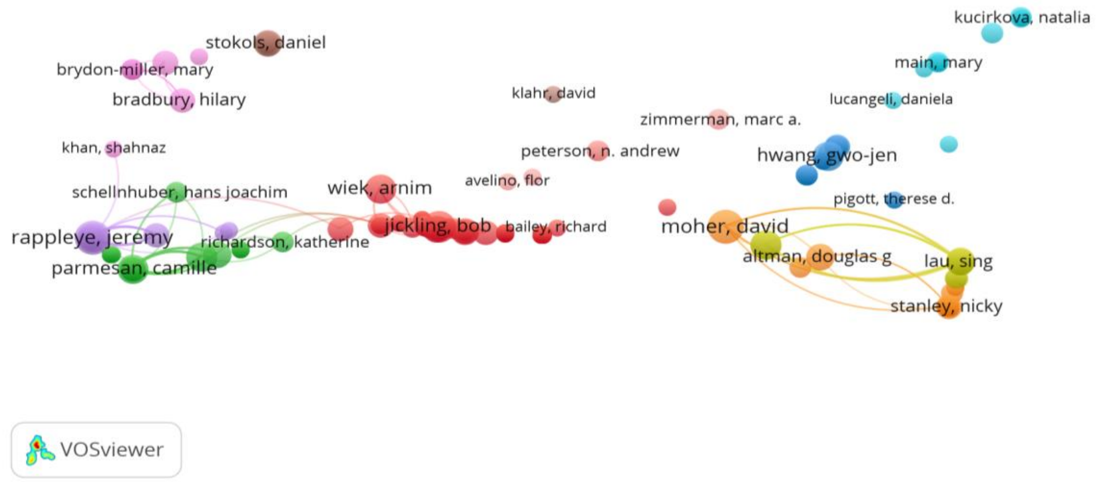

Figure 7. Author co-citation

Co-citation of Cited References

The co-citation analysis of cited references in the field of digital environmental education in ECE, with a minimum citation threshold of two, revealed that only 17 out of 1765 sources met this criterion. This indicates that a select group of references has significantly influenced the field. Among these, the works of Beit-hallahmi et al. (2014), Dezutter et al. (2006), Ivtzan et al. (2011), Hanley (2002), and Venter et al. (2010) stand out as the most co-cited references. Each of these studies has been cited eight times, with a total link strength of 32.

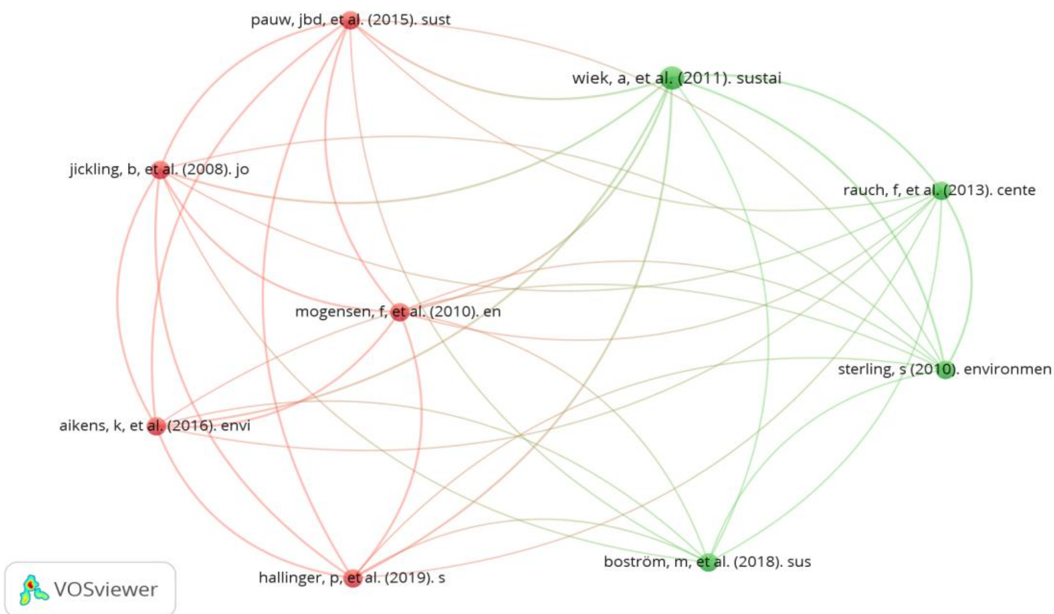

Figure 8. Co-citation of cited references

Interestingly, some of the 17 items were not connected to each other, with only 9 showing interconnections. This suggests that while a small number of references are highly influential, the field also contains isolated studies that do not frequently co-cite other works. The high level of co-citation for the connected references emphasizes their pivotal role in providing essential frameworks or findings. These key studies are central to ongoing scholarly conversations and advancements in digital environmental education.

Bibliographic Coupling Analysis by Country

Figure 9 presents the bibliographic coupling analysis by country, illustrating the research connections and influence among nations contributing to digital environmental education in early childhood. The bibliographic coupling analysis, focusing on countries as the unit of analysis, revealed that South Africa, Vietnam, and Thailand are leading with 65 citations each and a total link strength of 148. This indicates a significant level of research activity and influence from these countries in the field of digital environmental education. The strong presence of South Africa underlines the continent's growing contributions to this research area. Vietnam and Thailand's prominence highlight the active role of Asian countries in advancing digital environmental education in early childhood education.

Interestingly, among the top ten countries, seven are from Europe, two from Asia, and one from Africa. This distribution suggests that Europe is a major hub for research in this field, contributing the majority of influential studies. The presence of multiple European countries in the top ten may reflect well-established research networks and funding opportunities that support extensive academic work. The inclusion of South Africa and two Asian countries (Vietnam and Thailand) in the top ranks demonstrates the global nature of research efforts and the increasing contributions from diverse regions, indicating a collaborative and widespread interest in the digitization of environmental education in ECE.

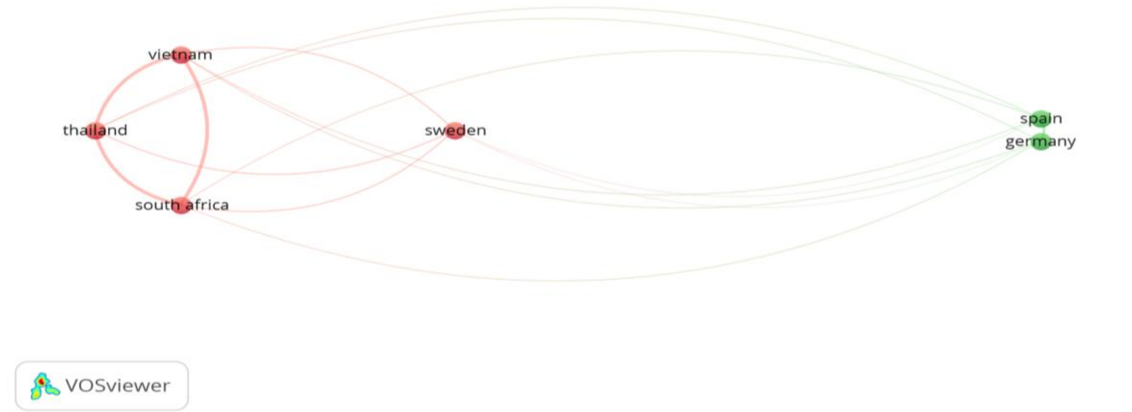

Figure 9. Bibliographic coupling analysis by country

Co-authorship

The co-authorship analysis, focusing on authors as the unit of analysis, offers a detailed understanding of collaborative relationships within the research field of digitizing environmental education in early childhood education. By examining the network of co-authors, this analysis identifies key researchers who play pivotal roles in facilitating and sustaining collaborative efforts. Figure 10 illustrates the co-authorship network among researchers, providing insights into the patterns and strength of collaboration within the field of digital environmental education in early childhood. The network visualization highlights that Jane Ellis is a central figure, frequently collaborating with other authors such as Bailey Sue, Farrelly Nicola, Downe Soo, and Stanley Nicky. This central positioning indicates Ellis's significant influence and leadership within the research community.

The analysis also reveals the presence of several interconnected subgroups, with varying strengths of collaborative ties. Authors like Hollinghurst Sandra, while connected to the main network, display fewer and weaker links, suggesting occasional or recent collaborations. The network's structure, with its mix of strong and peripheral connections, highlights opportunities for expanding collaborative efforts to include a broader range of contributors. This diversity of collaboration emphasizes the importance of key individuals in driving research forward and suggests potential for enhancing research productivity and innovation by fostering new collaborative relationships.

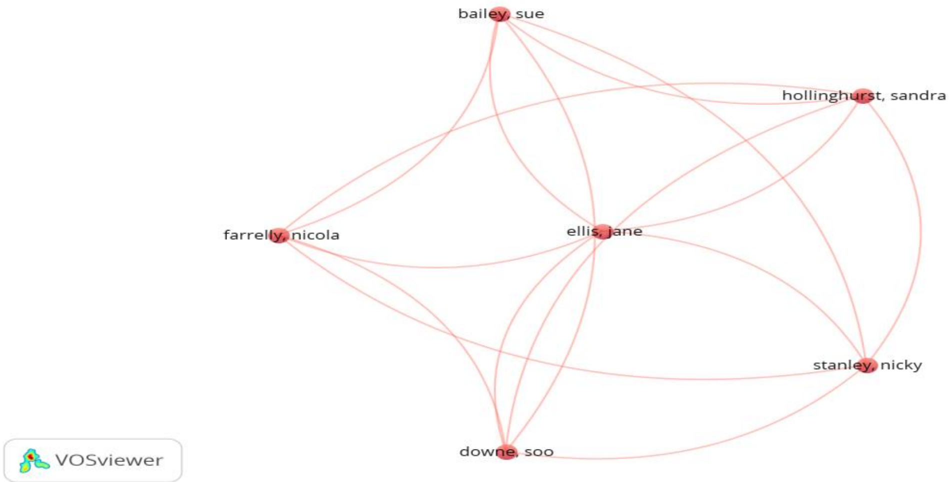

Figure 10. Co-authorship

Co-occurrence of Keywords in Digital Environmental Education in ECE

The co-occurrence analysis of keywords provides valuable insights into the thematic structure and research trends in digital environmental education within early childhood education. The visual map generated by VOSviewer reveals distinct clusters of keywords that highlight various focal areas of research. Each color represents a different cluster, indicating groups of related terms that frequently appear together in the literature. This clustering suggests the presence of interconnected subfields within the broader topic.

The red cluster prominently features terms like "theory," "teacher," "handbook," and "teacher education," indicating a strong emphasis on theoretical frameworks and educational methodologies related to digital environmental education. This cluster likely represents research focused on developing and evaluating educational practices and teacher training programs. These studies are crucial for advancing pedagogical strategies in digital environmental education. By examining these terms, researchers can gain insights into effective teaching methods and curriculum development.

The blue cluster includes keywords such as "climate change," "impact," "sustainable development," and "evidence." This suggests a focus on the outcomes and impacts of digital environmental education, particularly in relation to sustainability and climate change education. Researchers in this cluster are likely investigating the effectiveness of digital tools in fostering environmental literacy and sustainable behaviors among young children. This area of research is essential for understanding how early education can contribute to long-term environmental stewardship.

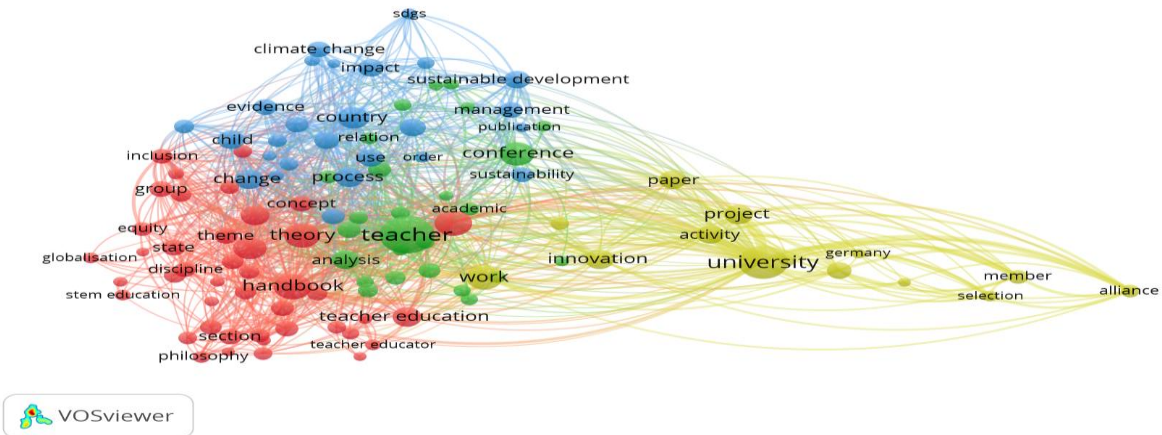

Figure 11. Co-occurrence of keywords in digital environmental education in ECE

The green cluster, with terms like "conference," "management," "publication," and "sustainability," appears to emphasize the dissemination and management of digital environmental education research. This cluster likely includes studies on the role of academic conferences, publication practices, and the management of digital educational resources. These aspects are vital for the propagation of research findings and the continuous improvement of educational practices.

The yellow cluster features terms such as "university," "project," "innovation," and "activity," highlighting the involvement of higher education institutions and innovative projects in the field. This cluster suggests a focus on collaborative projects, institutional initiatives, and the development of new digital tools and activities to support environmental education in ECE. The involvement of universities in such projects indicates a strong research and development component, driving forward innovations in digital environmental education.

Beyond identifying clusters, the co-occurrence map (figure 11) also reveals the structural relationships and knowledge flows across the subfields. The central positioning of keywords such as "teacher," "work," and "theory" suggests their integrative role across multiple thematic domains, acting as conceptual bridges between research on practice, policy, and pedagogy. The proximity of the red and green clusters indicates a strong link between theoretical development and research dissemination, highlighting the role of academic publishing in shaping pedagogical approaches. Meanwhile, the spatial isolation of the yellow cluster particularly around terms like "university," "alliance," and "innovation" points to institution-led projects that may be less integrated into classroom-level pedagogical discourse, highlighting a potential gap between innovation development and practical application in early learning environments.

Discussion

The results of this bibliometric study point to a notable shift in the body of knowledge on early childhood education research on digitizing environmental education. The paucity of publications throughout the early years, 1968-1980s, indicates how digital technology integration with environmental education in ECE is still in its infancy. This early period's low production can be seen in the context of larger worldwide trends in digital education and environmental consciousness, which were just starting to gain momentum as areas of scholarly interest (Pegrum, 2016; Selwyn, 2011). The gradual rise from the 1980s to the 2000s is related to the increased global attention that environmental and sustainable issues are receiving, as well as the developments in digital technology that started to have an impact on educational practices. This pattern emphasizes the relationship between advancements in technology and the growing understanding of the role that environmental education plays in influencing young children's views toward sustainability.

In this regard, the emergence of digital technologies in early childhood education throughout this time span reflects both a wider movement in educational philosophies stressing experiential and interactive learning as well as technological improvements. Digital technology integration made environmental education more dynamic and enabled students to interact with the material in creative ways that complemented international educational reforms (Buchanan et al., 2018). Furthermore, the gradual increase in publications during this period of time reflects the increased awareness of environmental issues and the importance of early education in resolving them on a worldwide scale. This stage of development emphasizes how crucial digitization is to improving environmental education's efficacy and accessibility while also supporting global educational objectives and sustainability initiatives.

Significantly, the notable expansion that took place between the years 2000 and 2010 signifies a paradigm-shifting era in which digital technology was thoroughly integrated into early childhood environmental education methodologies. Global sustainability programs, like the UN Decade of Education for Sustainable Development (Huckle & Wals, 2015), and the growing accessibility of better digital tools during this time period also corresponded with an increase in publications. A change in pedagogical techniques was made possible by technological improvements, especially in the area of interactive and mobile learning technologies (Kim & Smith, 2017). This allowed teachers to include environmental content into digitally mediated learning experiences for young children (Haleem et al., 2022). Furthermore, as a result of these technical advancements and the demands of modern education, there has been a growth in publications since 1996, which indicates increased scholarly interest (Dhawan, 2020).

Subsequently, the period from the 2010's to 2023, the observed peak in publication rates signifies the maturation of the field. The stabilization in research output suggests that foundational studies have been established, and current research is increasingly focused on building upon existing knowledge. This pattern is common in emerging academic fields, where an initial phase of rapid growth is followed by a more sustained level of scholarly activity, characterized by deeper exploration and refinement of prior findings (Zawacki-Richter et al., 2020). As a result, the field of digital environmental education in early childhood has entered a phase of consolidation, where new studies not only expand the existing literature but also address gaps in research, such as the underrepresentation of low-income and developing regions in the global discourse (Alò et al., 2020).

Nonetheless, given the crucial role early childhood education plays in fostering lifelong environmental attitudes, it is noteworthy that some regions are underrepresented in research on digital environmental education. Closing this gap is necessary for attaining the Sustainable Development Goals, particularly those related to inclusive and equitable education and urgent action on climate change (Ozturk, 2023). It is also critical for promoting greater equality in global research (Gupta & Vegelin, 2016). Digital tool accessibility is limited in many places, especially in low-income nations, which makes it difficult to incorporate technology-driven environmental education into ECE settings. Closing this gap will improve educational performance while simultaneously promoting early environmental literacy, giving the next generation the information and abilities they need to take on urgent global concerns (Biber et al, 2023).

Thus, to address the underrepresentation of research from developing countries, practical interventions are needed. These may include regional research funding initiatives that support local researchers, cross-national research partnerships between Global South and Global North institutions, and open-access publication incentives for low-resource settings (Sabzalieva et al., 2020). International organizations and education ministries can also develop policy frameworks that embed environmental education into early childhood curricula and teacher preparation programs (Leal - Filho et al., 2018). Such strategies can bridge epistemic gaps and enhance the global inclusivity of digital environmental education scholarship in early childhood contexts (Murcia et al., 2018).

Additionally, the way that digital environmental education is being integrated with more general global challenges like the fight against poverty, technological advancements, and the emergence of artificial intelligence (AI) emphasizes how important it is to use multidisciplinary approaches. Teachers can now connect environmental education with these changing global contexts in relevant and participatory ways due to the unique opportunities provided by digital technologies. Through integrating these resources into early childhood education, children could be given the tools they need to become change agents in their neighborhoods, encouraging environmentally friendly behaviors and building resilience in the face of rapidly changing technology (Kim & Smith, 2017). The potential of digital environmental education to promote critical thinking and environmental stewardship among young learners is vast, but it requires a concerted effort. Therefore, collaborative endeavors among researchers, policymakers, and educators are crucial to harnessing this potential and ensuring that digital tools in ECE contribute to a more inclusive, equitable, and sustainable future.

Equally important, key sources such as "*Perspectives in Teacher Education and Development", "Springer International Handbook of Education", "Journal of Qualitative Research in Education"* and *"World Sustainability Series"* have emerged as pivotal contributors to the discourse on digitizing environmental education in early childhood education. These sources play a crucial role in disseminating cutting-edge research, and their prominence within the field suggests a rigorous peer-review process and a broad readership, which likely contributed to their influential status. The high citation rates associated with these journals reflect their critical impact on shaping contemporary educational practices. This is consistent with Royle's et al. (2013) findings, which emphasize the role of leading journals in promoting innovative approaches to environmental education. The "World Sustainability Series", for instance, serves as a bridge between environmental science and educational theory, facilitating the integration of sustainability concepts into ECE curricula, a development highlighted in recent literature for its influence on educational innovation and research agendas (Waltman & Van Eck, 2012).

In terms of scholarly impact, citation analysis emphasizes an author's direct impact on the area by concentrating on how frequently their work is mentioned. Among the prominent contributors are authors like Philip Hallinger and Nguyen-Vien-Thong, whose studies on digital education and educational leadership, respectively, are often referenced. For example, Nguyen's (2018) investigation of digital learning tactics has been essential, demonstrating its broad suitability in early childhood education settings. These authors' high citation counts highlight both the fundamental nature of their work in promoting the integration of digital technology within ECE and their individual contributions. Their work has affected not just instructional strategies but also the way early childhood environmental education is framed.

Co-citation analysis, on the other hand, provides a broader perspective of scholarly effect by looking at the frequency with which two authors are referenced jointly in later works. Co-citation identifies important contributions such as David Mohar and Jeremy Rapleye, demonstrating their combined influence on the field's intellectual framework. Although the citation numbers of these authors may not be the greatest, their work is often mentioned in conjunction with other important studies, indicating that their research is valued as a key contributor to the development of the discourse on digital environmental education. This indicates that Rapleye and Mohar's research shows how their work is connected to larger scholarly discourses by providing fundamental frameworks or notions that others build upon (Trujillo & Long, 2018).

Taken together, these citation patterns highlight different types of scholarly contribution. Citation analysis emphasizes individual leadership and direct scholarly contributions, while co-citation analysis reveals how the work of various authors collectively forms the conceptual backbone of the field. This interconnectedness, as illustrated by co-citation, reinforces the idea that progress in the digitization of environmental education in ECE is built on collaborative intellectual foundations rather than isolated scholarly efforts (Hota et al., 2020).

Regionally, the prominence of scholars from Asia, such as Nguyen, reflects a regional concentration of research activity, which points to geographical disparities in the field. Although there are emerging contributions from other regions, such as Africa, where institutions like the University of Johannesburg are becoming increasingly involved, there is still a noticeable imbalance. As Adams (2013) noted, increasing international collaboration among scholars could significantly enhance research quality and innovation. Strengthening collaboration would foster a more inclusive and interdisciplinary approach, leading to richer, more diverse perspectives in the field of digital environmental education.

Moreover, institutions such as the University of Johannesburg, Mahidol University, and Ho Chi Minh City University of Science and Humanities have been identified as leading research centers in the field of digitizing environmental education in early childhood education. Their significant contributions highlight the global nature of research efforts in this area, challenging the traditional dominance of Western institutions. This shift signifies a growing recognition of the valuable insights and context-specific knowledge that institutions from diverse geographical regions can offer. Teferra and Knight (2008) argue that including perspectives from non-Western institutions promotes a more comprehensive and inclusive approach to educational innovation. This inclusion is particularly important for addressing the unique challenges and opportunities presented by different cultural and environmental contexts, which are often underrepresented in research.

Thus, a move toward a more representative and balanced contribution to the field is also reflected in the growing significance of institutions outside of the traditional western world. This pattern emphasizes how important it is to promote global cooperation and communication in order to close the gap between various geographic areas (Wagner et al., 2015). Such initiatives are essential to guarantee that the digitization of environmental education in early childhood education is based on state-of-the-art research and customized to fit the unique requirements of diverse communities. Institutions from Asia and Africa support a more equal and productive global education system, which is essential for tackling common issues like sustainability and climate change. They also contribute to a more inclusive research environment. Moreover, the research findings indicate that when it comes to the dissemination of knowledge in digital environmental education for early childhood education, books, book chapters, and conference proceedings significantly outnumber journal articles. In contrast to traditional bibliometric analysis, which tend to focus mostly on journal articles, this study highlights the diversity of publication within the discipline. The popularity of books and related formats points to a more complex method of disseminating knowledge since they provide in-depth analysis, case studies, and theoretical frameworks that shorter journal articles would not be able to fully address (Monroe et al., 2019). This pattern may point to a preference for publishing in formats that allow for longer conversations, especially in fields where pedagogical and multidisciplinary ideas are critically important. As the field matures, however, a greater focus on peer-reviewed journal articles could reinforce its empirical and theoretical foundations. Doing so would also increase its integration into mainstream academic discourse. Expanding the prevalence of journal articles would raise the visibility and academic credibility of digital environmental education in ECE.

At the same time, the limited availability of open access sources further complicates the accessibility of research findings in digital environmental education for early childhood education. Open access publications play a pivotal role in widening knowledge dissemination, enhancing global collaboration, and ensuring equitable access to educational innovations (Nguyen, 2018; Leal -Filho et al., 2018). The scarcity of open access resources identified in this study suggests potential barriers to knowledge sharing and collaborative research efforts, which may hinder the field's progress toward evidence-based practices and informed policy developments. This situation emphasizes the critical need for strategies that promote open access publishing initiatives, strengthen support for open science practices, and foster inclusive approaches that recognize the value of diverse publication formats while upholding rigorous scholarly standards.

Therefore, addressing these challenges is essential not only for advancing research but also for ensuring that findings are accessible to a broader audience, including practitioners, policymakers, teachers and researchers in resource-constrained settings. By facilitating access to high-quality research, the field can enhance its impact and relevance, ultimately contributing to the sustainable development goals related to education and environmental stewardship. Moreover, fostering a culture of openness in research will empower educators and stakeholders to implement innovative practices that address pressing environmental challenges, ensuring that future generations are equipped with the knowledge and skills necessary for a sustainable future.

Conclusion

The findings of this study offer significant insights into the evolution of digitizing environmental education in early childhood education from 1968 to 2023. The bibliometric analysis identified a substantial increase in academic interest, particularly notable in 2023 with a record 1503 publications. This rise underlines the growing recognition of digital tools' potential to enhance engagement and personalized learning in ECE environmental education (Haleem et al., 2022). By establishing a comprehensive baseline, the study marks key milestones and trends, providing a foundation for future research focused on the critical developmental phase of early childhood, where foundational attitudes and environmental knowledge are formed.

Hence, this study emphasizes the importance of global research efforts and collaborations, highlighting significant contributions from diverse geographical regions. It emphasizes the need for context-specific research and addresses critical gaps, such as the underrepresentation of research from developing countries. Future research should prioritize inclusivity and diversity to foster a more effective and equitable educational context. This aligns with global goals such as the Sustainable Development Goals (SDGs) related to quality education and climate action, recognizing the unique influence of early childhood education in fostering long-term environmental awareness (Mliless et al., 2024).

Overall, this study lays a strong foundation for future research and innovation in digitizing environmental education in ECE. By mapping existing literature and trends, it provides a valuable resource for researchers and policymakers aiming to advance this field. The findings emphasize the importance of interdisciplinary approaches and international collaboration, especially in the wake of challenges like the COVID-19 pandemic, which has accelerated the adoption of digital tools in education. Addressing identified gaps and leveraging global research efforts will be crucial in integrating digital technologies into early childhood environmental education, ultimately contributing to a more sustainable and technologically advanced educational framework. This ensures that early education stages foster a generation that is both environmentally literate and digitally proficient.

Recommendations

To enhance the integration of digital technologies in environmental education within early childhood education settings, specific recommendations for educators, policymakers, and researchers are essential.

For Teachers

Teachers should actively incorporate interactive and experiential digital tools into environmental education curricula, as these tools enhance young learners' engagement and understanding of sustainability issues. Utilizing platforms that combine digital storytelling, simulations, and virtual experiences can provide children with hands-on learning that fosters environmental awareness from an early age (Buchanan et al., 2018; Murcia et al., 2018; Haleem et al., 2022). Moreover, professional development programs are crucial for equipping teachers with the skills needed to effectively integrate these technologies into their classrooms. Continuous teacher training in emerging digital technologies and their educational applications should be prioritized to keep pace with technological advancements (Selwyn, 2011). Teachers should also be encouraged to share best practices through professional networks to build a collective knowledge base for digital environmental education.

For Policymakers

Policymakers must ensure that national education policies prioritize the integration of digital technologies in environmental education, particularly in early childhood settings. This could include the development of funding programs that support the acquisition of digital learning tools in low-income and underrepresented regions, thereby addressing disparities in digital access and promoting inclusivity (Alò et al., 2020). Governments should foster collaborations between educational institutions, technology providers, and environmental agencies. This aligns with the Sustainable Development Goals, particularly Goal 4 on inclusive education and Goal 13 on climate action (Gupta & Vegelin, 2016). Additionally, legislative frameworks should encourage schools to adopt evidence-based digital practices that promote environmental responsibility from early childhood. Public-private partnerships may also be leveraged to support long-term investment in digital learning infrastructures.

For Researchers

Researchers should continue to investigate the long-term impacts of digital environmental education in ECE settings, focusing on how digital tools can foster environmental stewardship among young learners. Further research is needed to explore the effectiveness of various digital platforms and how these tools influence children's cognitive and emotional responses to environmental issues (Zawacki-Richter et al., 2020). Additionally, comparative studies that examine the accessibility and effectiveness of digital environmental education across different socio-economic contexts would provide valuable insights for both global and local implementation strategies (Hajj-Hassan et al., 2024). Collaborative research efforts between institutions in high-income and low-income regions could bridge existing knowledge gaps and contribute to the development of more equitable digital education systems.

For Ministries of Education

Ministries of education should establish national strategies that institutionalize digital environmental education in early learning systems. These strategies should ensure curriculum alignment, teacher capacity-building, infrastructure development, and monitoring mechanisms. Ministries can play a key role in creating centralized repositories of digital learning materials and guiding schools on their effective use. Policies should also promote equitable access to digital tools and internet connectivity, particularly in underserved regions, to reduce disparities. By investing in structured implementation plans, ministries can scale up digital environmental education and contribute meaningfully to national and global sustainability agendas (ElMassah & Mohieldin, 2020).

For Donors and Development Partners

Donors and international development partners have a key role to play in supporting digital environmental education initiatives, especially in resource-constrained settings. They can fund pilot projects that test scalable digital interventions for teaching sustainability concepts in ECE. Investment in open-source digital tools and teacher training initiatives can ensure broader access and long-term sustainability. Donors should also support research collaborations that include scholars from developing countries to promote more inclusive and context-sensitive innovations. Finally, donor funding should align with national education priorities and sustainability frameworks to ensure long-term impact and systemic integration.

Scientific Ethics Declaration

* The author declares that the scientific, ethical, and legal responsibility of this article published in JESEH journal belongs to the author.

Conflict of Interest

* The author declares that he has no conflict of interest

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Investigation of Pre-Service Teachers' Artificial Intelligence Literacy and Views on the Use of Artificial Intelligence in Education

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Abstract

This study aims to investigate the artificial intelligence (AI) literacy levels of pre-service teachers and their views on the use of AI in education. Adopting a mixed-methods approach, the study employed both quantitative and qualitative techniques to ensure comprehensive analysis. The quantitative data were collected using the "Artificial Intelligence Literacy Scale," while qualitative data were gathered through open-ended questions developed by the researchers. The sample consisted of 323 pre-service teachers from different departments and grade levels at Nigde Omer Halisdemir University Faculty of Education. Statistical analyses, including independent samples t-tests and one-way ANOVA, were used to examine differences in AI literacy levels based on variables such as gender, age, grade level, field of study, parental education level, and use of AI technologies. Content analysis was applied to the qualitative data. The findings revealed that pre-service teachers generally possess high levels of AI literacy. Significant differences were observed based on personal factors such as having AI applications, receiving technology-related education, and using AI in academic tasks. However, no significant differences were found for gender, age, or parental education level. Qualitative findings indicated that pre-service teachers mostly use AI tools for academic purposes, recognize their benefits in terms of time-saving and knowledge access, but also express ethical concerns and the need for critical awareness. The study highlights the importance of embedding AI literacy into teacher education programs to prepare future educators for the digital age.

Introduction

Problem Statement

The rapid development of artificial intelligence (AI) technologies has significantly transformed various aspects of modern life, including communication, commerce, healthcare, transportation, and education. From facial recognition software and automated vehicles to voice assistants such as Google Assistant and Siri, AI systems are now embedded in everyday activities (Güzey et al., 2023; İşler & Kılıç, 2021). These technologies not only shape user behavior and decision-making but also influence how people access, process, and apply information in both personal and professional contexts.

Artificial intelligence, in its broadest sense, refers to systems capable of mimicking human cognitive functions such as learning, reasoning, and problem-solving (Russell & Norvig, 2016). Definitions of AI vary according to disciplinary focus. Popov (1990) describes it as the effort to make computers perform tasks that typically require human intelligence. McCarthy (2004), one of the founders of the field, defined AI as the science and engineering of creating intelligent machines. Similarly, Nabiyev (2012) and Alpaydın (2013) emphasize the simulation of human cognitive processes through algorithms and data structures. Despite these definitional nuances, there is a general consensus that AI systems aim to imitate human thinking and adapt through experience (Çelebi & İnal, 2019; Obschanka & Audretsch, 2020).

The growing presence of AI technologies in daily life brings with it the need for individuals to develop a specific form of digital competence known as AI literacy. AI literacy is defined as the ability to understand, evaluate, and use AI systems effectively and ethically (Kong et al., 2022; Wang et al., 2022). It includes awareness of the capabilities and limitations of AI, the ability to use AI tools in real-world contexts, and an understanding of the social, ethical, and pedagogical implications of AI use (Su et al., 2023; González-Calatayud et al., 2021; Elçiçek, 2024). Without sufficient literacy in this area, individuals risk becoming passive consumers of technology rather than active, critical, and ethical users.

The integration of AI into education has become a global trend, supported by research and innovation aimed at improving teaching and learning processes. AI tools have been employed to personalize learning experiences, predict student performance, manage classroom behavior, assess assignments, and facilitate administrative tasks (Holmes et al., 2019; Bajaj & Sharma, 2018). These tools also offer opportunities to support learners with different needs and preferences, thereby promoting inclusive and equitable education systems. As Bajaj and Sharma (2018) note, students' learning styles vary widely—from preference for facts and experiments to theoretical reasoning—and AI can help adapt learning content accordingly.

From a policy and strategic perspective, many countries have begun to institutionalize AI in education. In Turkey, the Ministry of National Education (MoNE) has established a broad framework for AI integration. The International Forum on Artificial Intelligence Applications in Education, organized in 2024, focused on increasing AI literacy, improving teacher training, and establishing ethical and institutional guidelines for AI use (MoNE, 2024). Within the same context, courses such as "AI with Arduino," "Fundamentals of Data Science," and "Machine Learning with Python" have been introduced via the Teacher Informatics Network (ÖBA), reaching nearly 97,000 teachers. Furthermore, MoNE's recently established Department of Artificial Intelligence and Big Data Applications aims to develop AI strategies for education and to design learning materials that strengthen AI literacy (MoNE, 2025). These initiatives reflect a shift toward a teacher-centered digital transformation model supported by AI-based technologies.

Despite these efforts, there remains a lack of empirical studies on AI literacy in the context of pre-service teacher education in Turkey. While technological infrastructure has advanced and policy-level initiatives are growing, it is unclear how well-prepared future teachers are in terms of their understanding of AI tools, ethical considerations, and pedagogical applications. Moreover, as AI literacy is a multifaceted construct shaped by demographic, educational, and experiential factors, it is important to explore how these dimensions influence teacher candidates' competencies and attitudes.

A review of the existing literature reveals that most empirical research on AI literacy has focused on students in engineering, computer science, or informatics programs. For example, Güler and Polatgil (2025) found that university students in technology-related fields had high AI literacy levels, but that factors such as participating in digital projects and using AI tools had a greater impact than demographic characteristics. Mart and Kaya (2024) studied pre-service preschool teachers and reported low levels of knowledge about AI despite positive attitudes. Similarly, Banaz and Demirel (2024) observed that gender, class level, and online behavior were associated with AI attitudes among Turkish teacher candidates. However, none of these studies examined AI literacy in a comprehensive, mixed-method framework that includes both statistical and thematic data analysis across a diverse population of teacher candidates.

In addition, while some studies mention ethical issues, critical thinking, and personalization in education, they often treat these aspects as secondary. Yet, pre-service teachers not only need to use AI for academic tasks such as presentations, research, or lesson planning, but also to critically assess the reliability, bias, and ethical dimensions of the tools they use (Helvacı, 2025; Zhao et al., 2018). This points to a gap in both practice and research—teacher candidates are exposed to AI in daily and academic life but may lack the structured, reflective training needed to use it responsibly.

Therefore, this study aims to fill this gap by exploring both the AI literacy levels of pre-service teachers and their perceptions of AI use in education within a Turkish context. Employing a mixed-methods design, the study investigates how AI literacy varies according to gender, age, grade level, department, parental education, and the use of AI technologies. The study also analyzes open-ended responses to uncover teacher candidates' views on the role, benefits, risks, and limitations of AI in educational settings. By combining quantitative and qualitative insights, this research provides a holistic understanding of AI literacy among future educators. The findings are expected to inform curriculum development, teacher training policies, and the design of educational technologies, ultimately contributing to the creation of a digitally competent and ethically informed teacher profile for the 21st century.

In this direction, the problem of the study was determined as "What is the literacy status of pre-service teachers studying at Nigde Omer Halisdemir University Faculty of Education regarding AI and what are their views on the use of AI in education?". The sub-problems of this study are as follows:

1. How are the AI literacy levels of pre-service teachers in general?
2. Are there differences in pre-service teachers' AI literacy levels according to their gender?
3. Are there differences in pre-service teachers' AI literacy levels according to their ages?

4. Are there differences in pre-service teachers' AI literacy levels according to their grade levels?
5. Are there differences in pre-service teachers' AI literacy levels according to the field of study?
6. Are there differences in the AI literacy levels of pre-service teachers according to their mother's education level?
7. Are there differences in the AI literacy levels of pre-service teachers according to their father's education level?
8. Are there differences in the AI literacy levels of pre-service teachers according to whether they have AI applications on their mobile devices?
9. Are there differences in pre-service teachers' AI literacy levels according to their technology-related education?
10. Are there differences in pre-service teachers' AI literacy levels according to their use of AI in their studies?
11. What are the views of pre-service teachers on the use of AI in education?

Purpose and Importance of the Research

Today, the rapid spread of AI technologies in the field of education makes teachers' knowledge, attitudes and pedagogical approaches towards these technologies important. The effective and meaningful use of AI in education is possible not only through the integration of technological tools, but also through teachers' ability to integrate these technologies with pedagogical goals (Luckin et al., 2016). Determining pre-service teachers' AI literacy levels and their views on this field will contribute to the digital transformation of the education system by increasing the quality of teacher training processes. As a matter of fact, Luckin et al. (2016) state that AI systems in education do not aim to replace teachers, but to transform their roles and make teaching processes more personalised, efficient and inclusive. In addition, a comprehensive systematic review by Zawacki-Richter et al. (2019) revealed that AI applications in higher education are concentrated in four main areas: profiling and prediction, assessment and measurement, adaptive systems and personalisation, and intelligent tutoring systems. However, it is noteworthy that the vast majority of studies are computer and engineering science-based rather than education-based, and pedagogical or ethical dimensions are largely ignored. This situation reveals the need to equip teachers and pre-service teachers with the knowledge and skills to evaluate these technologies from critical, ethical and pedagogical perspectives in order to ensure the meaningful and responsible use of AI in education.

In this context, the main purpose of this study is to determine the AI literacy levels of pre-service teachers from different fields and grade levels and to examine whether these levels show a significant difference according to various demographic and individual factors (gender, age, grade level, parental education level, etc.). In addition, it is aimed to develop a more holistic perspective on the subject by analysing qualitative data on pre-service teachers' views on AI technologies and their interactions with these technologies. Another factor that increases the importance of the research is the findings revealing that the majority of pre-service teachers today benefit from AI technologies in education in various ways. Among these benefits, instrumental uses such as preparing homework, accessing information, producing presentations and planning personal learning processes stand out. However, despite this widespread use, it was also found that a significant number of pre-service teachers experienced various deficiencies in producing creative questions about AI, ethical awareness and critical thinking competences. This situation reveals the need for a structured and conscious education process regarding AI literacy in teacher training programmes (Helvacı, 2025).

In addition, the finding that pre-service teachers' levels of having AI applications on their mobile devices, receiving technology training and actively using these technologies significantly affected their AI literacy is also quite remarkable. These findings show that individual technology experiences and learning processes play an important role in determining the teacher profile of the digital age (Zhao et al., 2018). In conclusion, this study aims to make original contributions to the literature by analysing pre-service teachers' knowledge and skill levels related to AI and providing concrete suggestions on which points should be intervened in the teacher training process. In this respect, the study will make a meaningful contribution to the discussions on digital pedagogical competence and AI literacy at both national and international levels.

Method

Research Design

In this study, a mixed method research design was used to examine the AI literacy status of pre-service teachers and their views on the use of AI in education. As the research model, triangulation design was preferred. Mixed research involves the collection, analysis and interpretation of quantitative and qualitative research data within the scope of one or more studies (Leech & Onwuegbuzie, 2009). With the joint use of qualitative and quantitative research methods, the need for mixed method research design has increased in order to overcome the shortcomings of a single method and to conduct more qualified research (Greene, 2015).

In this study, triangulation research design, which is one of the mixed research methods, was used. With the triangulation method (Tunalı et al., 2016), which aims to check whether the resulting data are compatible with each other by applying both quantitative and qualitative research methods to the same hypothesis independently of each other, the presence of a significant relationship between the demographic characteristics of pre-service teachers and their AI literacy status was examined.

Participants

The study group of the research consists of a total of 323 pre-service teachers studying at Niğde Ömer Halisdemir University Faculty of Education in the 2024-2025 academic year. Convenience sampling method was used as the sampling method. Convenience sampling method is defined as collecting data from a sample that the researcher can easily access (Büyüköztürk, 2024, p.9). In this method, the researcher starts collecting data from the most accessible participants and forms the sample until he/she reaches a group of the size he/she needs and conducts a study on an event or sample that will provide the most savings (Cohen & Manion, 1998; Ravid, 1994). Applying a questionnaire to the captive audience is an example of this method (Balcı, 2022, p.108). This sampling approach offers the researcher the opportunity to collect data from the immediate environment (Aziz, 1990, p.48).

Table 1. Demographic characteristics of pre-service teachers in the sample

Variables	Feature	f	%
Gender	Woman	251	77,7
	Male	72	22,3
Age	17-19	56	17,4
	20-22	232	72,3
	23+	33	10,3
Class Level	1st Grade	37	11,5
	2nd Grade	71	22,0
	3rd Grade	160	49,5
	4th Grade	55	17,0
Programme Type	Mathematics and Science Education	121	37,5
	Educational Sciences	67	20,7
	Turkish and Social Studies Education	91	28,2
	Fine Arts Education	13	4,0
	Elementary Education	31	9,6
Mother Education Status	Primary School	138	42,7
	Middle School	82	25,4
	High School	72	22,3
	Undergraduate and Graduate	30	9,3
Father's Education Status	Primary School	76	23,5
	Middle School	88	27,2
	High School	89	27,6
	Undergraduate and Graduate	70	21,7
Do you have AI applications on your mobile devices?	Yes	273	84,5
	No	49	15,2
Have you received training on technology?	Yes	153	47,4
	No	170	52,6
Do you use AI in your work?	Yes	278	86,1
	No	43	13,3
Total		323	%100

The participants were determined on the basis of volunteerism among the pre-service teachers studying at Nigde Omer Halisdemir University Faculty of Education, to which the researcher had access. In addition, in the selection of the participants, attention was paid to include individuals from different grade levels (1st grade, 2nd grade, 3rd grade, 4th grade) and different departments (Mathematics and Science Education, Educational Sciences, Turkish and Social Sciences Education, Fine Arts Education, Elementary Education). This ensured diversity in the sample.

The demographic characteristics of the participants were collected with a personal information form. In the personal information form, information about the gender, age, grade level, programmes of study, mother's education level, father's education level, having AI applications on their mobile devices, receiving training on technology and using AI in their studies were collected. The frequencies and percentages of the demographic characteristics of the pre-service teachers participating in the study are given in Table 1.

As seen in Table 1, 77.7% (f = 251) of the 323 pre-service teachers constituting the research group were female and 22.3% (f = 72) were male. When the age distribution of the participants was analysed, it was determined that 72.3% (f = 232) were between the ages of 20-22, 17.4% (f = 56) were between the ages of 17-19, and 10.3% (f = 33) were 23 years and older. In the distribution according to grade levels, 49.5% (f = 160) of the participants were third grade students, 22% (f = 71) were second grade students, 17% (f = 55) were fourth grade students and 11.5% (f = 37) were first grade students.

Regarding the type of programme in which the pre-service teachers were enrolled, 37.5% (f = 121) were enrolled in Mathematics and Science, 28.2% (f = 91) in Turkish and Social Sciences Education, 20.7% (f = 67) in Educational Sciences, 9.6% (f = 31) in Elementary Education and 4% (f = 13) in Fine Arts Education. In the distribution of the participants' mothers' education level, 42.7% (f = 138) were primary school graduates, 25.4% (f = 82) were secondary school graduates, 22.3% (f = 72) were high school graduates and 9.3% (f = 30) were undergraduate and above.

The educational level of the fathers was 27.6% (f = 89) high school, 27.2% (f = 88) secondary school, 23.5% (f = 76) primary school and 21.7% (f = 70) bachelor's degree and above. Most of the participants (84.8%; f = 273) stated that they have AI applications on their mobile devices, and 86.6% (f = 278) stated that they use these applications in academic or personal studies. This shows that AI technologies have become widespread and actively used in pre-service teachers' educational environments. However, 47.4% (f = 153) of the pre-service teachers stated that they received a training on technology, while 52.6% (f = 170) stated that they did not receive such a training. The findings reveal that the sample group is mostly young, female, third-year students and highly exposed to technological tools and especially AI applications.

Data Collection Tools

Three different data collection tools were used in the study:

Personal Information Form

It was created by the researchers in order to determine the demographic characteristics of the pre-service teachers participating in the study. This form includes the gender, age, grade level, programme of study, mother's education level, father's education level, having AI applications on mobile devices, receiving training on technology and using AI in studies.

Artificial Intelligence Literacy Scale

"Artificial Intelligence Literacy Scale" developed by Wang et al. (2022) and adapted into Turkish by Çelebi et al. (2023) was used to measure the AI literacy status of the pre-service teachers participating in the study. The scale has 4 sub-dimensions and 12 items. The sub-dimensions are categorised as "Awareness, Use, Evaluation and Ethics" and there are three items in each sub-dimension. The scale items are prepared in the form of a 7-point Likert scale ranging from the most negative to the most positive and have the response options "Strongly Agree, Agree, Partially Agree, Undecided, Partially Disagree, Disagree, Strongly Disagree". Therefore, the lowest score that can be obtained from the scale is 12 and the highest score that can be obtained is 84.

In this scale, there are also 3 reverse coded items, one each in the sub-dimensions of "Awareness, Use and Ethics". In order to use the scale in the research, the adapters of the scale were asked for their permission via e-mail. The adapters of the scale reported via e-mail that they would be pleased to use the scale in the research and that they gave their permission. The reliability study of the scale was conducted by the scale adapters and the internal consistency coefficient of the scale (α) was found to be 0.85 (Çelebi, 2023). In this study, the internal consistency

coefficient (α) was calculated as 0.831. It was concluded that this scale, which was adapted into Turkish, is a reliable and valid tool to measure the AI literacy status of adults who are not specialised in AI.
Open-ended Questions

In order to determine the views of the pre-service teachers participating in the study on the use of AI in education, 6 open-ended questions were directed to the participants with a questionnaire form. The questions were developed by the researchers. The open-ended questions prepared to be applied to the pre-service teachers participating in the research are as follows;

1. What are the activities you have carried out in your daily life with AI technology?
2. According to you, in which areas are AI technologies used? Can you give an example?
3. According to you, how can AI applications or products be used to increase work efficiency?
4. What kind of solutions do you think AI offers us in our daily lives?
5. In your opinion, what are the factors that we should pay attention to when using AI?
6. Can you create at least 3 question sentences to be asked in an AI application?

Data Collection Process

In the research process, qualitative and quantitative data were collected simultaneously from the pre-service teachers participating in the research on the basis of volunteerism. The necessary informed consent text was presented to the pre-service teachers participating in the research. In the scale kit, firstly, within the scope of informed consent, the purpose of the research, that the data will be used only within the scope of this research, that the information will not be shared with third parties, how the questionnaire form should be filled in and information about the researchers were given. Then, personal information form, open-ended questions and scale items were included. In order to conduct the research, the approval of the ethics committee was obtained from Nigde Omer Halisdemir University Ethics Committee dated 25.06.2025 and numbered 2025/11-25. Qualitative data were obtained with the personal information form and open-ended questions prepared by the researchers. Quantitative data were obtained with the “Artificial Intelligence Literacy Scale” developed by Wang et al. (2022) and adapted into Turkish by Çelebi et al. (2023).

Data Analysis

SPSS programme was used to analyse the data in the study. Arithmetic averages, frequencies and percentages were determined for analyses. In order to test the hypotheses to be used in data analysis, the distribution of the data obtained should be examined. If the data distribution shows “normal probability distribution” or “normal distribution”, parametric tests are used; nonparametric tests are used for data that do not show normal distribution (Bayrakcı, 2018). In order to test whether the data collected from the pre-service teachers participating in the study showed normal distribution, normality analysis and Kolmogorov-Smirnov and Shapiro-Wilk skewness values were examined. Since the sample group was sufficient in number, Kolmogorov-Smirnov values were taken into consideration in the study. The descriptive analyses of the Artificial Intelligence Literacy scale are given in Table 2.

Table 2. Descriptive analysis of the scale

Scale	$\overline{X}$	sd	Hydrangea	Skewness	Kurtosis	Kolmogrov-Simirnov Statistics	P
Artificial Intelligence Literacy	5.248	.949	5.250	-.577	.876	.087	.000

When Table 2 is analysed, it is seen that the mean score is 5.25 and the median value is 5.25. These values indicate that the participants’ AI literacy levels are generally high. The standard deviation value of the scale is .95, indicating that the scores exhibit a balanced distribution around the mean. The skewness value of the distribution was calculated as -.577 and kurtosis value as .876. Both values are in the range of ±1 and it can be said that the data show an approximately normal distribution. As a result of the analysis, Kolmogorov-Smirnov was found as .087 and the skewness coefficient value as -.577. The fact that the skewness coefficient value is between “+1 and -1” values shows that the data obtained have a normal distribution (Çokluk et al., 2010).

However, the p value (.000) obtained as a result of the Kolmogorov-Smirnov test was statistically significant, which revealed that the distribution deviated from normal. However, when the sample size is taken into consideration, it is known that this test is very sensitive and can give significant results even in small deviations. Therefore, considering that the skewness and kurtosis values were within acceptable limits, it was accepted that the data were approximately normally distributed and parametric tests were used in the comparisons. The data obtained from open-ended questions were analysed by content analysis method, codes, categories and themes were determined and frequencies and percentages were given in the form of tables.

Results

The data obtained in this part of the study were analysed within the framework of 11 (eleven) sub-problems. The findings and interpretations are given in an order appropriate to the order of the sub-problems.

Findings Related to the First Sub-Problem

The first sub-problem of the study was expressed as "How are the AI literacy levels of pre-service teachers in general?". For this purpose, the scores of pre-service teachers from the artificial intelligence literacy scale were calculated and the distribution of the scores is shown in Table 3. In the table, the column titled "possible scores" includes the lowest and highest values that can be obtained from the scale.

Table 3. Distribution of pre-service teachers' scores on artificial intelligence literacy

Scale	n	$\overline{X}$	Mod	Median	sd	Lowest to highest scores	Possible scores
Artificial Intelligence Literacy	323	62.962	66.000	63.000	11.362	27.00-84.00	12.00 - 84.00

When Table 3 is analysed, it is seen that pre-service teachers' artificial intelligence literacy levels are generally high. The mean of the participants' scores in this area ($\overline{X}$) is 62.96. The mode value is 66.00 and the median value is 63.00, and the fact that these values are close to the mean shows that the score distribution is symmetrical and extreme outliers are limited. In addition, the standard deviation (sd = 11.36) reveals that the scores of the individuals are homogeneously distributed around the mean. The realised score range varies between 27.00 and 84.00, and these values indicate a medium-high level of concentration within the possible score limits of the scale (12.00-84.00). The findings obtained show that pre-service teachers have sufficient knowledge and awareness in terms of AI literacy.

Findings Related to the Second Sub-Problem

The second sub-problem of the study was expressed as "Are there differences in the AI literacy levels of pre-service teachers according to their gender?". For this purpose, arithmetic averages of pre-service teachers' scores from the AI literacy scale were calculated and comparisons were made according to gender variable with t-test. The results obtained are given in Table 4.

Table 4. t-test analysis results of pre-service teachers' artificial intelligence literacy levels according to their gender

Scale	Gender	n	$\overline{X}$	sd	df	t	p
Artificial Intelligence Literacy	Woman	251	5.290	.845	321	1.480	.140
	Male	72	5.103	1.241			

When Table 4 is analysed, the mean score $\overline{X}$ =5.29, standard deviation sd = 0.85 for female participants (n = 251) and the mean score $\overline{X}$ =5.10, standard deviation sd = 1.24 for male participants (n = 72). The t(321)=1.480, p=.140 value obtained as a result of the analysis shows that there is no statistically significant difference between the groups since it is above the significance level of .05. This result reveals that pre-service teachers' AI literacy levels do not show a significant difference according to gender and that this skill is at similar levels regardless of gender.

Findings Related to the Third Sub-Problem

The third sub-problem of the study was expressed as "Are there differences in the AI literacy levels of pre-service teachers according to their ages?". In the analysis of this sub-problem, arithmetic averages of the scores obtained from the scales were calculated and comparisons were made according to the age variable with one-way analysis of variance (ANOVA). The mean score and standard deviation values obtained from the scale according to the age variable of the participants are given in Table 5 and the results of the variance analysis are given in Table 6.

Table 5. Distribution of pre-service teachers' artificial intelligence literacy level scores according to age groups

Scale	Age Groups	n	$\overline{X}$	sd
Artificial Intelligence Literacy	17-19	56	5.257	.767
	20-22	232	5.250	.949
	23 and above	33	5.174	1.202

According to the findings in Table 5, the mean score of AI literacy of the participants in the 17-19 age group (n = 56) was calculated as $\overline{X}$ = 5.26, sd = 0.77; the mean score of the 20-22 age group (n = 232) was calculated as $\overline{X}$ = 5.22, sd = 0.95; and the mean score of the 23 and over age group (n = 33) was calculated as $\overline{X}$ = 5.17, sd = 1.20. These values obtained reveal that there is a general similarity between age groups in terms of AI literacy levels. However, it is seen that the standard deviation values increase with age; this situation shows that there are greater differences in the AI literacy levels of individuals in older age groups and a more heterogeneous distribution is exhibited. The results of one-way analysis of variance (ANOVA) performed to determine whether these observational differences are statistically significant are presented in Table 6.

Table 6. Results of analysis of variance according to the age groups of pre-service teachers' scores of artificial intelligence literacy levels

Scale	Source of variance	Sum of squares	df	Mean squares	F	p
Artificial Intelligence Literacy	Between groups	0.179	2	.089	.099	.906
	Within groups	287.134	318	0.903		

When Table 6 is analysed, no significant difference was found between age groups in terms of AI literacy levels, $F(2, 318) = 0.10$, $p = .906$. The total value of squares between groups (SD = 0.179) is quite low compared to the total value of squares within groups (SD = 287.134). This result shows that the small mean differences observed between the age groups are not statistically significant and are most likely due to random differences. Therefore, it can be said that the age variable does not have a significant effect on the AI literacy levels of pre-service teachers.

Findings Related to the Fourth Sub-Problem

The fourth sub-problem of the study was expressed as "Are there differences in the AI literacy levels of pre-service teachers according to their grade levels?". In the analysis of this sub-problem; arithmetic averages of the scores obtained from the scales were calculated and comparisons were made according to the class level variable with one-way analysis of variance (ANOVA). The mean score and standard deviation values obtained from the scale according to the grade level variable of the participants are given in Table 7 and the results of the variance analysis are given in Table 8.

Table 7. Distribution of pre-service teachers' artificial intelligence literacy level scores according to their grades

Scale	Classroom	n	$\overline{X}$	sd
Artificial Intelligence Literacy	1st grade	37	5.385	.943
	2nd grade	71	5.118	.737
	3rd grade	160	5.305	.992
	4th grade	55	5.159	1.062
	Total	323	5.248	.949

When Table 7 is analysed, it is seen that the scores of pre-service teachers' AI literacy levels are similar according to their grade levels. The average score of 1st grade students ($\overline{X}$ = 5.39, sd = 0.94) is the highest, followed by 3rd grade students ($\overline{X}$ = 5.30, sd = 0.99) and 4th grade students ($\overline{X}$ = 5.16, sd = 1.06). The lowest average score belongs to 2nd grade students ($\overline{X}$ = 5.12, sd = 0.74). Across all grades, the average score of the participants regarding AI literacy was calculated as $\overline{X}$ = 5.25 (sd = 0.95). These findings show that pre-service teachers have a similar level of AI literacy regardless of their grade level.

Table 8. Results of analysis of variance according to the grades of pre-service teachers' scores of artificial intelligence literacy levels

Scale	Source of variance	Sum of squares	df	Mean squares	F	p
Artificial Intelligence Literacy	Between groups	2.854	3	.951	1.055	.368
	Within groups	287.542	319	.901		

According to the results of one-way analysis of variance (ANOVA) presented in Table 8, there was no statistically significant difference between pre-service teachers' AI literacy levels and their grade levels, $F(3, 319) = 1.06$, $p = .368$ ($p>.05$). This finding shows that pre-service teachers' AI literacy levels do not change according to the grade level they study.

Findings Related to the Fifth Sub-Problem

The fifth sub-problem of the study was expressed as "Are there differences in the AI literacy levels of pre-service teachers according to the field of study?". In the analysis of this sub-problem; arithmetic averages of the scores obtained from the scales were calculated and comparisons were made according to the field of study variable with one-way analysis of variance (ANOVA). The mean score and standard deviation values obtained from the scale according to the field of study variable of the participants are given in Table 9 and the results of the variance analysis are given in Table 10.

Table 9. Distribution of pre-service teachers' artificial intelligence literacy level scores according to the fields of study

Scale	Field of Study	n	$\overline{X}$	sd
Artificial Intelligence Literacy	Mathematics and Science Education	121	5.157	.820
	Educational Sciences	67	5.546	.937
	Turkish and Social Sciences Education	91	5.241	1.108
	Fine Arts Education	13	5.025	1.047
	Elementary Education	31	5.077	1.802
	Total	323	5.248	.949

When Table 9 is analysed, it is seen that the mean scores of pre-service teachers' AI literacy levels differ according to the fields of study. While the mean score of AI literacy of pre-service teachers studying in the field of Mathematics and Science Education ($\overline{X}$ = 5.16, sd = 0.82), it is observed that this mean is higher in Educational Sciences ($\overline{X}$= = 5.55, sd = 0.94). The mean scores obtained in Turkish and Social Studies Education ($\overline{X}$ = 5.24, sd = 1.11), Fine Arts Education ($\overline{X}$ = 5.03, sd = 1.05) and Elementary Education ($\overline{X}$ = 5.08, sd = 1.80) are similar to the other fields. The general average is at the level of ($\overline{X}$ = 5.25, sd = 0.95) for all groups. These findings indicate that the AI literacy levels of pre-service teachers may vary according to the field of study.

Table 10. Results of analysis of variance according to the fields of study of pre-service teachers' scores of artificial intelligence literacy levels

Scale	Source of variance	Sum of squares	df	Mean squares	F	p	Significant Difference
Artificial Intelligence Literacy	Between groups	8.495	4	2.124	2.396	.049*	Could not be determined.
	Within groups	281.901	318	.886			

*p<.05 level

The findings in Table 10 showed that there was a statistically significant difference between the groups, $F(4, 318) = 2.396$, $p = .049$. The sum of squares between groups was calculated as 8.495 and the sum of squares within groups was calculated as 281.901. This result indicates that there are significant differences in AI literacy scores according to the fields of study. However, according to the results of the Tukey HSD post hoc test, no significant differences were found in pairwise comparisons between groups ($p > .05$). In line with these findings, the fact that significant differences were not found in the post hoc tests although the analysis of variance was significant may be due to the uneven distribution of sample sizes (e.g., Mathematics and Science Education n = 121 while Fine Arts Education n = 13) and the high standard deviation values observed in some groups (e.g., Elementary Education sd = 1.802). In addition, the fact that the ANOVA results were at the borderline significance level ($p = .049$) and the calculated effect size was small ($\eta^2 = .029$) may have made it difficult to statistically determine the differences between the groups.

Findings Related to the Sixth Sub-Problem

The sixth sub-problem of the study was expressed as "Are there differences in the AI literacy levels of pre-service teachers according to their mother's education status?". In the analysis of this sub-problem; arithmetic averages of the scores obtained from the scales were calculated and comparisons were made according to the mother's education status variable with one-way analysis of variance (ANOVA). The mean score and standard deviation values obtained from the scale according to the participants' mother's education status variable are given in Table 11, and the results of the variance analysis are given in Table 12.

Table 11. Distribution of pre-service teachers' artificial intelligence literacy level scores according to mother's education level

Scale	Mother's education status	n	$\overline{X}$	sd
Artificial Intelligence Literacy	Primary School	138	5.248	.881
	Middle School	82	5.236	.882
	High School	72	5.244	1.069
	Undergraduate and Graduate	30	5.322	1.158
	Total	322	5.251	.949

The distribution of the scores of pre-service teachers' AI literacy levels according to their mothers' education level is presented in Table 11. When descriptive statistics are analysed, small differences are observed between the AI literacy levels of pre-service teachers according to their mother's education level. The average AI literacy levels of individuals whose mothers have undergraduate and graduate education levels have the highest value ($\overline{X}$ = 5.32, sd = 1.16). This is followed by individuals with high school ($\overline{X}$ = 5.29, sd = 1.07), primary school ($\overline{X}$ = 5.25, sd = 0.88) and secondary school ($\overline{X}$ = 5.24, sd = 0.88) level mothers, respectively. Although there was no significant difference between the groups in terms of mean scores, it was observed that the level of AI literacy increased as the level of education increased, albeit in a limited way. This shows that the development of AI literacy may depend not only on familial/environmental factors but also on the individual's own education process, level of interaction with technology and professional interest. One-way analysis of variance (ANOVA) was performed to determine whether the AI literacy levels of pre-service teachers showed a significant difference according to their mothers' education level. The results of the analysis are given in Table 12.

Table 12. Results of analysis of variance according to the mother's education level of pre-service teachers' artificial intelligence literacy levels

Scale	Source of variance	Sum of squares	df	Mean squares	F	p
Artificial Intelligence Literacy	Between groups	.173	3	.058	.063	.979
	Within groups	289.528	318	0.910		

According to the ANOVA result, no statistically significant difference was found between the groups: $F(3, 318) = 0.063$, $p = .979$. This finding reveals that AI literacy scores are similar according to the mother's education level. In other words, pre-service teachers' AI literacy levels seem to have developed independently of their mothers' education level. This result indicates that participants' AI awareness is shaped by individual factors, teaching process and personal interest in technology rather than familial socio-cultural background. In addition, the fact that pre-service teachers receive education in similar university environments and are in widespread contact with technology in today's digital age can be considered among the factors explaining this similarity.

Findings Related to the Seventh Sub-Problem

The seventh sub-problem of the study was expressed as "Are there differences in the AI literacy levels of pre-service teachers according to their father's education level?". In the analysis of this sub-problem; arithmetic averages of the scores obtained from the scales were calculated and comparisons were made according to the father's education status variable with one-way analysis of variance (ANOVA). The mean score and standard deviation values obtained from the scale according to the participants' father's education status variable are given in Table 13, and the results of the variance analysis are given in Table 14.

Table 13. Distribution of pre-service teachers' artificial intelligence literacy level scores according to father's education level

Scale	Father's Education Status	n	$\bar{X}$	sd
Artificial Intelligence Literacy	Primary School	76	5.153	.962
	Middle School	88	5.366	.853
	High School	89	5.284	.955
	Undergraduate and Graduate	70	5.158	1.039
	Total	323	5.248	.949

When Table 13 was analysed, it was seen that the general average was ($\bar{X}$ = 5.25, sd = 0.95). The mean scores of the groups according to the father's education level are as follows: primary school ($\bar{X}$ = 5.15, sd = 0.96), secondary school ($\bar{X}$ = 5.37, sd = 0.85), high school ($\bar{X}$ = 5.28, sd = 0.96) and undergraduate/graduate ($\bar{X}$ = 5.16, sd = 1.04). Descriptive findings show that there is no consistent increasing or decreasing trend between father's education level and AI literacy.

Table 14. Results of analysis of variance according to the father's education status of pre-service teachers' artificial intelligence literacy level scores

Scale	Source of variance	Sum of squares	df	Mean squares	F	p
Artificial Intelligence Literacy	Between groups	2.596	3	.865	.959	.412
	Within groups	287.799	319	.902		

The results of the one-way analysis of variance (ANOVA) conducted to test the effect of father's education status on the AI literacy scores of pre-service teachers are given in Table 14. According to the results of the analyses, there is no statistically significant difference between the groups; $F(3, 319) = 0.96$, $p = .412$. This finding supports that pre-service teachers' AI literacy levels are independent of their father's education level.

Findings Related to the Eighth Sub-Problem

The eighth sub-problem of the research was expressed as "Are there differences in the AI literacy levels of pre-service teachers according to the status of having AI applications on their mobile devices?". For this purpose, arithmetic averages of pre-service teachers' scores from the AI literacy scale were calculated and comparisons were made according to the variable of having AI applications with t-test. The findings obtained are given in Table 15.

Table 15. t-test analysis results according to the preservice teachers' having artificial intelligence applications on their mobile devices in artificial intelligence literacy levels

Scale	Having Artificial Intelligence Applications	n	$\bar{X}$	sd	df	t	p
Artificial Intelligence Literacy	Yes	273	5.290	.942	320	1.992	.047*
	No	49	4.998	.961			

$p<.05$ level

When Table 15 is analysed, it is seen that the AI literacy levels of pre-service teachers differ significantly according to their having artificial intelligence applications on their mobile devices. The mean scores ($\bar{X}$ = 5.29, sd = 0.94, n = 273) of pre-service teachers who have AI applications on their mobile devices are higher than the mean scores ($\bar{X}$ = 4.99, sd = 0.96, n = 49) of pre-service teachers who do not have AI applications. As a result of the t-test for independent samples, this difference was found to be statistically significant, $t(320) = 1.99$, $p = .047$. This finding shows that having AI applications on their mobile devices may have an increasing effect on pre-service teachers' AI literacy levels.

Findings Related to the Ninth Sub-Problem

The ninth sub-problem of the study was expressed as "Are there any differences in the AI literacy levels of pre-service teachers according to the status of receiving education related to technology?". For this purpose, the arithmetic averages of the scores of pre-service teachers from the AI literacy scale were calculated and comparisons were made according to the variable of receiving education about technology with t-test. The results obtained are given in Table 16.

Table 16. t-test analysis results according to the preservice teachers' artificial intelligence literacy levels according to the status of receiving technology-related education

Scale	Receiving Technology Training	n	$\overline{X}$	sd	df	t	p
Artificial Intelligence Literacy	Yes No	153 170	5.397 5.115	.981 .902	321	2.689	.008*

** p<.05 level*

When Table 16 is analysed, it is seen that the mean scores of pre-service teachers who have received technology education ($\overline{X}$ = 5.40, sd = 0.98, n = 153) are higher than pre-service teachers who have not received technology education ($\overline{X}$ = 5.12, sd = 0.90, n = 170). As a result of the independent samples t-test analysis, it was determined that this difference was statistically significant, t(321) = 2.69, p = .008. This finding shows that receiving education related to technology significantly affects pre-service teachers' AI literacy levels.

Findings Related to the Tenth Sub-Problem

The tenth sub-problem of the research was expressed as "Are there differences in the AI literacy levels of pre-service teachers according to their use of AI in their studies?". For this purpose, arithmetic averages of the scores of pre-service teachers from the AI literacy scale were calculated and comparisons were made according to the variable of using AI in studies with t-test. The results obtained are given in Table 17.

Table 17. t-test analysis results of pre-service teachers' artificial intelligence literacy levels according to their use of artificial intelligence in their studies

Scale	Using Artificial Intelligence in Studies	n	$\overline{X}$	sd	df	t	p
Artificial Intelligence Literacy	Yes No	278 43	5.289 4.941	.953 .856	319	2.252	.025*

**p<.05 level*

According to the independent sample t-test results presented in Table 17, pre-service teachers' AI literacy levels differ significantly according to their use of AI in their studies. The mean AI literacy score of pre-service teachers who used AI ($\overline{X}$ = 5.29, sd = 0.95, n = 278) was higher than those who did not use AI ($\overline{X}$ = 4.94, sd = 0.86, n = 43). This difference is statistically significant, t(319) = 2.25, p = .025. This finding shows that pre-service teachers' active use of AI technologies in their studies can be effective in increasing their AI literacy levels.

Findings Related to the Eleventh Sub-Problem

The eleventh sub-problem of the study was: "What are the opinions of pre-service teachers regarding the use of artificial intelligence in education?" The open-ended responses were analyzed using content analysis and organized under seven main themes. The results are presented in tables and discussed accordingly. Based on the analysis, seven themes were identified: (1) Daily Use of AI, (2) Areas Where AI Is Used, (3) Contribution of AI to Work Efficiency, (4) AI Solutions in Daily Life, (5) Considerations in Using AI, (6) Questions Generated for AI Applications, and (7) AI Applications and Categories. The frequency and percentage distributions of pre-service teachers' responses are presented in the tables below.

Daily Use of AI

Table 18. Findings regarding the purposes of pre-service teachers for using artificial intelligence technology in daily life

Codes	Categories	f*	%
Educational Use	Homework, presentation preparation, research, project / thesis writing, academic text support, slide preparation, getting ideas	297	92.0
Obtaining Information and Asking Questions	Obtaining information on topics of interest, posing questions, quick access to information, consultation	149	46.1
Visual and Design Production	Logo design, image/video creation, photo editing, cartoon, banner, animation	39	12.1
Personal Assistant and Daily Planning	Daily planning, setting alarms, creating a study programme, navigation, time management	19	5.9
Entertainment and Social Use	Chatting, fortune-telling, storytelling, humour, solitude relief	16	5.0
Participants who stated that they do not use	Pre-service teachers who stated that they never or rarely use artificial intelligence technologies	20	6.2

** Participants reported use under more than one category; therefore, the total number of frequencies (f) may exceed the number of participants. Percentages were calculated over the general total.*

As presented in Table 18, the majority of participants (f = 297, 92%) reported using artificial intelligence primarily for educational purposes. This includes preparing assignments, presentations, academic texts, and research. For example, S1 stated, "*I use AI for my homework,*" while S30 remarked, "*I use it for writing reports and doing assignments.*" This reflects a strong tendency to utilize AI as a practical academic support tool. Additionally, 149 participants (46.1%) indicated using AI to obtain information or ask questions. S2 explained, "*I ask about things I don't know and get information for my homework,*" and S302 added, "*If I can't find an answer on Google, I ask AI.*" A smaller group (f = 39, 12.1%) used AI for visual and design purposes, such as creating logos or images. S65 shared, "*I design logos and create images,*" while S68 noted, "*I design cartoons.*" Some participants (f = 19, 5.9%) utilized AI for personal planning, such as setting reminders and organizing their day. S62 explained, "*Siri helps me organize my life.*" Entertainment and social interaction were cited by 16 participants (5%), who reported using AI for chatting or fun purposes. For instance, S138 said, "*I chat with AI when I'm alone,*" and S59 mentioned, "*I had my fortune read.*" Finally, 20 participants (6.2%) stated that they do not use AI at all or only use it rarely. As S45 noted, "*I don't use AI.*"

Areas Where AI Is Used

Table 19. Areas of use of artificial intelligence technologies according to the views of pre-service teachers

Codes	f	%*
Education	265	82.0
Health	95	29.4
Trade and business life	83	25.7
Scientific research / academia	71	22.0
Engineering and software	63	19.5
Daily life	51	15.8
Art, design and media	47	14.6
Defence industry and security	32	9.9
Agriculture, transport and automotive	27	8.4
Banking and finance	18	5.6
Law	11	3.4
Games and entertainment	21	6.5
Religious services	3	0.9
I don't know / undecided	5	1.5

** Since the participants indicated more than one usage area, the total percentage exceeds 100%.*

In Table 19, education was identified as the most prominent area where AI is used, cited by 265 participants (82%). Participants emphasized AI's use in preparing lessons, conducting research, and academic planning. S1 said, *"It should be especially used in education and research,"* while S14 commented, *"I use it for homework, organizing, and doing research."* Health was mentioned by 95 participants (29.4%) as a significant domain, with

S183 stating, *"Surgeries can be performed with AI."* Commerce and business life followed with 83 responses (25.7%). S63 noted, *"AI is used in customer service and solves problems instantly through chat."* Scientific research and academia were mentioned by 71 participants (22%). S56 gave the example: *"It is used for writing articles and planning in academia."* Other areas included engineering and software (f = 63, 19.5%), daily life (f = 51, 15.8%), media and art (f = 47, 14.6%), defense (f = 32, 9.9%), agriculture and transportation (f = 27, 8.4%), banking (f = 18, 5.6%), law (f = 11, 3.4%), and entertainment (f = 21, 6.5%). A small group (f = 5, 1.5%) indicated uncertainty with statements such as *"I don't know."*

Contribution of AI to Work Efficiency

Table 20. Frequency and percentage distributions of themes related to artificial intelligence and work efficiency

Codes	f	%*
Time Saving and Speed	80	24,8
Idea and Knowledge Acquisition	60	18,6
Workload Reduction / Automation	45	13,9
Planning, Organisation and Decision Making	35	10,8
Educational and Creative Use	30	9,3
Critical Views / Ethical Concerns	10	3,1
Vague / No Opinion Responses	20	6,2
Other / General Expressions	43	13,3

** Since the participants indicated more than one usage area, the total percentage exceeds 100%.*

According to Table 20, the most cited benefit of AI in improving work efficiency was time saving and speed (f = 80, 24.8%). Participants appreciated the way AI accelerates tasks and processes. For example, S63 stated, *"Pages of work can be done in seconds. It definitely saves time."* Next, 60 participants (18.6%) highlighted idea generation and access to knowledge. S5 noted, *"It can help generate new ideas at work,"* and S50 added, *"We can ask AI to provide ideas."* Workload reduction through automation was emphasized by 45 participants (13.9%). S26 shared, *"AI tools can replace manual labor,"* while S53 explained, *"It helps complete tasks that would take a long time otherwise."* Thirty-five participants (10.8%) appreciated AI's role in planning and organization. S18 said, *"It supports strategy planning and product creation,"* and S289 added, *"AI helps to proceed in a structured way."* AI's educational and creative applications were cited by 30 participants (9.3%), with S281 commenting, *"I use it for drawing graphs and preparing presentations,"* and S304 noting, *"It supports creative thinking."* Critical perspectives were voiced by 10 participants (3.1%). S60 stated, *"AI limits human creativity,"* and S93 warned, *"It reduces employment opportunities."* Vague or unclear responses (f = 20, 6.2%) and general expressions (f = 43, 13.3%) were also observed, such as S123's remark: *"It can be used in any subject."*

AI Solutions in Daily Life

Table 21. Thematic distribution of preservice teachers' responses to the question "what kind of solutions does artificial intelligence offer in our daily life?"

Codes	Categories	f	%*
Time Saving and Fast Access	Saving time, speeding up work, shortening processes, fast information	158	55,2
Access to Information and Learning Support	Access to information, homework help, ease of research, course support	136	47,6
Convenience and Practicality	Ease of daily tasks, simplification of work	122	42,7
Problem Solving and Guidance	Sample solutions, guidance, counselling	91	31,8
Creativity and Different Perspective	Generating new ideas, broadening perspective	79	27,6
Personalisation and Digital Assistance	Individual suggestions, assistant role, habit analysis	44	15,4
Critical/Conscious Use and Ethical Concerns	Suspicion of accuracy, ethical rules, careful handling	13	4,5
Other (Unspecified / Irrelevant / Blank)	Expressions left blank or not understood	37	11,5

** Since the participants indicated more than one usage area, the total percentage exceeds 100%.*

As shown in Table 21, the leading perceived benefit of AI in daily life was time saving and fast access to results, cited by 158 participants (55.2%). S104 said, *"It helps us reach results faster."* Learning support and information access followed (f = 136, 47.6%). S14 stated, *"It helps with homework and offers various ideas."* Ease and practicality were noted by 122 participants (42.7%), with S310 stating, *"It simplifies many of our daily tasks."* Problem solving and guidance were emphasized by 91 participants (31.8%). Participants highlighted AI's potential for counseling and support. Creativity and broadening perspectives were cited by 79 participants (27.6%), with general remarks such as, *"It offers different viewpoints."* Personalization and digital assistance were referenced by 44 participants (15.4%). S62 said, *"It suggested a skincare routine based on my habits."* Critical awareness was present among 13 participants (4.5%). S60 commented, *"It offers practical solutions, but its accuracy is debatable."* Finally, 37 responses (11.5%) were either blank or lacked clear relevance.

Considerations in Using AI

Table 22. Thematic distribution of factors to be considered in the use of artificial intelligence

Codes	Categories	f	%
Ethics and Safety	Personal data privacy	68	21.9
	Compliance with ethical principles	44	14.1
Accuracy and Reliability	Risk of misinformation	53	17.0
	Source confirmation	36	11.6
Use in Education	Risk of laziness	32	10.3
	Loss of authenticity	22	7.1
Technological Limitations	Algorithmic errors	18	5.8
Social Impacts	Weakening of human relations	12	3.9
Practicalities of Use	Asking clear questions	9	2.9

Table 22 presents factors participants consider important in AI usage. Ethical concerns and safety were cited most frequently (f = 112, 36%), especially regarding personal data privacy (f = 68) and adherence to ethical principles (f = 44). S41 emphasized, *"Protecting our private information should be a priority."* Accuracy and reliability concerns followed (f = 89, 29%), including the risk of misinformation (f = 53) and the need for source verification (f = 36). S96 said, *"We should compare AI-generated information with other sources."* In educational use, 32 participants (10.3%) warned about laziness, while 22 (7.1%) feared the loss of authenticity. S275 noted, *"Using AI constantly might reduce our thinking ability."* Technological limitations (f = 32, 10.3%), social impacts (f = 21, 6.8%), and practical tips such as asking clear questions (f = 9, 2.9%) were also highlighted. S210 stated, *"We need to ask well-formulated questions to get accurate results."*

Questions Generated for AI Applications

Table 23. Question sentences on artificial intelligence application: codes, frequencies and sample participant responses

Codes	f	%
Information, Counselling and Guidance	85	28
Education and Student Support Practices	50	17
Artificial Intelligence Technology, Ethics and Future Questions	40	13
Questions on Everyday Life	30	10
Creativity, Entertainment and Artistic Demands	25	8
Respondents who did not answer / left blank	93	29

According to Table 23, 85 participants (28%) generated questions related to professional guidance. S10 asked, *"What trainings should I take to become a good psychological counsellor?"* Fifty participants (17%) focused on educational support. S14 asked, *"Can you create an activity to help me learn this topic?"* Forty participants (13%) explored ethical or future-oriented questions. S13 posed, *"Can AI surpass human creativity?"* and *"How can it make ethical decisions without consciousness?"* Thirty participants (10%) submitted practical everyday life questions. S12 inquired, *"What's the weather tomorrow and how should I dress?"* Creative and entertainment-focused questions came from 25 participants (8%). S11 asked, *"Can you write a detective story for me?"* However, 93 participants (29%) did not respond or provided irrelevant content, indicating variability in creativity and AI engagement.

AI Applications and Categories

According to Table 24, the most preferred AI application by pre-service teachers was ChatGPT with a usage rate of 27.2% (*n* = 272), followed by Google Assistant with 20.6% (*n* = 206) and Siri with 11.2% (*n* = 112). This shows that pre-service teachers are more likely to use language-based AI systems for functions such as text generation, information access and academic support. Less well-known applications that require technical knowledge (e.g. Claude, Scite.ai, DALL-E, Synthesia) were used by only 1 to 6 people.

Table 24. Artificial intelligence applications used by pre-service teachers

AI Applications	n	AI Applications	n
Siri	112	Bing Chat	11
Google Assistant	206	DALL-E	6
Microsoft Cortana	15	Synthesia	2
ChatGPT	272	Google Notebook LM	19
Socrates	4	ImageBind	3
MathGPTPro	4	Gemini	23
Pictory	2	Microsoft Bing	1
Google Bard	17	Copilot	3
Alexa	5	Canva	2
Claude	2	Microsoft Bing-ai	2
Scite.ai	2	Klling.ai	1
My AI	1	Gamma	2
OpenAI	1	Grok	5
Deepseek	6	Deeply	1

When the AI applications used by pre-service teachers are analysed by categorising them according to their functions, Table 25 emerges. Table 25 shows the categories to which the AI applications used by pre-service teachers belong, the definitions of these categories and sample applications belonging to each category.

Table 25. Categories of artificial intelligence applications used by pre-service teachers

Category	Description	Sample Applications
Language and Text Based Assistants	AI applications for text generation, question answering, translation and knowledge-based textual support.	ChatGPT, Claude, Google Bard, Groq, Kimi.ai
Voice Digital Assistants	Digital assistants, usually built into mobile devices, with which users interact with voice commands.	Siri, Google Assistant, Microsoft Cortana, Alexa
Visual and Video Production Tools	Creative production-oriented AI tools used to create visual or video content.	DALL-E, Synthesia, ImageBind, Canva
Education-Oriented AI Tools	Special purpose applications developed for the production of educational content or to support learning processes.	Socrates, MathGPTPro, Google Notebook LM
AI Assisted Search and Browsers	Search engine-based platforms and browsers that provide AI support to information screening and production processes.	Bing Chat, Copilot, Microsoft Bing, BingXov
Other	Other applications that do not fall directly into the above categories and are intended for limited or specific use.	Scite, My AI

Accordingly, the applications were categorised under the headings of “Language and Text Based Assistants”, “Voice Digital Assistants”, “Visual and Video Production Tools”, “Education Oriented AI Tools”, “AI Supported Search and Browsers” and “Other”. According to the frequency of use, the most preferred category was language and text-based assistants with a rate of 44.9%. This category includes applications such as ChatGPT, Claude, Bard that serve users’ needs for text generation, answering questions and accessing information. Voice-based digital assistants (e.g. Siri, Google Assistant) ranked second with 33.6%, indicating that AI integrated into mobile devices in daily life are intensively used by pre-service teachers. AI supported search and browsers (e.g. Bing Chat, Copilot) were used by 7.3%, education-oriented AI tools (e.g. Socrat, MathGPTPro) by 5.2%, visual and video production tools (e.g. DALL-E, Synthesia) by 4.3% and other tools (e.g. Scite, My AI) by 4.7%. These findings reveal that pre-service teachers mostly access AI technologies through language-based and general ease-of-use tools, whereas they tend to use tools for visual production and specialised areas in a more limited way.

Conclusion and Discussion

The aim of this study is to determine the AI literacy levels of pre-service teachers and to examine whether these levels differ in line with various demographic and individual variables. According to the findings obtained, it was determined that pre-service teachers generally have high levels of AI literacy. This situation shows that individuals raised in the digital age are more familiar with technological tools and their awareness of AI technologies has increased (Kaya & Başarmak, 2023; Topal & Tekin, 2021).

According to the results of the study, demographic variables such as gender, age, grade level, and parental education level do not make a significant difference on AI literacy. This finding shows that male and female students have similar AI literacy levels in terms of AI literacy. Especially today, university education and easily accessible digital content may have minimised such differences between people. When similar studies in the literature are examined; in the study conducted with pre-school pre-service teachers, no significant differences were found between males and females within the scope of AI literacy (Mart & Kaya, 2024). However, in the study examining the AI literacy levels of students, the gender variable created a significant difference in AI literacy level (Elçiçek, 2024). In a similar study, a significant difference was found between male and female pre-service teachers in terms of AI literacy (Banaz & Demirel, 2024). In a study conducted by Asio (2024), it was concluded that the gender variable did not have a significant effect on AI literacy. According to the findings, the reason why different results were obtained in the AI literacy levels of the gender variable may be due to the different samples used in each study (Güler & Polatgil, 2025).

On the other hand, significant differences were observed in the AI literacy levels of pre-service teachers according to their fields of study. It was observed that pre-service teachers in the field of Educational Sciences had higher scores in this field. This result can be explained by the intensity of technology-supported contents included in the curricula and the differences in digital competencies specific to the field (Kuşçu et al., 2014). However, in the post-hoc analyses, it was not statistically determined which groups these differences were between. This may be associated with the unbalanced distribution of the sample size between the groups.

Another important finding obtained within the scope of the research is that the pre-service teachers' having AI applications on their mobile devices and receiving technology-related training significantly affect their AI literacy levels. These findings support that technology literacy gained through direct experience and education improves individuals' attitudes and skills towards AI (Zawacki-Richter et al., 2019). In a study in the literature, significant differences were observed between individuals' ability to use information technologies and AI literacy levels; it is seen that as the level of individuals' ability to use information technologies increases, their AI literacy levels increase (Güler & Polatgil, 2025). Likewise, the use of AI in studies also shows a positive relationship with individuals' AI literacy levels. This shows that constructivist learning approaches to technology use support the development of higher-level cognitive skills in individuals (Mishra & Koehler, 2006).

The results of content analysis of qualitative data also coincide with quantitative findings. Pre-service teachers stated that they actively used AI technologies especially in educational activities (homework preparation, presentation creation, information acquisition). This finding shows that the potential of integrating AI into the learning process is recognised and a highly instrumental approach to these technologies is developed (Luckin et al., 2016). In addition, pre-service teachers also drew attention to the functions of AI such as time saving, quick access to information and guidance, and emphasised the facilitating effect of AI technologies on the learning process.

However, some of the pre-service teachers also expressed concerns about the use of AI such as ethics, security and authenticity. This finding points to the importance of individuals developing not only technical competence but also ethical sensitivity. In particular, the need for conscious use of information accuracy, resource utilisation and data security should be evaluated in the context of digital citizenship and critical technology literacy (Ribble, 2015). AI literacy is a holistic concept that includes ethical and social elements as well as technical knowledge

(Türel et al., 2024). Studies have shown that both theoretical and practical trainings are necessary for higher education students to acquire this skill (Černý 2024).

Finally, it is seen that some of the pre-service teachers are inadequate in producing creative and intellectual questions about AI. This situation shows that pre-service teachers should not only develop their skills in using AI tools, but also their capacities to effectively direct, question and use these tools for creative purposes.

Recommendations

In faculties of education, course contents should be developed in which pre-service teachers can evaluate AI technologies not only as users but also as producers and critical individuals, and AI literacy should be handled with an interdisciplinary approach. In curricula, issues such as ethics, data security and authenticity with AI should be emphasised more and applied courses and scenario-based activities should be used in this direction. Project-based learning and problem-solving oriented pedagogical approaches should be encouraged to support pre-service teachers' ability to produce more creative and critical questions with AI applications.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the authors.

* This study was approved by the Ethics Committee of Nigde Omer Halisdemir University at its meeting dated 25 June 2025, with decision number 2025/11-25.

Conflict of Interest

* The authors declare that they have no conflicts of interest

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Anxiety about Artificial Intelligence as an Emerging Field of Science: The Example of Preschool Teacher Candidates

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Abstract

The importance of artificial intelligence in daily life is increasing every day. This situation is inevitably reflected in educational environments. However, using artificial intelligence also causes anxiety. This study aims to determine the anxiety levels of preschool preservice teachers regarding artificial intelligence and examine them using various variables. The study was conducted using a survey, a quantitative research method. Data was collected from 208 volunteer participants using a convenience sampling method. The 16-item Artificial Intelligence Anxiety Scale was used as the data collection tool. t-test, ANOVA, percentage, and frequency were used in data analysis to obtain findings. In addition to the techniques used in interpreting the findings, the criterion for determining the level of artificial intelligence anxiety was used. The interpretation of the research findings revealed that preschool teachers had moderate levels of anxiety regarding artificial intelligence. This anxiety did not differ among preschool teachers' grade levels, daily internet use, knowledge about artificial intelligence, or number of siblings. However, it was found that there were differences in terms of gender.

Introduction

In the Society 5.0 era, the use and development of artificial intelligence was crucial, parallel to industrial developments and technological innovations. In this era, the use of artificial intelligence is inevitable in every field, especially in human resources management (Palos-Sánchez et al., 2022, Lungu, Tabur & Batog, 2025). Its use and support in school settings are also crucial. Because the advancement of technology is expected to create a bright future for artificial intelligence (AI)-supported educational environments (Wang, 2025). AI facilitates accessing, structuring, and using information. It can also guide the use, differentiation, and teaching of existing information.

Concept of Artificial Intelligence and Anxiety

With the rapid development of digitalization in the 21st century, AI is not limited to the technology sector; it has become a pioneer of significant transformations in nearly every field, including education. Defined as the ability of computer-aided systems to perform learning, problem-solving, reasoning, and decision-making skills similar to human intelligence (Russell & Norvig, 2021; Meylani, 2024), AI can continuously improve itself with the data it obtains, learn from previous experiences, and flexibly adapt to new conditions it encounters (Gadhoum, 2022). This advanced technology is actively used in diverse fields such as engineering, sociology, psychology, and education, and is reshaping people's lifestyles (Doğan, 2002; Chui et al., 2018; Luckin et al., 2016).

The use of AI in education provides many innovative opportunities, such as personalized learning experiences, automated grading systems, learning analytics, and content creation (Holmes et al., 2019; Meço & Coştu, 2022). However, these developments also raise several issues, such as data security, ethical principles, a sense of justice, and a lack of social interaction (Köse et al., 2023; Sivanganam et al., 2025). The increasing digitalization of education and the proliferation of AI-based applications have made it imperative for people to develop a conscious awareness of these technologies. However, the technological uncertainties that come with this process can also lead to increased anxiety in people (Beaudry & Pinsonneault, 2010; Johnson & Verdicchio, 2017). Anxiety about AI is defined as a multifaceted psychological state that includes fear, uncertainty, and perception of threat that people feel about unclear situations and unpredictable outcomes in controlling these systems (Rachman, 1998; Brynjolfsson & McAfee, 2014).

Artificial Intelligence in the Context of Preschool Teachers

Preservice teachers' attitudes toward AI, considered a cornerstone of the education system, and their anxiety levels regarding AI have a significant impact on shaping future educational models (Mishra & Koehler, 2006; Henderson & Corry, 2021). While preschool teachers strive to align their pedagogical training with technological advancements, they also face uncertainties about how AI will shape their professional roles, individual autonomy, and the emotional relationships they will establish with their students (Selwyn, 2019; Dinello, 2005). Indeed, various studies indicate that some field teachers lack knowledge about the integration of AI in classroom practices, and therefore sometimes exhibit apprehensive or hesitant attitudes toward AI Technologies (Ertmer & Ottenbreit-Leftwich, 2010; Inan & Lowther, 2010; Uygun, 2024; Fakhar et al., 2024). While it offers significant opportunities in education, teachers' anxiety levels are seen as a significant determining factor in the formation of positive or negative attitudes toward this technology. Preservice teachers, particularly those studying in education faculties, may exhibit some affective reactions when exposed to such technologies early on. This may directly impact their AI literacy, technology integration skills, and instructional design competencies (Banaz & Demirel, 2024; Kaman, 2025).

Current studies indicate that preservice teachers can develop positive attitudes toward AI tools despite their limited knowledge of AI technologies (Fakhar et al., 2024). However, it is striking that systematic studies focusing specifically on early childhood education are insufficient in number (Çevik & Baloğlu, 2007; Yalçınalp & Cabı, 2015; Takıl et al., 2022; Şen, 2024). Preservice preschool teachers' attitudes and anxiety levels toward AI are of particular importance because this group will be working with children in the concrete operational stage and therefore has considerable pedagogical responsibilities regarding technology use. In this context, it can be argued that pre-service preschool teachers' concerns about AI may stem not only from a lack of knowledge but also from many factors such as professional values, ethical responsibilities, and social sensitivity (Parlak, 2017; Sivanganam et al., 2025).

On the other hand, it has been emphasized that AI-supported applications can be used effectively in preschool education, thanks to their advantages in increasing individualized learning opportunities for the early diagnosis and education of some children with learning disabilities (Drigas & Ioannidou, 2012). However, the realization of this positive potential depends on preschool teachers understanding these technologies without anxiety and making them educationally useful.

Importance of Research

While studies on attitudes and anxieties related to technology and AI have increased in recent years, systematic research focusing on preschool teacher candidates remains limited. Studies have focused primarily on teachers' anxiety levels regarding computer and general technology use, and these anxieties have been shown to influence the adoption processes of instructional technologies (Çevik & Baloğlu, 2007; Yalçınalp & Cabı, 2015). However, these studies are largely limited to basic digital skills and do not adequately address preservice teachers' affective responses to more advanced technologies, such as artificial intelligence. Furthermore, some recent studies suggest that teachers may experience anxiety due to factors such as perceptions of diminished professional autonomy in their interactions with AI technologies, difficulties in establishing connections with their students, and resistance to technological innovations (Henderson & Corry, 2021; Kaya et al., 2024).

The use of AI in educational settings has been examined from various perspectives. Studies have included participants such as teachers, preschool teachers, nursing students, and dentists. Yo and Nazir (2021) used AI to improve university students' English language skills, while Rai et al. (2025) used AI to provide better patient care and practical problem solutions for dentists. There are also studies examining university students' attitudes towards AI (Mart & Kaya, 2024; Giray Yakut et al., 2025; Saatçioğlu & Topsakal, 2025). In addition, Kong & Zhu (2025) examined university students' ethics of AI, and Küçükkara et al. (2024) examined preschool teachers' views on AI. Finally, Tarsuslu et al. (2024) examined the AI anxiety levels of nurses, Ülkü et al. (2025) of university students, Arı (2024) of classroom teachers and Banaz (2024) of Turkish teachers. Based on these studies, it was planned to examine the AI anxiety of preschool teacher candidates in order to contribute to both the field and the identification of deficiencies.

Purpose of the Study

The purpose of this study was to examine preschool teacher candidates' AI anxiety levels across various variables, including gender, grade level, internet use, knowledge of AI, and number of siblings. In this context, the following questions were sought.

1. What are the AI anxiety levels of preschool teacher candidates?
2. Is there a significant difference between the gender of preschool teacher candidates and their AI anxiety levels?
3. Is there a significant difference between the grade level of preschool teacher candidates and their AI anxiety levels?
4. Is there a significant difference between the daily internet usage time of preschool teacher candidates and their AI levels?
5. Is there a significant difference between the AI knowledge of preschool teacher candidates and their AI anxiety levels?
6. Is there a significant difference between the number of siblings of preschool teacher candidates and their AI anxiety levels?

Method

The study was conducted using a survey, a quantitative research method. The aim here was to choose a method that would enable rapid and effective solutions to the research problem, while maintaining high levels of reliability and validity (Çepni, 2010). This method is often used to gather the opinions of a specific group on a topic in an unbiased manner. Therefore, this method was chosen in accordance with the purpose of the study. This method was used to determine participants' agreement with the scale items, along with certain variables (Gender, grade level, internet use, and knowledge of AI).

Sample

Convenience sampling was used throughout the study. This method reached the target group of preschool teachers. Participants were invited to participate voluntarily, and those who agreed were provided with the data collection scale. 208 preservice teachers studying at Muş Alparslan University participated in the study. Demographic information for the participating preservice teachers is provided in Table 1.

Table 1. Demographic information of the sample group

Variable		f	%	Variable		f	%
Gender	Female	177	81.10	Knowledge of AI	Yes	145	69.7
	Male	31	14.90		No	63	30.3
Grade Level	1. Grade	90	43.3	Internet Use	1-2 Hour	47	22.6
	2. Grade	80	38.5		3-4 Hour	89	42.8
	3. Grade	18	8.7		5+ Hour	72	34.6
	4. Grade	20	9.6	Number of Siblings	3 or less	48	23.08
					More than 3	160	76.92

An examination of Table 1 reveals that the majority of participants are female (81.10%) and knowledgeable about the use of AI (69.7%). Furthermore, the majority of participants are first grade (43.3%) and second grade (38.5%) students and use the internet 3-4 hours per day (42.8%). Finally, the majority of participants (76.92%) have more than three siblings, meaning they live in a multi-child household. The table indicates that the frequency values of the variables are generally not very close to each other. It should be noted that this may affect data analysis.

Data Collection

Data were collected via a Google form link consisting of two sections: participant demographics and scale items. The demographic information section collected data such as gender, grade level, internet usage history, and knowledge of AI. The original 21-item Artificial Intelligence Anxiety Scale, developed by Wang and Wang (2019) and adapted to Turkish by Akkaya et al. (2021), was used as the scale. The scale items were rated on a 5-point Likert-type scale, ranging from "Strongly Disagree" to "Strongly Agree." The fit indices of the scale were acceptable ($\Delta\chi^2$ = 167.218, SD = 98 χ^2/SD = 1.706, RMSEA = .067, NFI = .925, RFI = .909, CFI = .963). Cronbach's Alpha reliability value of the adapted scale was determined as 0.81, and in this study, it was calculated as 0.92.

Data Analysis

The data obtained within the scope of the study was transferred electronically to Microsoft Excel, where the variables were coded and transferred to the SPSS package program. Findings were obtained from the data using techniques such as t-test, ANOVA, percentage, and frequency. In addition to the techniques used to interpret the findings, the criteria for determining the level of anxiety in AI were used.

Table 2. Criteria for determining the level of anxiety in AI

Score Range	AI Anxiety Level
1.00-1.80	Very low
1.81-2.60	Low
2.61-3.40	Moderate
3.41-4.20	High
4.21-5.00	Very high

According to Table 2, a specific range is obtained by dividing the scores obtained from a 5-point Likert-style scale by 5. Interpretations are made based on the corresponding values within these ranges. It can be used to interpret the level of an individual or group on a topic (Gülen, 2016). The interpretation corresponding to the range within which the average scores obtained from the scale items fall are used to determine the level.

Results

The findings obtained within the scope of the study are presented in the order of the research questions.

Findings Regarding Preschool Teachers' AI Anxiety Levels

In this section, the responses of preschool teachers participating in the study to the scale items were examined both individually and according to the overall average.

Table 3. Findings regarding preschool teachers' AI anxiety levels

Scale Items	X	SD
1. Item	2.84	1.04
2. Item	2.57	1.02
3. Item	2.5	0.96
4. Item	2.44	1.03
5. Item	2.44	1.02
6. Item	3.42	1.14
7. Item	3.63	1.12
8. Item	3.33	1.19
9. Item	3.57	1.09
10. Item	3.62	1.17
11. Item	3.37	1.05
12. Item	3.47	1.02
13. Item	3.41	1.04
14. Item	3.41	1.18
15. Item	3.39	1.15
16. Item	3.33	1.2
N:208	3.17	1.09

Table 3 shows the means and standard deviations obtained by preschool teacher candidates for each item. When these values are examined and the criteria specified in Table 2 are considered, it can be said that the participants had a moderate level of anxiety regarding almost the majority of the items. Indeed, an examination of the overall meaning (X=3.17) indicates that the preschool teacher candidates' anxiety level regarding the use of AI is at a moderate level. Similarly, an examination of the standard deviations for each item reveals homogeneity among participants whose values are close to each other regarding the scale items. In addition to these findings, Table 4 examines the relationship between participants' AI anxiety levels and gender.

Findings Regarding Preschool Teacher Candidates' Gender and AI Anxiety Levels

Table 4. Findings regarding preschool teacher candidates' gender and AI anxiety levels

Gender	N	$\bar{x}$	Std. Deviation	Std. Error Mean	t	*p*	n^2
Female	177	3.21	.73	.055	2.21	.028	.023
Male	31	2.90	.68	.122			

An independent samples T-test was used to determine the significant difference between the gender of the preschool teachers and their AI anxiety levels. According to the results of this test, a significant difference was determined between the gender of the preservice teachers, and their AI anxiety levels (p=.028<.05). This difference was observed to be in favor of females. The difference was considered to be at a good level (n^2=.023) based on the impact factor calculation (Cohen et al., 2007). Furthermore, an examination of the participants' grade levels and AI anxiety levels yielded Table 5.

Findings Regarding the Grade Levels and AI Anxiety Levels of the Preschool Teachers

Table 5. Findings regarding the grade levels and AI anxiety levels of the preschool teachers

	Sum of Squares	df	Mean Square	F	Homogeneity (p)	*p*
Between Groups	2.828	3	.943	1.799	.812	.149
Within Groups	106.915	204	.524			
Total	109.743	207				

An ANOVA test was used to determine the difference between the participating preservice teachers' grade levels and their AI anxiety levels. According to Table 5, no difference was found between AI anxiety levels and grade levels (P=0.149>0.05). Similarly, Table 6 was obtained when the participants' daily internet use time and AI anxiety levels were examined.

Findings Regarding Preservice Teachers' Daily Internet Use Time and AI Anxiety Levels

Table 6. Findings regarding preschool preservice teachers' daily internet use time and AI anxiety levels

	Sum of Squares	df	Mean Square	F	Homogeneity (p)	*p*
Between Groups	.583	2	.292	.547	.914	.579
Within Groups	109.160	205	.532			
Total	109.743	207				

An ANOVA test was used to determine the relationship between the daily internet use time and AI anxiety levels of the participating preservice teachers. According to the findings in Table 6, no difference was found between AI anxiety levels and daily internet use time (P=0.579>0.05). Furthermore, Table 7 examines the participants' knowledge of AI, and their AI anxiety levels, yielding the following findings:

Findings Regarding Preservice Teachers' AI Knowledge and AI Anxiety Levels

Table 7. Findings regarding preschool preservice teachers' AI knowledge and AI anxiety levels

AI knowledge	N	Mean	Std. Deviation	Std. Error Mean	t	*p*
Yes	145	3.19	.74	.061	-1.254	.211
No	63	3.26	.69	.087		

An independent samples t-test was used to determine the difference between preschool teachers' AI knowledge and AI anxiety levels. According to Table 7, there is no significant difference between AI knowledge and AI anxiety levels (p=>0.05). Finally, Table 8 was obtained when the participants' sibling status and AI anxiety levels were examined.

Findings Regarding the Number of Siblings and AI Anxiety Levels

Table 8. Findings regarding the number of siblings and AI anxiety levels of preschool preservice teachers

Siblings	N	Mean	Std. Deviation	Std. Error Mean	t	*p*
3 or less	48	3.20	.83	.119	.406	.685
More than 3	160	3.15	.70	.055		

An independent samples T-test was used to determine the difference between the number of siblings of preserves teachers and their AI anxiety levels. According to Table 8, there is no significant difference between the number of siblings, 3 or less, or more than 3, and the level of AI anxiety (p=0.685>0.05).

Discussion

According to the analysis of the research data, it can be said that preschool teacher candidates have a moderate level of anxiety about AI. This anxiety varies by gender, but there is no difference in terms of grade level, daily internet use duration, knowledge about AI, or number of siblings.

Preschool teacher candidates' AI anxiety levels can be said to be moderate (according to the criteria for determining AI anxiety levels). Indeed, it is known that averages around 3 on a 5-point Likert-style scale can generally be interpreted as moderate. Similarly, Arı (2024) and Banaz (2024) determined that the AI anxiety levels of classroom teachers and Turkish teachers were "undecided," meaning moderate. This result is generally related to university students' perspectives on AI. Indeed, there are both positive and negative opinions. Yakut et al. (2025) determined that university students are afraid of AI, while Chen et al. (2024) determined that it causes anxiety and stress. In addition, Küçükkara et al. (2024) determined that preschool teachers are concerned about the lack of sufficient knowledge and studies in the field of AI. Contrary to all these findings, Ülkü et al. (2025) determined that AI anxiety can positively affect innovative behavior. Chen et al. (2024) found that AI anxiety positively impacted university students' motivated learning, while Schiavo et al. (2024) found that AI literacy acceptance was positively affected. Meylani (2024) also determined that teachers' AI anxiety was effective in increasing motivation and participation in technology. Generally, while university students' anxiety about AI is fueled by factors such as fear, anxiety, and the unknown, it appears that they desire to demonstrate innovative initiatives due to factors such as acceptance, motivation, and participation. The balance of these factors is thought to influence the moderate level of AI anxiety among preschool teacher candidates.

It can be said that there is a significant difference between preschool teacher candidates' AI anxiety scores and their gender, favoring women. This difference may be due to the fact that there are four times more women than men. However, Arı (2024) and Banaz (2024) found a difference between AI anxiety and gender in their studies, again favoring women. Similarly, Salimi et al. (2025) found consistency and invariance between AI anxiety and gender in their study. These findings suggest that women may have higher anxiety levels than men. In general, it can be said that women have higher AI anxiety than men.

No difference was found between preschool teacher candidates' grade levels, daily internet use time, knowledge about AI, number of siblings, and AI anxiety scores. This is because the findings for these variables were not significant. This is suspected to be due to the fact that the frequency distributions of the variables are not close to each other. Similarly, Arı (2024) found no significant difference between daily internet use time and AI anxiety in his study. Additionally, Mart and Kaya (2024) and Saatçioğlu and Topsakal (2025) examined AI attitudes in their studies and reached results similar to the findings of the present study. In addition, Kaya et al. (2022) determined a significant difference between the AI knowledge levels and AI anxiety of participants aged between 18 and 51. Wang (2025) determined in his study that preschool teachers' AI-supported educational activities yielded beneficial results. While there are studies that are similar to the research findings, there are also studies that are not. According to these findings, there are generally no significant differences between the demographic information and AI anxiety levels of preschool teachers. This may be due to differences in demographic data frequency values or to participants' lack of knowledge about AI. Ultimately, AI production occurs independently of preservice teachers. However, coordination with AI engineers is necessary to increase preservice teachers' use of AI and ensure its easy integration into education (Zhai et al., 2021).

Conclusion

The interpretation of the research findings revealed that preschool teacher candidates have a moderate level of anxiety about AI. It was found that females differ more than males in terms of AI anxiety levels among preschool teacher candidates. No difference was found between preschool teacher candidates' grade level, daily internet use, AI knowledge, or number of siblings and AI anxiety.

Recommendations

Qualitative studies are needed to determine the reasons for preschool teacher candidates' anxiety levels. It is also recommended to determine AI anxiety levels in other branches or professions of the teaching profession. This is crucial for addressing teachers' predispositions toward AI, understanding the ethical issues surrounding AI, and integrating AI into classrooms. Research is needed to determine the reasons for AI anxiety levels between genders. Studies can clarify the similar prevalence of demographic variables among preschool teacher candidates.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the authors.

* Ethical approval for this research was approved by the Scientific Research and Ethics Committee of Muş Alparslan University. Meeting number 26 in 2025.

Conflict of Interest

* The authors declare that they have no conflicts of interest

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Use of Artificial Intelligence in Biology Education: A Systematic Review of Literature

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Abstract

In recent years, the use of artificial intelligence (AI) has become increasingly widespread and has attracted significant attention worldwide. In this study, a systematic review was conducted to determine the use of AI in biology education and the prevailing trends in its application. The study aimed to conduct a comprehensive review of articles published between 2010 and 2024 that employed artificial intelligence in biology education. In line with this aim, a total of 49 keywords were searched from Web of Science, SCOPUS, ERIC and IEEE Xplore databases. The entire process was summarized in the PRISMA diagram. 39 articles were deemed eligible for inclusion in the systematic review. The selected articles were analyzed in terms of publication year, research method, country of conduct, study group, number of participants, subject area, artificial intelligence technologies used, artificial intelligence applications used, and their outcomes. An evaluation of the articles according to the main topics in biology revealed that there is a lack of sufficient research on the evolutionary history of biodiversity and the models and processes of evolution. It was also found that there is a lack of sufficient research in the literature on artificial intelligence-supported educational games and simulations in biology education. In this context, it is recommended that the use of artificial intelligence technologies in biology education be expanded to include educational games, which are frequently used to motivate students and encourage learning, and simulations, which are suitable for development in many areas of biology education.

Introduction

First, in 1950, Alan M. Turing proposed considering the question "*Can a machine think?*" in his article titled "Computing Machinery and Intelligence." In this context, he presented a thought experiment called the "Turing test" to bring together the concepts of thinking and machines in order to demonstrate that a machine can think or, in other words, exhibit human-like intelligence (Turing, 1950). In 1959, Prof. Dr. Cahit Arf, in his article "*Can a Machine Think and How Can It Think?*", presented and explained examples of machine design demonstrating that machines can think. According to Arf, machines can be designed to perform analytical and logical operations such as establishing analogies, using language, calculating, and eliminating. Therefore, there are similarities between the human brain and machine functioning. However, Arf argued that the most fundamental differences between the human brain and a machine stem from the human brain's ability to function with aesthetic awareness, to make decisions, and to feel free to choose whether or not to carry out a given task (Arf, 1959). It is reported in the literature that the difficulty in determining the parameters of artificiality or in identifying the reasons why machines differ from human intelligence makes it difficult to define artificial intelligence, and the following statement is made regarding this issue;

"They are much less than human intelligence—they can only calculate. And they are much more—they can calculate larger numbers and faster than humans. We have cause to be in awe at the super-human brilliance of their feats of calculation." (Cope et al., 2021).

As can be understood, machines are emphasized as possessing superhuman intelligence in calculations. Artificial intelligence can be defined as the ability of machines to exhibit and simulate human-like intelligent behavior. In other words, it can be defined as software used to perform tasks or produce outputs that are considered to require human intelligence (Oxford University Press, n.d.).

There are several significant milestones in the historical development of artificial intelligence. The first of these was Marvin Minsky (1969) and John McCarthy (1971), who laid the foundations of the field based on representation and reasoning. McCarthy, the founder of the term artificial intelligence, received the Turing Award for his contributions. Later, Allen et al. (1975) established the foundations of artificial intelligence with their study on symbolic models of human cognition and problem solving; Ed Feigenbaum and Raj Reddy (1994) pioneered the development of expert systems that aim to solve real-world problems by encoding human knowledge; Judea Pearl (2011) developed probabilistic reasoning techniques and integrated them into artificial intelligence; and finally, Yoshua Bengio, Geoffrey Hinton, and Yann LeCun (2019) made deep learning an essential part of modern technology. These prominent figures, who significantly contributed to the development of artificial intelligence, were also awarded the Turing Award (Erman, Hayes-Roth, et al., 1980; Feigenbaum, & McCorduck, 1983; LeCun et al., 2015; Luckin, et al., 2016; McCarthy, 1987; Minsky & Papert, 1969; Newell, & Simon, 1976; Pearl, 2009).

Artificial intelligence can be described as an umbrella term encompassing numerous technologies and applications. Language models, one of the AI technologies, facilitate tasks such as grammar assistance, question answering, search engine response optimization, text generation, and translation. However, it is often difficult and complex to distinguish the texts generated by language models from those produced by humans. This can lead to academic fraud, deliberate misuse, and plagiarism. Therefore, while language models offer significant benefits, they also present challenges (Brown, et al., 2020). If AI is used effectively, all the challenges brought about by AI technologies can be overcome with the power of human intelligence (Akintande, 2024).

Cognitive tutors, one of the AI applications, support students' learning processes by providing personalized feedback and contribute to long-term learning. In this regard, cognitive tutors can be considered a powerful educational tool. However, it should be noted that AI can never replace real teachers, as the functioning and operations of AI are fundamentally different from human intelligence (Koedinger & Corbett, 2005). Machines cannot substitute for teachers, but they can serve as supportive tools (Crovello, 1974).

In their study, Lu, et al. (2024) found that chatbots (ChatGPT), an application of artificial intelligence, can be used to score students' short-answer questions and demonstrate good-to-moderate consistency when compared to teacher scorings. Similarly, Jukiewicz (2024) used ChatGPT to evaluate student assignments and found positive correlation between these AI-based evaluations and teacher evaluations. The study concluded that ChatGPT can be used as an effective tool for grading student assignments, considering its high-quality assessment, unbiased grading, time-saving, and feedback-generating capabilities. Elgohary and Al-Dossary (2022) determined that the use of artificial intelligence-supported virtual classrooms significantly improved the field training and teaching skills of female teacher candidates (84.40%). Almeda, et al. (2018) developed artificial intelligence-supported models that predict students' course success on an online learning platform. The study found that these models performed quite well in predicting student success. Predicting student success is crucial for providing support to students identified as being at-risk. Accordingly, Mubarak et al. (2022) developed a machine learning-based prediction model for early identification of students at risk of dropping out. As a result of the study, the use of this model enabled the identification of at-risk students with an accuracy rate of 84%. Benhamdi et al. (2017) presented a recommendation approach that provides personalized learning materials for e-learning environments based on students' preferences, memory capacities, interests, and readiness. They found that this recommendation approach increases the quality of learning. Ijaz et al. (2017) combined artificial intelligence and virtual reality to create a virtual replica of the city of Uruk and used AI-controlled 3D avatars to recreate daily life. They found that this application, which allowed students to walk the streets of this city and talk to its residents, resulted in increased motivation and interest in their learning experiences. Aluthman (2016) examined the effects of the AI technology–based Criterion® system, which employs natural language processing (NLP), on the writing performance of students enrolled in an academic writing course in the English Language Department at a university. This system, which provides instant feedback, evaluation, and automatic scoring, was found to improve students' writing mechanics, with moderate progress in style, grammar, and usage. Koć-Januchta et al. (2020) developed a digital biology textbook using AI-supported question-and-answer technologies and visuals. The study revealed that students' engagement in asking questions and interacting with visuals was positively correlated with retention. The usability of this digital textbook was perceived positively by students. The use of artificial intelligence in education is becoming increasingly widespread (Holmes et al., 2023). In the field of education, artificial intelligence can measure knowledge, support learning, and enable automatic transfer between numbers and meaning. In this context, AI holds promise for the future in education and assessment. However, educators should be aware of the inherent limitations of AI (Cope et al., 2021). It is evident that AI has a significant impact on teaching and learning both within the educational sector and in educational institutions (Chen et al., 2020).

Artificial intelligence is used in a wide range of fields, including industry, marketing, financial services, engineering, medicine, pharmacy, physical education, physics education, chemistry education, science education, biology education, mathematics education, and language teaching (Broussard et al., 2019; Cooper 2023; Ding et al., 2023; Fernández, 2019; Hamet & Tremblay, 2017; Hessler & Baringhaus, 2018; Holmes et al., 2004; Iyamuremye et al., 2024; Jarek & Mazurek, 2019; Miller et al., 2025; Nasution, 2023; Parunak, 1996; Pham &

Pham, 1999; Xu et al., 2022). Artificial intelligence technologies such as deep learning are used to examine and categorize biological data (Webb, 2018). In general, artificial intelligence in biology is used in areas including disease detection and diagnosis, medication management, personalized medicine, biological data analysis, synthetic biology, investigating and integrating complex mechanisms at various scales, bioinformatics, radiography, image processing, and genetic data analysis (Aripin et al., 2024; Bhardwaj et al., 2022; Hassoun et al., 2021). The use of artificial intelligence is considered to potentially cause a revolutionary change in biology in the 21st century (Hassoun, 2021).

The use of computers in biology education helps improve teaching, makes it possible to teach difficult topics, increases students' interest in the course, reduces tedious tasks related to simple topics, and allows students to learn at their own pace and review course materials as often as they wish In this context, the use of computers in biology education can improve teaching quality. However, excessive use should be avoided, and optimization should always be ensured in computer use (Crovello, 1974).

There are numerous systematic reviews on the use of artificial intelligence: AI in education (Wang et al., 2024; Zhai et al., 2021), AI in student assessment (González-Calatayud et al., 2021), AI and learning analytics in teacher education (Salas-Pilco et al., 2022), AI technologies in K-12 education (Martin, Zhuang, & Schaefer, 2024), the use of ChatGPT in K-12 education (Zhang & Tur, 2024), AI applications in online higher education (Ouyang, Zheng, & Jiao, 2022), AI in English language teaching (Sharadgah & Sa'di, 2022), AI in science education (Almasri, 2024), AI in science teaching and learning (Heeg & Avraamidou, 2023), AI in biology and biology learning (Aripin et al., 2024), and bibliometric analyses on the quality and role of AI in improving biology education (Lidiastuti et al., 2025). However, studies specifically focusing on the use of AI in biology education are relatively limited. Therefore, compiling and presenting the literature on the use of artificial intelligence in biology education, which has become increasingly widespread in recent years and has made a significant impact worldwide, is considered important in determining the status and trends in the use of AI in biology education. This study aimed to conduct a systematic review by comprehensively examining articles published between 2010 and 2024 to determine the current status and trends in the use of artificial intelligence in biology education. Accordingly, the present study is expected to provide a general overview of AI use in biology education and contribute to the existing literature.

Purpose of the Study and Sub-Problems

The purpose of this study is to determine how artificial intelligence is used in biology education and to identify trends related to its use. Accordingly, answers were sought to the following sub-questions:

1) Which artificial intelligence technologies are used in studies on the use of artificial intelligence in biology education?
2) Which artificial intelligence applications are used in studies on the use of artificial intelligence in biology education?
3) What are the outcomes of studies on the use of artificial intelligence in biology education?
4) What is the distribution of studies on the use of artificial intelligence in biology education by year?
5) What is the distribution of studies on the use of artificial intelligence in biology education by research method?
6) What is the distribution of studies on the use of artificial intelligence in biology education by country?
7) What is the distribution of studies on the use of artificial intelligence in biology education by study group and the number of participants?
8) What is the distribution of studies on the use of artificial intelligence in biology education by the number of participants?
9) What subject areas do studies on the use of artificial intelligence in biology education focus on?

Method

A systematic review is a method that allows for the comprehensive and systematic screening of published studies in a given field, using various inclusion and exclusion criteria to answer research questions and problems. What distinguishes systematic reviews from other types of literature reviews is that they are comprehensive, objective, and reproducible. Their reproducibility stems from the fact that the researcher explicitly specifies the search terms, databases, and the inclusion and exclusion criteria at the beginning of the study. This also indicates that the systematic reviews are evidence-based. Systematic reviews are therefore regarded as important studies that minimize bias and yield reliable findings (Higgins & Green, 2008; Karaçam, 2013; Page et al., 2021; Zawacki-

Richter, 2020). In this study, a systematic review was conducted to determine the use of artificial intelligence technologies, which are becoming increasingly widespread in education, in biology education and to identify the current trends in this field. A five-phase systematic review process was followed to address the research problems:

Phase 1: Article Collection, Review, and Initial Selection

Databases and Search Terms, Article Collection

To review the relevant literature, four international databases (Web of Science, SCOPUS, ERIC, and IEEE Xplore) were searched for articles. For each database, the terms "artificial intelligence" and "biology education" were searched in the entire text (all fields). These terms were searched by combining them using AND or +. To access all the data, the search strings were expanded. Seven different alternative terms for "artificial intelligence" and seven different alternative terms for "biology education" were added. By crossing these strings with each other, a total of 49 searches were conducted in each database. All search strings used are presented in Table 1. The database search and downloading of relevant studies were completed between May and June 2025.

Table 1. Search strings used to search databases

Topic	Search string
Artificial intelligence	"artificial intelligence" OR "machine learning" OR "AI" OR "natural language processing" OR "deep learning" OR "artificial neural networks" OR "expert systems"
AND Biology education	"biology education" OR "biology learning" OR "biology teaching" OR "biology instruction" OR "biology curriculum" OR "biology laboratory" OR "biology textbook"

Article Review and Initial Selection

All articles retrieved after searching the databases were uploaded to Zotero. A separate collection was created for each database in Zotero. All collections were then compiled into a single collection under the name "Combined Folder." The articles in this collection were reviewed, and duplicate articles were excluded. The remaining articles were then evaluated for eligibility according to the predefined inclusion criteria. The articles were first reviewed by their titles, then by their abstracts, and finally by their full texts, independently by two authors. Disagreements between the two authors were resolved through discussion.

Initial Inclusion Criteria

Six criteria were applied to determine the eligibility of studies for inclusion in this study: (1) Being appropriate for biology education content; (2) Not being a book, book chapter, conference proceeding, or thesis; (3) Being empirical research; (4) Being written in English; (5) Having been conducted between 2010 and 2024. Therefore, articles that were not published between 2010 and 2024, were not empirical, were not written in English, and were not appropriate for biology education were not included in this study. In addition, books, book chapters, conference proceedings, and these were not included in this study.

The inclusion and exclusion procedures employed in this systematic review were summarized using the The PRISMA diagram (Moher et al., 2009) (Figure 1). The articles retrieved from Web of Science (n=220), SCOPUS (n=9,121), ERIC (n=68), and IEEE Xplore (n=77) databases were combined into one folder. 3,335 duplicate articles encountered in different databases were excluded, leaving 6,151 articles. First, the titles of these articles were screened, and 4,934 articles deemed outside the scope of the study were excluded. Then, the abstracts of the remaining articles were screened, and 1,002 articles were excluded for being irrelevant to the scope of the study. Finally, the full texts of the remaining 215 articles were examined in detail and evaluated according to the initially determined eligibility criteria. As a result of the evaluation, 176 articles were excluded based on the eligibility criteria: (1) 102 articles identified as being from fields such as physical education, medicine, nursing, pharmacy, chemistry, and physics; (2) 19 articles identified as being written for purposes such as systematic review, meta-analysis, compilation, and program promotion, and therefore not empirical; (3) 6 articles identified as conference proceedings; and (4) 49 articles identified as being published between 1989 and 2025 were excluded. Since all reviewed articles were written in English, no exclusion was made based on language criteria.

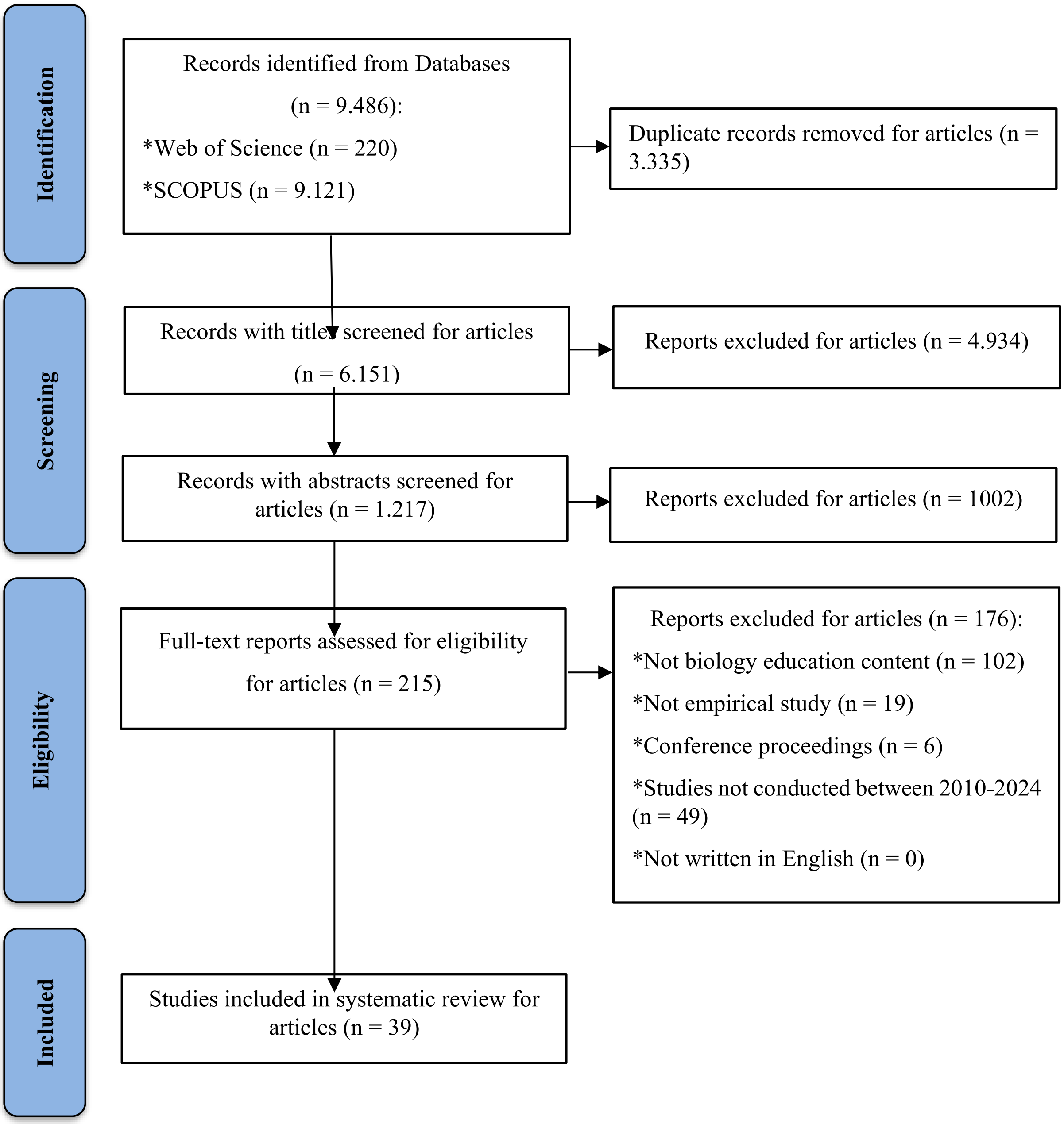


Figure 1. PRISMA diagram

As shown in the PRISMA diagram in Figure 1, a total of 9,486 articles were initially retrieved from the databases. After excluding duplicate articles encountered in different databases, the titles of the remaining 6,151 articles were independently screened by two authors. A 94% (5,790 / 5,790 + 361) agreement was reached between the authors regarding the articles to be included in the study. After the necessary eliminations, the abstracts of the remaining 1,217 articles were independently screened by the two authors, resulting in a 97% (1,185 / 1,185 + 32) agreement regarding the articles to be included in the study. Finally, the full texts of the remaining 215 articles were independently screened by two authors, resulting in a 99% (213 / 213 + 2) agreement regarding the articles to be included in the study based on the eligibility criteria. In order to ensure the reliability of the study, these agreement rates were calculated according to the formula of Miles and Huberman (2016).

Phase 2: Final Article Selection

Artificial intelligence is a broad field encompassing a wide range of technologies, including machine learning, natural language processing, computer vision, generative AI, expert systems, robotic systems, deep learning, large language models, and natural language generation. Each technology is further divided into sub-applications. In this study, 39 articles selected for full-text review were examined in detail and classified according to their AI technologies.

Phase 3: Data Determination

For the 39 articles included in the study, a table was created in Excel to determine the following characteristics: (1) publication year, (2) research method, (3) country of conduct, (4) study group, (5) number of participants, (6) subject area, (7) AI technologies used, (8) AI applications used, and (9) outcomes. The authors independently listed the characteristics to be examined in the articles. Any disagreements between the authors were then reviewed, and the lists were revised accordingly. Ultimately, agreement was reached between the authors regarding the dataset to be used in the study.

Phase 4: Data Extraction and Audit

Following the selection of articles to be included in the study and the determination of data, all excluded articles were removed from Zotero through the joint effort of the two authors. Additionally, the dataset was reviewed by a professor specializing in the field of biology education to ensure data accuracy. Finally, the data were verified, and the final dataset was prepared.

Phase 5: Analysis

This study aimed to address nine sub-problems. Descriptive analysis was used to analyze articles on the use of artificial intelligence in biology education based on the AI technologies used, publication year, research method, country of conduct, study group, and number of participants. In descriptive analysis, the dataset is categorized according to pre-determined themes. Descriptive analysis is carried out in four stages: (1) creating a framework for descriptive analysis, (2) processing the data according to the thematic framework, (3) defining the findings, (4) interpreting the findings (Yıldırım & Şimşek, 2016, pp. 239-240).

Content analysis was used to analyze articles on the use of artificial intelligence in biology education according to the artificial intelligence applications used, the outcomes, and the subject area. Content analysis is carried out in four stages: (1) coding the data, (2) identifying themes, (3) organizing codes and themes, and (4) defining and interpreting the findings (Yıldırım & Şimşek, 2016, pp. 242-252). The data set used in this study was coded by generating codes directly from the data using inductive analysis in accordance with the "coding based on concepts extracted from the data" type (Strauss & Corbin, 1990). Excel, IBM-SPSS 24, and MAXQDA 2018 programs were used in the analysis and presentation of the data.

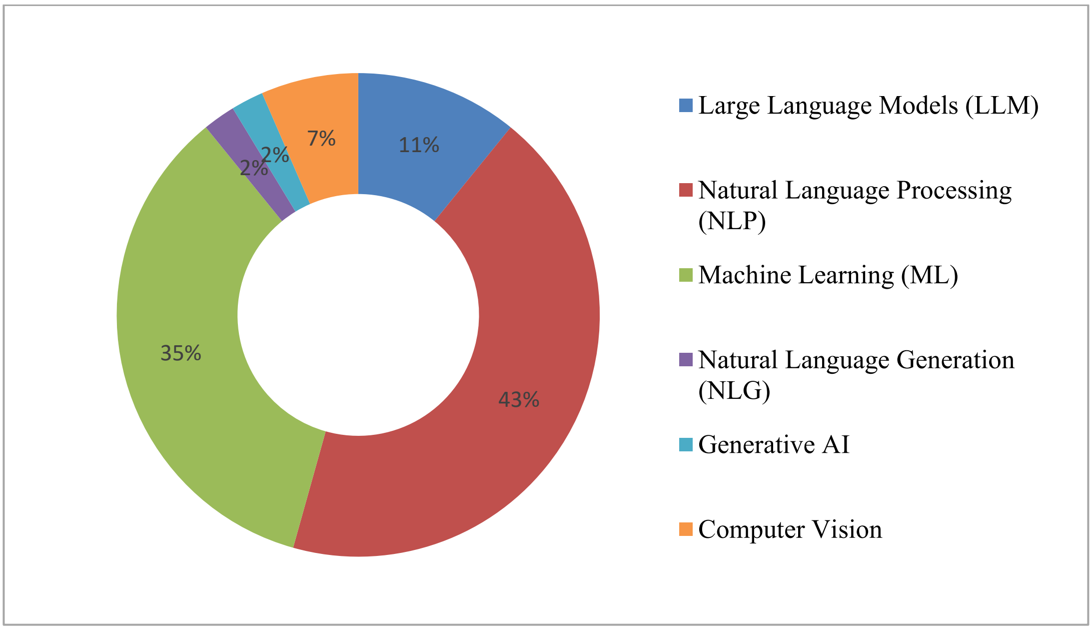


Figure 2. Artificial intelligence technologies used in the reviewed articles

Results

Descriptive analysis was employed to analyze articles on the use of artificial intelligence in biology education according to the AI technologies used. Some articles employed more than one AI technology (Ariely et al., 2023; Chaudhri et al., 2013; Ha et al., 2011; Jho & Ha, 2024; Royse et al., 2024; Sripathi et al., 2023; Zhang & VanLehn, 2016). Therefore, all AI technologies were evaluated separately. As a result, the total number obtained represented the total number of AI technologies used (*f* = 46). The distribution of AI technologies used according to the analysis results is shown in the doughnut chart (Figure 2). As shown in Figure 2, "Natural Language Processing (NLP)" (*f*=20; 43%) was the most frequently used AI technology in articles using AI in biology education, followed by "Machine Learning (ML)" (*f*=16; 35%) and "Large Language Models (LLM)" (*f*=5; 11%). The least frequently used AI technologies in these studies were "Natural Language Generation (NLG)" (*f*=1; 2%) and "Generative AI" (*f*=1; 2%).

In this study, content analysis was used to analyze articles on the use of artificial intelligence in biology education according to the AI application used. The AI applications used in 39 articles were listed. In some articles, more than one AI application was employed (Aleksandrovich et al., 2024; Ceylan & Karakuş, 2024; Chaudhri et al., 2013; Chen & Liu, 2024; Cogliano et al., 2022; Koć-Januchta et al., 2020; Koć-Januchta et al., 2022; Peffer et al., 2020; Zafeiropoulos & Kalles, 2024; Zhang & VanLehn, 2016). Therefore, all AI applications were evaluated separately, and the total number obtained represented the total number of AI applications used. The AI applications used in the reviewed articles were coded independently by the two authors. A total of 56 codes were generated. At this stage, 95% (53 / 53 + 3) agreement was reached between the authors (Miles & Huberman, 2016).

Table 2. Artificial intelligence applications used in the reviewed articles

Themes	Codes	*f*	%
Chatbots and Question-Answer Systems	Educational Chatbots (*f* =11) Question-Answer Technology (*f* =2) Educational Question-Answer Systems (*f* =1) Web-Based Question Compilation (*f* =1) Knowledge-Based Question Generation (*f* =1)	16	28,57
Automated Assessment and Feedback	Automated Assessment Systems (*f* =9) Automated Computer-Scoring Model ACSM) (*f* =1) Constructed-Response Classifier-CRC (*f* =1) Summarization Integrated Development Environment (SIDE) (*f* =1) An Online Formative Assessment Tool Called "Evograder" (*f* =1)	13	23,21
Basic Artificial Intelligence Techniques and Algorithms	Neural Networks (*f* =2) Data Clustering and Network Analysis (*f* =2) Genetic Algorithms (*f* =1) Text Mining (*f* =1) Computerized Lexical Analysis (*f* =1) Text Classification (*f* =1) Bayesian Structure Learning (*f* =1)	9	16,07
Knowledge-Based Systems	Knowledge Representation (*f* =3) Knowledge-Acquisition (*f* =2) Knowledge Base (*f* =2)	7	12,50
Learning Analytics and Predictive Models	Learning Analytics (*f* =2) Predictive Learning Analytics (*f* =1) Predictive Modeling (*f* =1)	4	7,14
Image Processing and Multimodal Interaction	Image Recognition Technologies (*f* =3) Multimodal Interaction Design (*f* =1)	4	7,14
Intelligent Tutoring Systems and Personalized Learning	Virtual Tutors (*f* =1) Personalized Assistants (*f* =1)	2	3,57
Educational Games	Educational Computer Game (*f*=1)	1	1,79
Total		56	100

Similar codes were combined to create themes. The themes were determined as follows: (1) Chatbots and Question-Answer Systems, (2) Automated Assessment and Feedback, (3) Basic Artificial Intelligence Techniques and Algorithms, (4) Knowledge-Based Systems, (5) Learning Analytics and Predictive Models, (6) Image

Processing and Multimodal Interaction, (7) Intelligent Tutoring Systems and Personalized Learning, and (8) Educational Games. Expert opinion was consulted to ensure the accuracy and consistency of the codes with the themes. The expert was provided with two separate lists: one containing the codes and the other containing the themes and was asked to match the codes with the themes. According to the results, the agreement was calculated as 96% (54 / 54 + 2) (Miles & Huberman, 2016). For codes and themes where disagreements occurred, agreement was reached through discussion. All codes, themes, and their frequencies are presented in Table 2.

An examination of Table 2 reveals that in articles on the use of artificial intelligence in biology education, AI applications are clustered under eight themes, each consisting of 28 codes with a total frequency of 56. The theme with the highest frequency was "*Chatbots and Question-Answer Systems*" (*f*=16), followed by "*Automated Assessment and Feedback*" (*f*=13), and "*Basic Artificial Intelligence Techniques and Algorithms*" (*f*=9). The highest-frequency code within the "*Chatbots and Question-Answer Systems*" theme was "Educational chatbots" (*f*=11). Articles using educational chatbots used platforms such as ChatGPT, Bard/Gemini, BingChat/Microsoft Copilot, and YouChat. The code "Automated assessment systems" for the theme "*Automated Assessment and Feedback*" represented articles that did not specifically specify the name of the program used, but simply included the general phrase "Automated assessment systems." If a program, such as EvoGrader, was explicitly mentioned, the program name itself was used as the code. The theme with the lowest frequency was “Educational Games”, represented by only one article. This article discussed the use of a machine learning-based educational computer micro-game as a teaching tool (Brom et al., 2011).

Table 3. Outcomes of the reviewed articles

Themes	Codes	*f*	%
Educational Technology & Tool Development Outcomes	Feedback & Smart Guidance (*f*=8) Usability (*f*=2) Smart Microscope Design (*f*=1) Smart Textbook Development (*f*=1) Digital Textbook Use (*f*=1) Textbook Analysis (*f*=1) Creating a Virtual Collection (*f*=1) Creating a Virtual Laboratory (*f*=1) Digital Assistance/Guidance (*f*=1) Visual Analysis/Measurement Automation (*f*=1) Supporting Fieldwork (*f*=1) Modeling Learning Progress (*f*=1)	20	32,79
Cognitive Learning Outcomes	Student success (*f*=3) Knowledge acquisition and retention (*f*=3) Conceptual understanding and changes (*f*=2) Detection of misconceptions (*f*=1) Learning gain (*f*=1) Students' knowledge retention and transfer (*f*=1) Systems thinking skills (*f*=1)	12	19,67
Affective & Motivational Outcomes	Motivation (*f*=5) Student perception (*f*=2) Student engagement and satisfaction (*f*=1) Student attitude (*f*=1) Epistemological beliefs about science-(EBAS) (*f*=1) Feeling and thought analysis (*f*=1)	11	18,03
Teacher & Institutional Outcomes	Teacher Workload & Assessment Quality (*f*=8) Effectiveness & Sustainability of the Program/Department (*f*=2)	10	16,39
Metacognitive & Strategic Outcomes	Cognitive load (*f*=2) Cognitive strategy use (*f*=1) Self-regulation (*f*=1)	4	6,56
Assessment & Feedback Outcomes	Assessing Question Answering Performance (*f*=3) Assessing Question Writing Quality (*f*=1)	4	6,56
Total		61	100

In this study, content analysis was conducted to analyze articles on the use of artificial intelligence in biology education according to their outcomes. The outcomes of these articles were identified and noted. Since some articles aimed at multiple outcomes (Aleksandrovich et al., 2024; Ceylan & Karakuş, 2024; Chen & Liu, 2024; Jho & Ha, 2024; Kim & Kim, 2022; Koć-Januchta et al., 2022; Koć-Januchta et al., 2020; Uhl et al., 2021; Wang, et al., 2019; Yin et al., 2024; Zafeiropoulos & Kalles, 2024), all outcomes were evaluated separately. Therefore, the total number reached at the end of the analysis represents the total number of outcomes, not the total number of articles. All reviewed articles were coded in terms of outcomes by two authors. A total of 61 codes were generated. A 98% (60 / 60 + 1) agreement was reached between the authors (Miles & Huberman, 2016). The generated codes were grouped among themselves to create themes. The themes were (1) Educational Technology and Tool Development Outcomes, (2) Cognitive Learning Outcomes, (3) Affective and Motivational Outcomes, (4) Teacher and Institutional Outcomes, (5) Metacognitive and Strategic Outcomes, and (6) Assessment and Feedback Outcomes. To validate the code–theme compatibility, expert opinions were obtained from two professors working at the faculty of education in a state university. Each expert was provided with separate lists of codes and themes and asked to match the codes with the themes so that none remained unmatched. Accordingly, the experts' agreement was determined as 97% (59 / 59 + 2) and 98% (60 / 60 + 1), respectively. In the final analysis, agreement was reached through discussion for the codes and themes where disagreements occurred. All codes, themes, and their frequencies obtained from the analysis are presented in Table 3.

An examination of Table 3 revealed that the outcomes of articles on the use of artificial intelligence in biology education were grouped under 6 themes, consisting of 32 codes with a total frequency of 61. The theme with the highest frequency was "*Educational Technology and Tool Development Outcomes*" (*f*=20), followed by "*Cognitive Learning Outcomes*" (*f*=12) and "*Affective and Motivational Outcomes*" (*f*=11). The themes with the lowest frequency were "*Metacognitive and Strategic Outcomes*" (*f*=4) and "*Assessment and Feedback Outcomes*" (*f*=4). The code with the highest frequency within the theme "*Educational Technology and Tool Development Outcomes*" was "Feedback & Intelligent Guidance" (*f*=8). This code represented articles that used platforms/applications that provided instant personalized feedback to students, and articles that guided students in using an AI-supported smart microscope that included a physical interaction kit (Ariely et al., 2023, 2024; Jho & Ha, 2024; Wang et al., 2019; Yin et al., 2024; Zafeiropoulos & Kalles, 2024). The most frequently observed outcomes in the "*Cognitive Learning Outcomes*" theme were "Student success" (*f*=3) and "Knowledge acquisition and retention" (*f*=3), while the most common outcome in the "*Affective and Motivational Outcomes*" theme was "Motivation" (*f*=5). In the theme "*Teacher and Institutional Outcomes*", the code with the highest frequency was "Teacher Workload & Assessment Quality" (*f*=8), which represented articles that specifically aimed to reduce teacher workload in assessing written responses from large student populations by using AI-based tools (Beggrow et al., 2014; Beigman et al., 2017; Ha et al., 2011; Haudek et al., 2012; Jescovitch et al., 2021; Jho & Ha 2024; Moharreri et al., 2014; Sripathi et al., 2023). Finally, within the "*Assessment and Feedback Outcomes*" theme, the code "Evaluating Question-Answering Performance" (*f*=3) represented articles evaluating the scientific question answering performance of chatbots such as ChatGPT (Dao & Le, 2023; Elmas et al., 2024; Crowther et al., 2023). A descriptive analysis was conducted to determine the distribution of the 39 articles reviewed in this study by publication year. Based on the results of this analysis, a column chart was created to show the distribution of the articles by publication year (Figure 3).

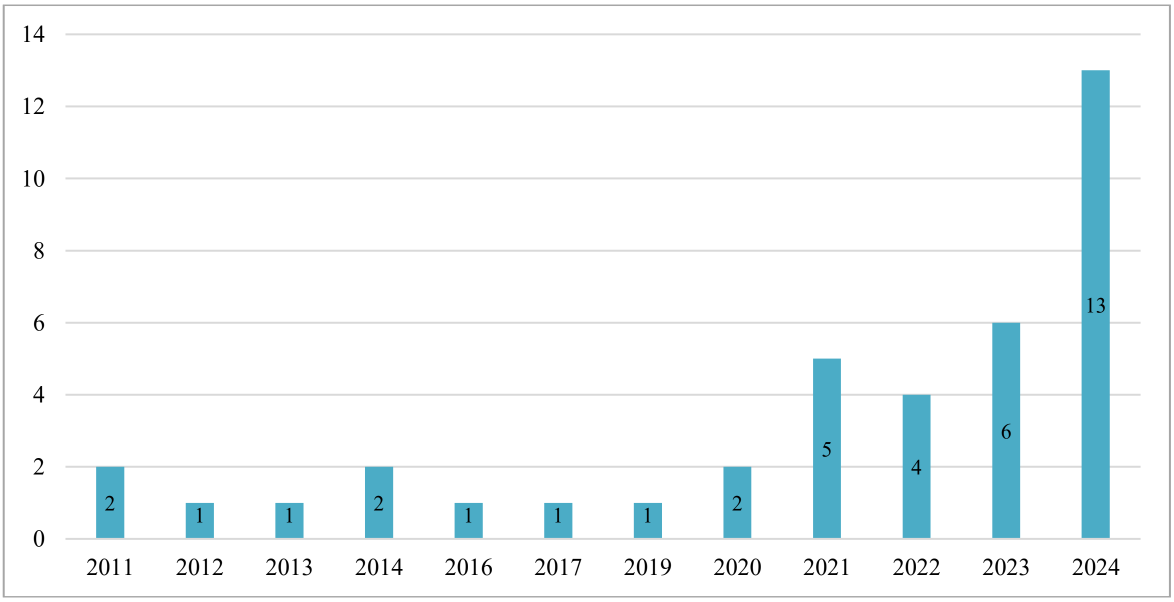


Figure 3. Distribution of reviewed articles by publication year

As shown in Figure 3, the number of articles on the use of artificial intelligence in biology education has steadily increased over the years, with a sharp rise observed in 2021. In particular, 2024 witnessed more than a twofold increase compared to the previous year. Therefore, 2024 was the year with the highest number of studies (f=13; 33.33%). However, no studies were found in 2015 and 2018. A descriptive analysis was conducted to determine the distribution of reviewed articles by research methods. Based on the analysis results, a pie chart was created to show the distribution of articles by research method (Figure 4).

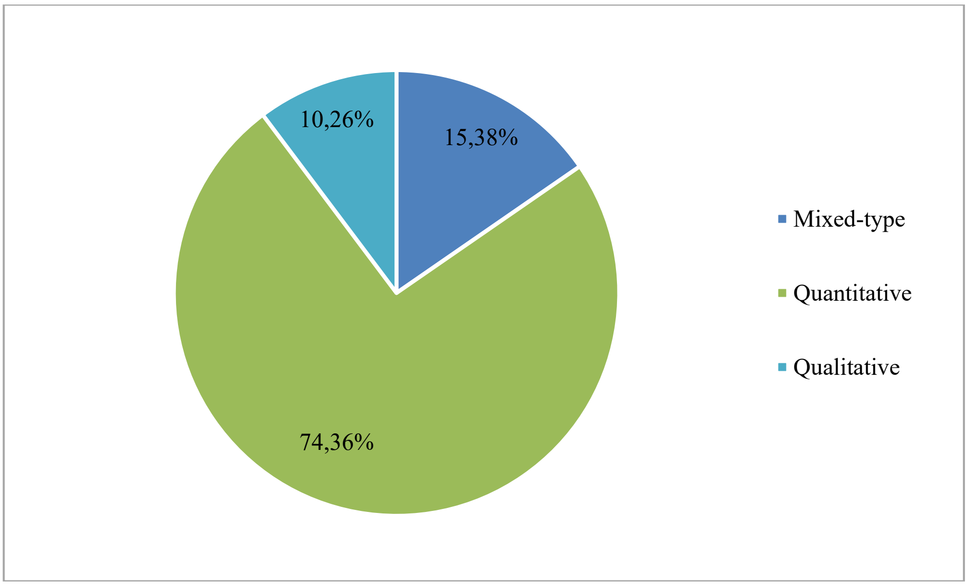
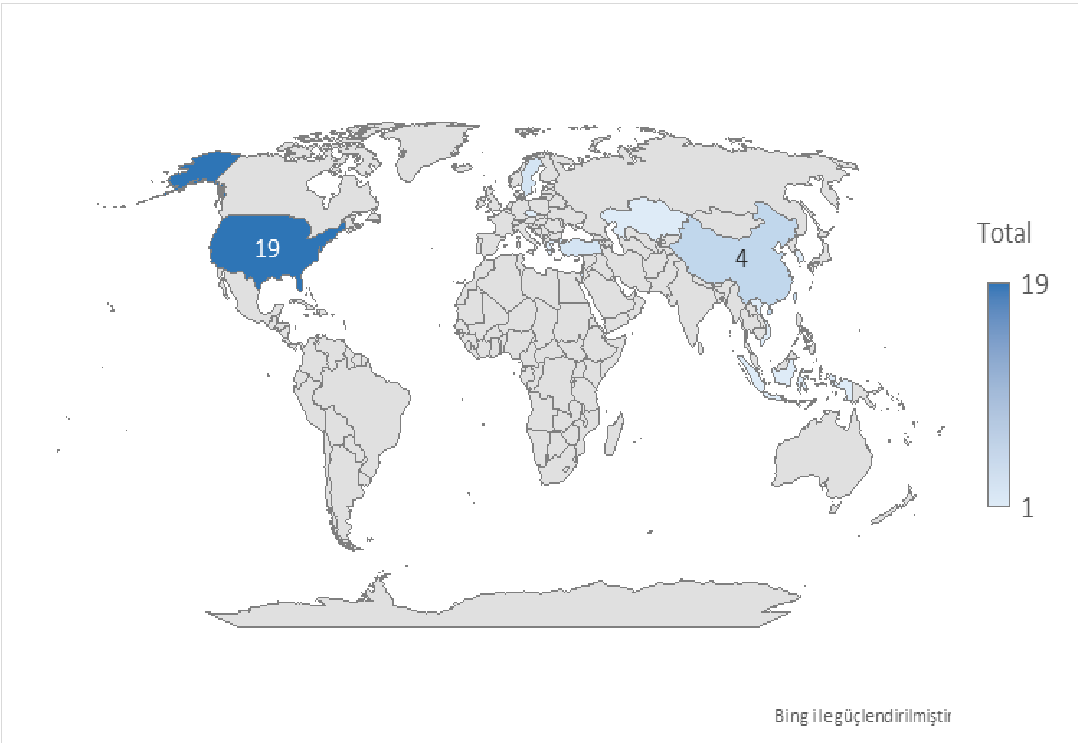


Figure 4. Distribution of reviewed articles by research method



USA	19	Indonesia	1
China	4	South Korea	1
Taiwan	3	England	1
Israel	2	Kazakhstan	1
Sweden	2	Vietnam	1
Türkiye	2	Greece	1
Czech Republic	1		

Figure 5. Distribution of reviewed articles by country

Figure 4 shows that quantitative methods were generally used in articles on the use of artificial intelligence in biology education (*f*=29; 74.36%). Mixed research methods were the second most preferred method (*f*=6; 15.38%). The least commonly used research method in these studies was qualitative research methods (*f*=4; 10.26%). A descriptive analysis was conducted to determine the distribution of the reviewed articles by country. Based on the analysis, the countries where the articles were conducted and their frequencies were visualized on a world map. On the map, the number of articles conducted in each country was highlighted using different shades of color, and the frequencies of articles conducted in each country were also presented descriptively (Figure 5). Figure 5 shows that articles on the use of artificial intelligence in biology education were conducted in 13 countries (USA, China, Taiwan, Israel, Sweden, Turkey, Czech Republic, Indonesia, South Korea, UK, Kazakhstan, Vietnam, and Greece). The country with the most articles was the US (48.72%), followed by China (10.26%) and Taiwan (7.69%).

Descriptive statistics were used to determine the distribution of the articles by study group. Brock et al. (2024) analyzed textbooks in their study, and therefore, the study group in their article was analyzed as "textbooks." Dao and Le (2023) evaluated the performance of various large language models in answering biology exam questions, and the study group in their article was analyzed as "large language model applications (ChatGPT, Microsoft Bing Chat, Google Bard)." Crowther et al. (2023) examined the performance differences of chatbots based on large language models, and the study group in their article was analyzed as "chatbot versions (ChatGPT, Google Bard, YouChat)." Elmas et al. (2024) evaluated the validity of the responses produced by ChatGPT when asked scientific questions, and the study group in their article was analyzed as "ChatGPT." Some articles were found to have been conducted on more than one study group (Dao & Le, 2023; Peffer, et al., 2020; Wang et al., 2019; Zafeiropoulos & Kalles, 2024). Therefore, all study groups were evaluated separately. Consequently, the total number obtained in the analysis represented the total number of study groups. The results of the analysis are presented in Table 4.

Table 4. Distribution of reviewed articles by study group

Study Group	*f*	%
University students	22	47,83
High school students	6	13,04
Middle school students	4	8,70
ChatGPT	3	6,52
Google Bard	2	4,35
Faculty members	2	4,35
Biology graduates	1	2,17
Teachers	1	2,17
Textbooks	1	2,17
YouChat	1	2,17
Biology experts	1	2,17
Post-secondary students	1	2,17
Microsoft Bing Chat	1	2,17
Total	46	100

An examination of Table 4 revealed that the study group of articles on the use of artificial intelligence in biology education was composed primarily of university students (*f*=22; 47.83%), followed by high school (*f*=6; 13.04%) and middle school students (*f*=4; 8.70%). Artificial intelligence applications such as ChatGPT, YouChat were also considered as study groups and had a significant proportion (*f*=7; 15.21%). The distribution of articles by the number of participants was determined using descriptive statistics through the IBM-SPSS 24 program. In the study conducted by Brock et al. (2024), the number of textbooks reviewed was considered as the number of participants. Some articles evaluated the question performance of artificial intelligence technologies, so the number of questions was considered as the number of participants (Dao & Le, 2023; Elmas, Adiguzel-Ulutas et al., 2012). The results of the analysis are presented in Table 5.

Table 5. Data on the number of participants in the reviewed articles

	N	Min.	Max.	Mean	Std. Deviation
Number of participants	39	5	4937	498,62	1013,78

Table 5 shows that the number of participants in articles on the use of artificial intelligence in biology education ranged from a minimum of 5 to a maximum of 4,937. On average, articles on the use of artificial intelligence in biology education had 499 participants.

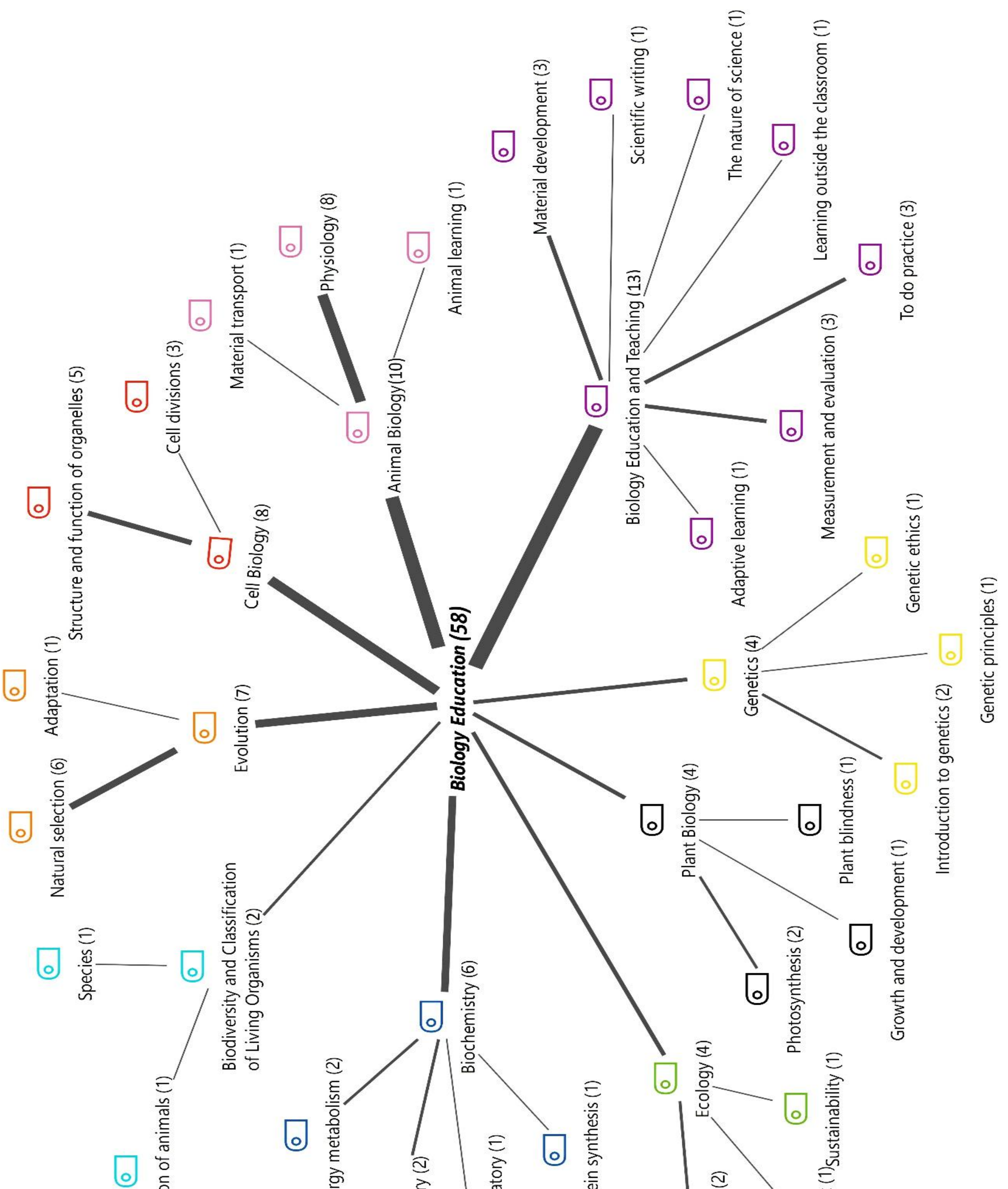


Figure 6. Distribution of reviewed articles by subject area

Content analysis was used to analyze articles using AI in biology education according to their subject areas. In an Excel table, the subject areas of the 39 reviewed studies were listed. Some articles focused on more than one subject area (Ariely et al., 2024; Beigman et al., 2017; Brock et al.2024; Ceylan & Karakuş, 2024; Chaudhri et al., 2013; Crowther et al., 2023; Dao & Le, 2023; Elmas et al., 2024; Koć-Januchta et al., 2020; Koć-Januchta et al., 2022; Lin & Ye, 2023). Therefore, all subject areas were evaluated separately. Consequently, the total number obtained in the analysis represented the total number of subject areas, not the total number of articles. The subject areas in the analyzed articles were coded independently by both authors. A total of 58 codes were generated after negotiation. A 98% (57 / 57 + 1) agreement was reached between the authors (Miles & Huberman, 2016). Similar codes were grouped to form themes. The themes were organized according to basic topics in biology education.

The themes were composed of concepts that best represented the codes. The themes were determined as (1) Biology Education and Teaching, (2) Animal Biology, (3) Cell Biology, (4) Evolution, (5) Biochemistry, (6) Genetics, (7) Plant Biology, (8) Ecology, and (9) Biodiversity and Classification of Living Organisms. Two experts, both professors in the biology education department at a state university, were consulted to ensure that the codes accurately represented these themes. The professors were given lists of codes (listed alphabetically) and themes (with brief descriptions). They were asked to independently match the codes to the themes. The Miles and Huberman (2016) formula was used to determine reliability. Accordingly, the agreement of the experts was determined as 98% (57 / 57 + 1) and 95% (55 / 55 + 3), respectively. Agreement was reached on the theme and code matching where there was disagreement.

The 58 codes and 9 themes identified as a result of the analysis were transferred to the MAXODA 2018 program. After completing the necessary coding, a map was created using MAXMaps. This map was based on the "Code-Subcode-Departments model." In this model, the themes represented the codes, the codes represented the subcodes, and biology education represented the department. All analyzed articles were related to biology education. Therefore, inclusiveness was taken into account in the selection of the department name. In the created map, each theme and its related codes were shown in a different color. The line widths of all connections in the map reflected the frequencies (Figure 6).

Figure 6 shows that studies on the use of artificial intelligence in biology education were grouped under 9 themes based on subject area, and these themes consisted of 29 codes with a total frequency of 58. The theme with the highest frequency was "Biology Education and Teaching" (f=13), followed by "Animal Biology" (f=10) and "Cell Biology" (f=8). In the "Biology Education and Teaching" theme, the codes with the highest frequencies were "To do practice," "Measurement and evaluation," and "Material development." In the "Animal Biology" theme, the code with the highest frequency was "Physiology." In the "Cell Biology" theme, the code with the highest frequency was "Structure and function of organelles." The theme with the lowest frequency was "Biodiversity and Classification of Living Organisms," which included two codes with the equal frequencies: "Classification of animals" and "Species."

Conclusions and Recommendations

In this study, a systematic review was conducted to determine the use of artificial intelligence in biology education and related trends. A total of 49 keywords were searched from the Web of Science, SCOPUS, ERIC, and IEEE Xplore databases. All articles retrieved from the search were stored in Zotero. Inclusion and exclusion procedures were applied based on the initially established criteria, first by title, then by abstract, and finally by full text. The entire process was summarized in the PRISMA diagram. 39 articles were included in the systematic review. The included articles were analyzed in terms of publication year, research method, country of conduct, study group, number of participants, subject area, artificial intelligence technologies used, artificial intelligence applications used, and outcomes.

Natural Language Processing (NLP) was found to be the most frequently used AI technology in articles on the use of artificial intelligence in biology education, followed by Machine Learning (ML) and Large Language Models (LLM). In their study, Salas-Pilco et al. (2022) examined the studies conducted between 2017 and 2021 on the use of artificial intelligence and learning analytics in teacher education. They reported that ML was the most commonly used artificial intelligence technology in the articles they reviewed. The results of this study are similar to the results of our study. In a study in which a systematic literature review was conducted on the use of artificial intelligence in English language teaching, articles published between 2015 and 2021 were analyzed. The analysis revealed that the AI technologies used in the reviewed articles were NLP, data mining, deep learning, decision tree, ML, cloud computing and edge computing, support vector machine, expert system, neural network, and genetic algorithms (Sharadgah & Sa'di, 2022). The results of this study are similar to the results of the current study in terms of the use of NLP and ML. Ouyang et al. (2022) conducted a study aiming to provide an overview of AI applications in online higher education. Designed as a systematic literature review, this study included studies using artificial intelligence in online higher education between 2011 and 2020. The analysis of the selected articles revealed that Decision Tree, Neural Network, Naive Bayes, and Support Vector Machine were the most frequently used AI Technologies in these articles. The usage rate of NLP technologies was determined to be 6.25%. The results of this study contradict the results of the present study. The different context and application areas focused on in the study by Ouyang et al. (2022) are considered to have a decisive impact on the types and usage rates of the AI technologies used. In studies using AI technologies in biology education, NLG and Generative AI are among the least preferred AI technologies. However, the use of Generative AI in educational contexts can offer many advantages. Specifically, it allows for the creation of personalized learning systems customized to students' learning styles and individual needs (Holmes et al., 2023). Similarly, GenAI models can be effectively used to produce interactive educational materials, enrich learning experiences, and simulate educational scenarios (Sengar et al., 2025). Therefore, it was observed that Generative AI technologies are used in only a limited number of studies in biology education, indicating a need for further research in this area.

The analysis of articles on the use of artificial intelligence in biology education according to the AI application used revealed that the theme with the highest frequency was "Chatbots and Question-Answer Systems," followed by "*Automated Assessment and Feedback*" and "*Basic Artificial Intelligence Techniques and Algorithms*" within the "*Chatbots and Question-Answer Systems*" theme, the code with the highest-frequency was "Educational chatbots." Articles using educational chatbots used platforms such as ChatGPT, Bard/Gemini, BingChat/Microsoft Copilot, and YouChat. Research on the use of ChatGPT in teaching and learning indicates that it offers numerous advantages, including advanced communication capabilities, versatility, natural language processing, performance evaluation, and text generation enhancement. However, the use of ChatGPT in teaching and learning also has several disadvantages, including error detection issues, plagiarism and originality concerns, privacy and data security risks, dependency, response quality, and bias (Ali et al., 2024). Another study investigating the use of ChatGPT in K-12 education similarly emphasized that ChatGPT offers significant advantages, such as facilitating educators' roles and responsibilities, creating instructional materials, lesson planning, and optimizing student learning experiences through personalized learning, but also drawbacks related to ethics, data privacy, and academic dishonesty. Additionally, the use of ChatGPT in K-12 education is considered potentially promising (Zhang & Tur, 2024). ChatGPT is seen as an effective AI tool for designing units, assessment criteria and exams in the field of science (Cooper, 2023). In a study analyzing articles using AI technologies in K-12 education between 2017 and 2022, it was reported that the AI technology applications used in the articles included virtual reality devices, machine learning modeling tools, chatbots, AI robots, and smart teachers (Martin et al., 2024). The results of this study are similar to the results of the current study. In a systematic review of studies on AI use in science education between 2014 and 2023, Almasri (2024) found that AI was used in areas such as exam creation, assessment, improving the learning environment, and predicting academic performance.

The results of the study conducted by Almasri (2024) are consistent with the themes identified in the current study (*Chatbots and Question-Answer Systems, Automated Assessment and Feedback, Learning Analytics and Predictive Models*). Aripin et al. (2024), in their study on the use of artificial intelligence in biology and biology learning, identified AI technology models used in biology education as adaptive modeling, experience point data modeling, interactive books, smart classrooms, and virtual laboratories. In this context, they indicated that AI in biology learning encompasses assessment and evaluation, instructional media, virtual classrooms, enrichment of learning, teaching assistance, and learning aids. These categories determined by Aripin et al. (2024) are consistent with the themes identified in the current study (*Educational Games, Intelligent Tutorial Systems and Personalized Learning, Knowledge-Based Systems, Automated Assessment and Feedback*). Similarly, in a systematic review of studies on AI use in science teaching and learning between 2010 and 2021, it was found that the most frequently used AI applications were automated assessment and feedback, predictive modeling, and personalized learning (Heeg & Avraamidou, 2023). These categories align with the themes identified in the present study (*Automated Assessment and Feedback, Learning Analytics and Predictive Models, and Intelligent Tutorial Systems and Personalized Learning*).

Based on the analysis of articles on the use of artificial intelligence in biology education within the scope of this study, the theme with the highest frequency was identified as "Educational Technology and Tool Development Outcomes," followed by "*Cognitive Learning Outcomes*" and "*Affective and Motivational Outcomes*". The themes with the lowest frequency were "*Metacognitive and Strategic Outcomes*" and "*Assessment and Feedback Outcomes*". The most frequent code under the "*Teacher and Institutional Outcomes*" theme was "Teacher Workload & Assessment Quality," which included AI technologies used to reduce teacher workload in tasks such as reviewing students' written responses (Beggrow et al., 2014; Beigman, et al., 2017; Ha et al., 2011; Haudek et al., 2012; Jescovitch et al., 2021; Jho & Ha, 2024; Moharreri et al., 2014; Sripathi et al., 2023). Teachers can increase efficiency and effectiveness in tasks such as grading student assignments and providing feedback through the use of AI, which in turn leads to improved teaching quality (Chen et al., 2020). In their systematic review of articles on AI use in science teaching and learning, Heeg and Avraamidou (2023) stated that AI applications can alleviate the workload of science educators, increase students' interest in science through personalized learning environments, and optimize teaching processes to improve low learning outcomes in science classes. The categories identified by Heeg and Avraamidou (2023) are consistent with the themes identified in the current study (*Teacher and Institutional Outcomes, Affective and Motivational Outcomes, Cognitive Learning Outcomes, Educational Technology and Tool Development Outcomes*).

The number of articles on the use of artificial intelligence in biology education has gradually increased over the years, with a particularly sudden rise in 2021, and the highest number of articles was conducted in 2024. Lidiastuti et al. (2025) analyzed studies published between 2000 and 2025 through a bibliometric analysis in order to investigate the role of artificial intelligence in improving biology education. According to the results of the study, the use of artificial intelligence in biology education shows an increasing trend over the years, with the most significant increase occurring since 2018. They found that the highest number of articles was conducted in 2023. In a study analyzing articles using artificial intelligence technologies in K-12 education between 2017 and 2022, it was determined that the use of artificial intelligence technologies in K-12 education increased after 2019, with the peak in 2021 (Martin et al., 2024). A systematic review of articles using AI in student assessment from 2010 to 2020 indicated that the number of articles was higher between 2015 and 2020 (González-Calatayud et al., 2021). In a study conducted by Zhai et al. (2021), articles on the use of artificial intelligence in education between 2010 and 2020 were examined and it was determined that the use of artificial intelligence has increased over the years, with the highest number of studies being conducted especially in 2020. Almasri (2024), in a systematic review of AI use in science education from 2014 to 2023, similarly found that AI applications in science education increased over time, with the peak in 2023. Therefore, the results of the current study were found to be consistent with the literature.

In this study, it was determined that quantitative methods were generally used in the articles on the use of artificial intelligence in biology education, while qualitative methods were the least used research methods. Similarly, Zhai et al. (2021), in their study aiming to examine how artificial intelligence is applied in education and the trends in this area, analyzed studies using artificial intelligence in education between 2010 and 2020 and reported that quantitative research was predominant in studies on the use of artificial intelligence in education. In a study analyzing articles on the use of artificial intelligence technologies in K-12 education between 2017 and 2022, it was determined that qualitative methods were generally used in the articles, followed by quantitative methods (Martin et al., 2024). The results of the study by Martin et al. (2024) contradict the results of the current study. This is thought to be due to the difference in their focus areas. While the current study focused on biology education studies, Martin et al. (2024) focused on K-12 education.

In a study examining the articles on the use of artificial intelligence and learning analytics in teacher education between in the current study, it was determined that the most articles on the use of artificial intelligence in biology education were conducted in the United States, followed by China and Taiwan. Lidiastuti et al. (2025), in their bibliometric analysis of AI applications in biology education between 2000 and 2025, similarly reported that the highest number of publications was conducted in the United States, followed by China and Germany. In a systematic review of articles on the use of AI for student assessment between 2010 and 2020, it was determined that most studies were conducted in the United States according to the origins of the article authors (González-Calatayud et al., 2021). In a study analyzing articles on the use of AI technologies in K-12 education between 2017 and 2022, it was reported that most studies were conducted in the United States, followed by Korea and Brazil (Martin et al., 2024). 2017 and 2021, it was found that most studies were conducted in China, followed by the United States, Germany, and Canada (Salas-Pilco et al., 2022). In a study examining the articles on the use of artificial intelligence in science, it was determined that the country where the most studies were conducted was the United States, followed by Germany (Almasri, 2024). Therefore, the results of the current study were found to be consistent with the literature.

It was found that the study group of articles on the use of artificial intelligence in biology education mostly consisted of university students, followed by high school and middle school students. In a systematic review examining the articles on the use of artificial intelligence in education between 2010 and 2020, it was found that the study group in the articles mostly consisted of university students (Zhai et al., 2021). In another systematic review examining AI applications in education from 1984 to 2022, it was found that the study group of nearly half of the articles consisted of higher education students (Wang et al., 2024). In a study examining the articles using artificial intelligence in English language teaching between 2015 and 2021, it was found that the study group in the articles were generally higher education students (Sharadgah & Sa'di, 2022). In a study analyzing the articles on the use of artificial intelligence technologies in K-12 education between 2017 and 2022, it was determined that the study group of the articles consisted mostly of high school students (Martin et al., 2024). In a study examining articles on the use of artificial intelligence and learning analytics in teacher education between 2017 and 2021, it was determined that the study group of the articles generally consisted of pre-service teachers (PSTs) (Salas-Pilco et al., 2022). Almasri (2024), in a systematic review of AI use in science education between 2014 and 2023, found that studies were mostly conducted with undergraduate students, followed by high school and middle school students. Therefore, the results of the present study are consistent with the existing literature.

The number of participants in articles on the use of artificial intelligence in biology education was determined to be minimum 5 and maximum 4,937. The average number of participants in articles on the use of artificial intelligence in biology education was found to be 499. The studies on the use of artificial intelligence in biology education were categorized into 9 themes according to their subject areas [(1) Biology Education and Teaching, (2) Animal Biology, (3) Cell Biology, (4) Evolution, (5) Biochemistry, (6) Genetics, (7) Plant Biology, (8) Ecology and (9) Biodiversity and Classification of Living Organisms]. The theme with the highest frequency was "Biology Education and Teaching", followed by the themes "Animal Biology" and "Cell Biology". When evaluated according to the main topics included in the works "*Campbell Biology*" and "*Life: The Science of Biology*", which are accepted as fundamental in biology education and accepted worldwide, it was seen that there is insufficient research on the evolutionary history of biological diversity and the models and processes of evolution. (Sadava et al., 2014; Urry et al., 2022).

Overall, it can be concluded that the use of artificial intelligence in biology education is becoming increasingly widespread; however, not all technologies and applications are being utilized yet, and studies generally focus on chatbot and response system applications. The literature lacks sufficient studies on AI-supported educational games and simulations in biology education. In this context, it is recommended that the use of AI technologies in biology education be expanded through educational games, which are frequently used to motivate students and encourage learning, and simulations, which can be developed for various topics in biology education. For instance, AI-supported activities can be created to illustrate historical processes and geological periods that people cannot directly experience in their daily lives, such as natural selection, adaptation, and evolution. Additionally, mass extinction events can be simulated using AI. Researchers aiming to conduct studies on the use of AI in biology education are encouraged to address the gaps identified in the literature, specifically focusing on the "evolutionary history of biodiversity" and the "models and processes of evolution."

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest.

Acknowledgements or Notes

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A Comprehensive Bibliometric Analysis of Artificial Intelligence Research in the Field of Science Education

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Abstract

Today, the importance of artificial intelligence in science learning and teaching is rapidly increasing. The growing interest in this field and the resulting increase in academic publications on the subject make it challenging to understand its progress and trends on a global scale. Furthermore, a literature review reveals a notable lack of studies that offer a comprehensive perspective, reflecting the current state and research trends in this field. Therefore, this study aims to analyze the current state, evolution, and important research trends in studies on artificial intelligence in science education from 1985 to 2024, utilizing bibliometric methods. To this end, a total of 169 articles were analyzed from the Web of Science database using specific keywords. Analytical tools such as VOSviewer and SciMAT software were used for data visualization. The results indicate that research on artificial intelligence in science education from 1985 to 2024 has developed irregularly, with significant growth occurring in recent years. The country with the highest citation and production levels in this research field is the United States. The most productive journals in the area are the Journal of Science Education and Technology, Frontiers in Education, and the Journal of Research in Science Teaching. The leading authors are Cooper, G., and Zhai, X. Keyword analysis showed that "science education," "computer science education," "machine learning," "artificial intelligence assessment," "ChatGPT," and "learning analytics" are among the most frequently used terms and highlight emerging thematic clusters. Furthermore, this analysis showed that while artificial intelligence research in science education was initially more limited and focused on technology-related themes, it has recently shifted toward a research direction that includes learning analytics, interactive learning environments, computational thinking, and large language models. The results offer a guiding framework and valuable insights for practitioners and education researchers seeking direction in the evolving landscape of artificial intelligence in science education.

Introduction

In an era of rapid advances in information technology, artificial intelligence (AI), although a relatively recent scientific and technological field, has played a significant role in society's increasing digitization due to its rapid development in recent years (Jia et al., 2024). This important role has not only transformed many aspects of our daily lives and professional practices but has also had a comprehensive and profound impact on education (Guo et al., 2024; Song & Wang, 2020).

The integration of AI technologies into educational environments presents significant opportunities to enhance the quality and effectiveness of education in numerous areas, including personalized learning systems, automated assessment and feedback processes, virtual reality, chatbots, facial recognition systems, and innovative classroom systems. It also has the potential to transform and enhance traditional teaching and learning models (Akgun & Greenhow, 2021; Guo et al., 2024, Saydullayeva, 2025).

Science education plays a crucial role in equipping individuals with the skills they need to succeed in an increasingly complex and technology-driven world (Shofiyah et al., 2025). Science education is a practice-oriented learning field that involves abstract concepts, complex or challenging tasks, and requires higher-level cognitive skills. Utilizing AI-driven applications to improve learning outcomes in science education presents promising results for all ages and backgrounds. AI-driven virtual laboratories and simulations allow for safe and controlled execution of experiments that could be dangerous or expensive in a traditional classroom.

These virtual situations provide opportunities for students to explore scientific concepts and apply and develop their scientific skills (Ibáñez & Delgado-Kloos, 2018; Wahyono et al., 2019). AI applications enhance learning effectiveness by offering more comfortable, personalized, and interactive learning experiences tailored to each student's individual needs, skills, and learning preferences (Cooper, 2023; Dolenc & Aberšek, 2015). Furthermore, AI technologies can make science education more enjoyable, accessible, and engaging for students by providing them with interesting and immersive learning content, thereby eliminating the tediousness of teaching (Chen & Chang, 2024; Elkhodr et al., 2023). Additionally, AI-driven tools accelerate the learning process for students by providing detailed and timely feedback, and automated assessments relieve teachers of some of their excessive workload (Maestrales et al., 2021; Zhai et al., 2020). AI-driven tools, such as virtual assistants and chatbots, help students become more cognitively engaged in the learning process and encourage high motivation (Lee et al., 2022; Ng et al., 2024). AI recognizes students' emotional states, performance, and success levels in science classes, offering targeted intervention and support (Almeda & Baker, 2020; Çetinkaya & Baykan, 2020). Additionally, AI applications significantly help develop students' skills in problem solving, computational thinking, creative thinking, collaboration, STEAM literacy, and digital literacy (Irwanto, 2025).

Today, an increasing number of researchers are investigating the impact of incorporating AI technologies into science education on student learning. Evidence shows that AI technologies have noticeable effects and advantages in renewing and supporting the teaching and learning of science content, and improving learning outcomes, (Almasri, 2024; Heeg & Avraamidou, 2023). However, while the integration of AI into education holds tremendous promise, it also raises issues such as algorithmic bias, digital dependency, student competencies, ethical, social, and technical concerns, as well as teacher resistance (Adams et al., 2022; Garzón et al., 2025).

The increasing interest on AI technologies and its potential within science education community necessitates to cast a lens on how use of AI technologies impacts education. Consequently, to capture a complete picture, studies are needed to understand the current state and developments in the field and to identify supporting and guiding trends. However, few studies in the existing literature thoroughly examine the work related to AI in science education within global educational contexts, highlighting the trends, research gaps, and collaboration networks in the field especially from a review and bibliographic analyses perspective. Existing research presents a vague picture of AI use in science education with diverse approaches used on how to approach the problem.

Almasri (2024) conducted a systematic review of 74 empirical studies published between 2014 and 2023, focusing on the effects, perceptions, and challenges encountered in integrating AI into science teaching and learning. His research offers a comprehensive overview of the potential advantages and challenges of applying AI in science education settings. The research findings suggest that incorporating AI into science education has a positive impact on student learning outcomes, fosters participation in the learning process, and enhances student motivation. Heeg and Avraamidou (2023) conducted a systematic literature review to examine the current state of AI use in school science, analyzing 22 studies published in four international databases between 2010 and 2021. Their findings revealed that nine different AI applications were used, with most studies focusing on geoscience and physics, and that these applications were used to support knowledge construction or skill development. Jia et al. (2024) examined 76 articles indexed in the Web of Science (WoS) and Scopus from 2013 to 2023, using bibliometric and content analysis to identify the key role of artificial intelligence in science education at the primary and secondary levels, and to explore research trends. Their research showed that AI in science education has grown a lot in the last ten years. Atmaca-Aksoy and Irmak (2024) analyzed 89 studies retrieved from WoS databases using VOSviewer software in their research-on-research trends of articles on science education and AI, employing bibliometric methods. The study included research on annual publication trends, the most frequently used keywords, the most productive journals, countries, institutions, highly cited authors, and studies. Similarly, Genç and Koçak (2024) conducted a bibliometric study on publications related to AI in science education published in WoS between 2019 and 2023 by analyzing the scientific literature in the same year. Ayuni et al. (2024) conducted a bibliometric review of 146 documents published in Scopus from 1975 to 2024, utilizing the R program and VOSviewer to identify research trends in AI in science education. Akhmadieva et al. (2023) examined 202 publications on AI in science education published in Scopus, using bibliometric analysis to reveal the current state of the research field. Finally, Arıcı (2024) conducted a similar bibliometric analysis to examine trends in 80 articles in the current field listed in WoS.

Previous bibliographic analyses and review studies offer a broad overview of AI research in science education. However, differences in methodology such as literature selection, article inclusion criteria, and software used as well as limited sample sizes and short time frames, expose partial inconsistencies in research trends or limitations on understanding the bigger picture. To address this critical gap in literature, this article aims to conduct a bibliometric analysis to deeply examine the insights of research on AI in science education, thereby revealing the evolution of the field, its current state, and future research directions. To reach this goal, the following research questions were tackled:

1. What is the distribution of AI research in science education over the years, and what are the citation trends?
2. Which countries contribute the most to AI research in science education?
3. What were the productive journals that contribute to publishing research on AI in science education?
4. Who are the leading authors in AI research in science education?
5. What are the key research themes in AI within science education, and how are the related sub-themes shaped?
6. How have the main themes in AI research within science education evolved over time?

Method

Bibliometric analysis is a quantitative methodology used to analyze the information structure of publications in a specific research field, providing a comprehensive and global overview of the existing literature (Guo et al., 2024; Ulukök Yıldırım & Sönmez, 2024). Bibliometric studies provide a quantitative, measurable, and unbiased method to assess a study's contribution to the advancement of knowledge (Panday et al., 2025). This study employed bibliometric analysis to identify dominant trends, recent developments, and emerging themes from 1985 to 2024 aiming to deepen the understanding of research on artificial intelligence in science education. By examining an extensive time span, it provides a comprehensive overview of the field's evolutionary process and transformations in research topics.

Data Collection

A thorough online search was performed using the WoS database to gather relevant literature. The WoS database was chosen as it provides a comprehensive and reliable range of bibliometric data worldwide and is often used as the main data source in many bibliometric studies in the literature (Tonbuloğlu & Tonbuloğlu, 2023; Ulukök, 2022). To conduct a comprehensive literature search and ensure its accuracy, previous studies were reviewed, and research-specific keywords were identified (Heeg & Avraamidou, 2023; Jia et al., 2024). A search query was performed using the following search string (see Table 1) in the topic field based on the identified keywords. Following the final search conducted in September 2025, 1168 documents were initially retrieved. Following the filtering of the initial search results based on the categories including “Education and Educational Research,” “Education Scientific Disciplines,” “Education Special,” and “Psychology Educational,” the dataset was narrowed down to 741 publications. Articles published in 2025 were excluded from the study as they do not represent the whole year and the total number of articles was reduced to 642.

Article type was used as a second filter and non-article types, including conference papers, books and book chapters and editorial letters, were excluded, narrowing the selection to 296 articles. Language and citation index were other filters used to select articles. Non-English publications were removed, leaving a dataset of 287 articles. Only the articles indexed in ESCI, SSCI, SCI-Expanded, and A&HCI were included, resulting in a total of 284 articles. Finally, a manual review of the database-identified documents was conducted. Articles from disciplines unrelated to the topic, such as medical education, engineering education, and information science, were excluded. Ultimately, 169 articles published in English relevant to the study were included in the final dataset. The selected articles were downloaded in “plain text” format for processing with the tools used in this study. Details of the search strings are presented in Table 1.

Table 1. The search string for the research

Search within	Search string
Title, Abstract, and Keywords	Search within: Title, Abstract, and Keywords Search Keywords: (“artificial intelligence” OR “AI” OR “AIED” OR “machine learning” OR “intelligent tutoring system” OR “expert system” OR “recommended system” OR “recommendation system” OR “feedback system” OR “personalized learning” OR “adaptive learning” OR “prediction system” OR “student model” OR “learner model” OR “data mining” OR “learning analytics” OR “prediction model” OR “automated evaluation” OR “automated assessment” OR “robot” OR “natural language processing” OR “virtual agent” OR “algorithm” OR “machine intelligence” OR “intelligent support” OR “intelligent system” OR “deep learning” OR “AI education”) AND (“science educat*”)

Data Analysis

This study used a combination of open-source SciMAT v1.1.06 and VOSviewer version 1.6.20 software for bibliometric analysis and visualization. The reasons for choosing VOSviewer and SciMAT software are that they offer comprehensive analysis capabilities, provide professional-level data visualization, and are freely accessible. The VOSviewer software, developed by Van Eck and Waltman (2010) for the creation and visualization of bibliometric networks, utilizes a distance-based mapping technique to display elements. The program enables text mining based on keywords and terms in abstracts, citation and co-citation analyses, as well as overlaying, cluster density, and visualization of network maps (Van Eck & Waltman, 2020). Additionally, SciMAT, a powerful scientific mapping and data analysis software, allows for visualization of scientific fields over time through co-word analysis, allows detailed insights into research themes within a specific domain, and enables tracking the development of these themes across different periods (Liu et al., 2024).

VOSViewer software was used to perform citation analysis based on countries, journals, and authors, to conduct keyword analysis, and to create visual representations. In this way, the most productive journals, the most frequently used keywords, the countries that contributed the most, and the leading authors were identified. Detailed keyword analyses of the included publications were conducted and visualized using SciMAT software. For each study period, a graphical representation of the themes in the strategic diagrams and cluster networks was created, showing the thematic evolution of the research field over time. Figure 1 provides an example of such representations.

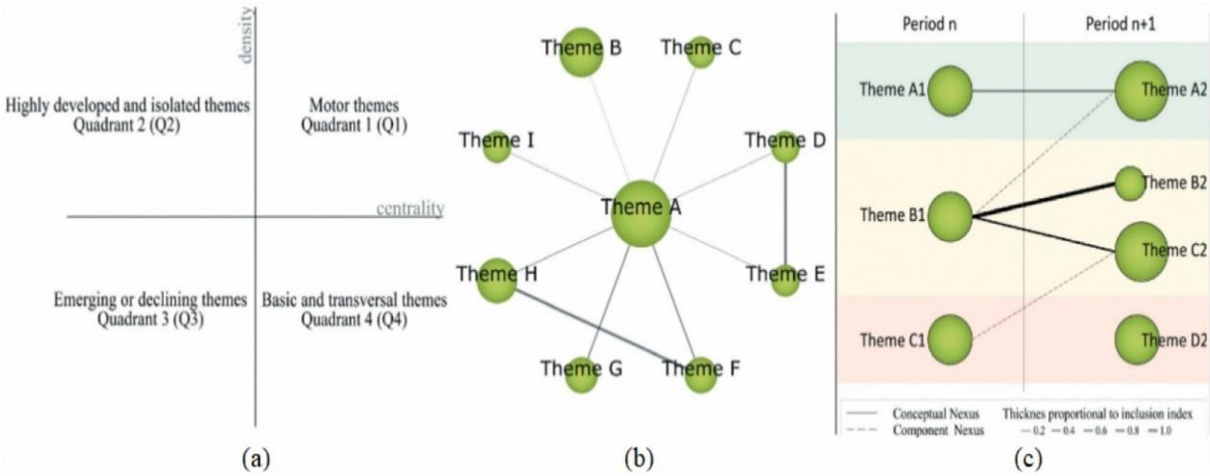

Figure 1. Example of a strategic diagram (a), example of a thematic network (b), and example of a thematic evolution map (c) (adapted from Viedma et al., 2020)

The strategic diagram (Figure 1(a)), a two-dimensional map divided into four quadrants, is created by considering two parameters: centrality, shown on the horizontal axis, which measures the level of interaction of one network with others, and density, shown on the vertical axis, which indicates the internal strength of the network (Cobo et al., 2011). In the strategic diagram (Figure 1(a)), the themes in the upper right quadrant are considered the motor themes of the field. These represent the most important and highly debated topics, characterized by high centrality and density. The upper left quadrant contains highly developed and isolated themes, characterized by low centrality and high-density values. Although these themes are highly specialized, they are not important for the field. The lower left quadrant contains themes that are emerging or declining over time. With low centrality and density values, these themes are considered weakly developed and marginal. Finally, the bottom right quadrant contains basic and transversal themes with low density and high centrality values. Despite their limited development, these themes are highly relevant to the research field (Özköse, 2023). This diagram clusters themes for each analysis period, helping to determine the significance of different themes (Jiménez et al., 2024).

Thematic networks (Figure 1(b)) illustrate the cohesion among research themes and emphasize the strength of the relationships between these themes (Severo et al., 2021). The change in themes over time is shown using a thematic evolution map (Figure 1(c)). In this thematic evolution map, the size of the green circles indicates the number of documents associated with each theme. Continuous lines between clusters represent themes sharing the same keywords as the theme itself, while dashed lines represent themes sharing common keywords other than the theme itself. The thickness of these lines indicates the inclusion index and shows the strength of the connection between two themes (Karakose et al., 2024; Liu et al., 2024).

Results

Annual Scientific Production

Figure 2 illustrates the yearly scientific output and citation distribution of publications related to AI in science education from 1985 to 2024.

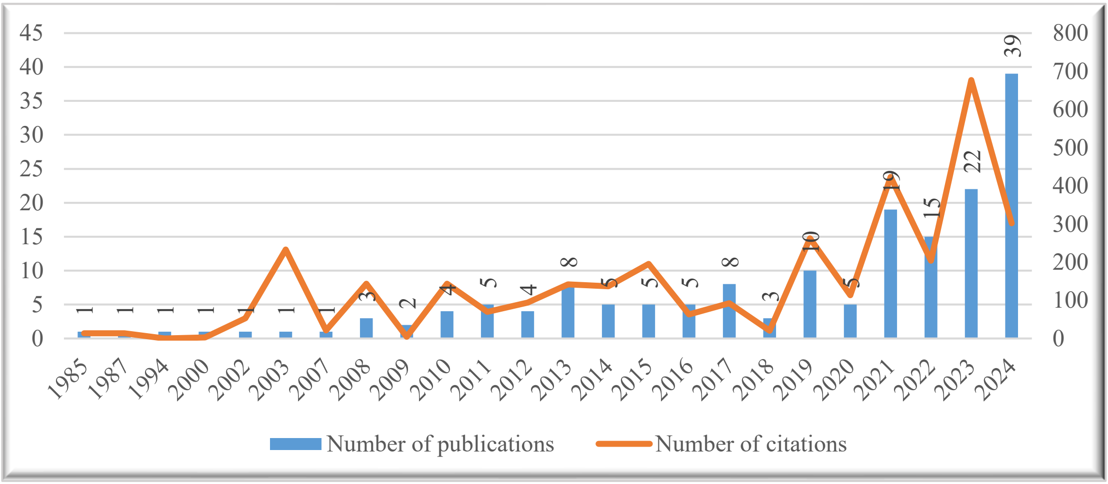

Figure 2. Distribution of publications and citations over the years

As shown in Figure 2 the first publication in this research area appeared in 1985. From that year until 2009, the number of publications remained low, with only a few articles published each year. Between 2010 and 2018, annual publication rates increased slightly, varying between 4 and 8 publications per year. In 2019, the number of publications reached double digits for the first time. Although a slight decline was observed in 2020, a general upward trend in AI-related science education research has continued since then. The highest number of publications was recorded in 2024, with a total of 39 articles published during that year. Overall, data reveal a fluctuating trend, yet upward trend characterized by periodic increases and decreases in publication numbers. This observed pattern reflects the growing interest in AI within science education, notable expansion of research activity, and the dynamic evolution of the field. Regarding the annual citations counts, citation trends have also risen in recent years, peaking in 2023 with 677 citations. The second-highest citations count occurred in 2021, with 423 citations.

Analysis of Country/Region Distribution

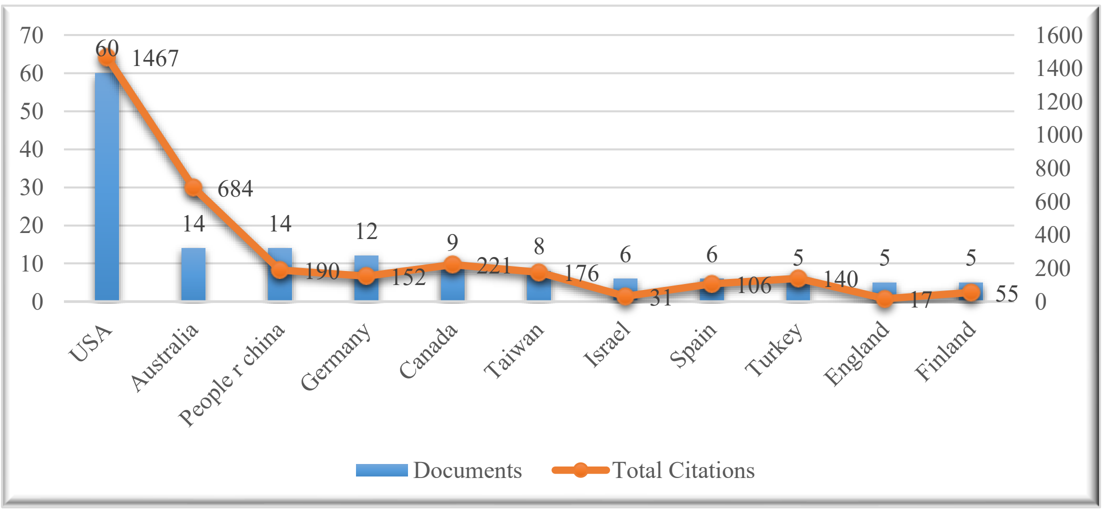

Figure 3. Distribution of citations and publications by country

VOSviewer analyses of scientific articles published in the field of AI in science education between 1985 and 2024 revealed that 37 countries have contributed to this area. Figure 3 presents detailed information on the top 11 countries that published the highest number of articles and received the greatest number of citations. As shown in Figure 3, the United States stands out as the most productive country with 60 publications, demonstrating the dominant position of its research in the field. Australia (14), the People's Republic of China (14), Germany (12), Canada (9), and Taiwan (8) follow. Israel and Spain each have six publications, while Turkey, England, and Finland also show significant participation. When it comes to the countries with the most citations, the United States clearly leads with 1,467 citations, while Australia and Canada rank in the top three with 684 and 221 citations, respectively. Turkey, in particular, has made significant contributions to this research by generating a notable citation impact with five articles, despite its low publication volume. Meanwhile, the co-authorship network between countries created using VOSviewer is shown in Figure 4. At least three documents per country were identified in the analysis. It is evident that the 19 countries meeting this criterion actively engage in related research and contribute significantly to the advancement of the field.

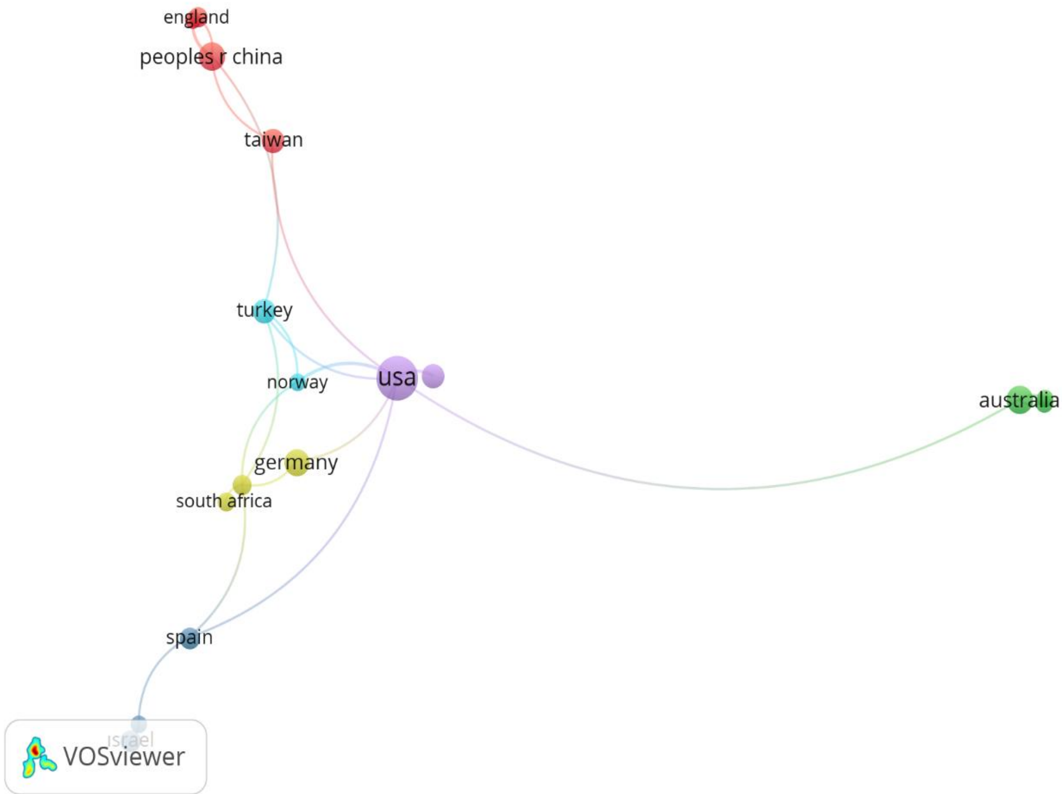

Figure 4. Co-authorship networks of countries

As shown in Figure 4, six distinct clusters were formed. The United States, which interacts with all clusters with a total link strength (TLS) of 9, emerges as the most collaborative country. Following the United States, Finland and China with a TLS of 5 each, and Norway and Turkey each with a TLS of 4, are among the other prominent contributing countries in this field. In contrast, countries such as the United Kingdom and Israel are represented by only one TLS each within the network, demonstrating a very limited level of collaboration.

Productive Journals

Figure 5 presents data on the most productive journals publishing scientific articles in the field of artificial intelligence in science education, along with the number of articles published in each. The Journal *of Science Education and Technology* ranks first with 18 articles published with a focus on AI in science education. *Frontiers in Education, Journal of Research in Science Teaching, Research in Science Education,* and *Education Sciences* have also made significant contributions to literature in this field. Overall, research on this topic has been published in a range of journals encompassing diverse thematic areas, including educational technology, science education, and interdisciplinary studies.

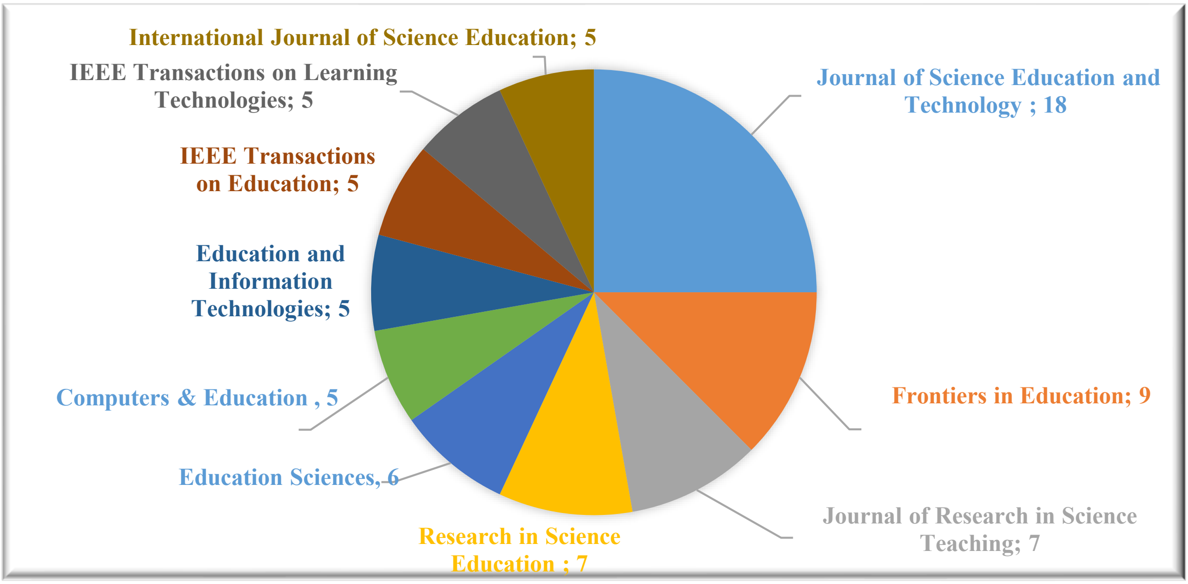

Figure 5. Most productive journals

Leading Authors in Terms of Productivity and Citations

In the citation analysis, which included authors with at least two publications, 27 authors met the criteria. Table 2 presents the number of articles and citations for 10 authors who have contributed to research on AI in science education.

Table 2. Leading authors in AI research in science education

Author	Documents	Citations
Zhai, X.	7	170
Nehm, R. H.	4	117
Huang, X.	3	35
Xie, C.	3	35
Cooper, G.	3	529
Tang, K.	3	46
Boone, W. J.	2	128
Chin, D. B.	2	86
Dohmen, I. M.	2	86
Schwartz, D. L.	2	86

As shown in Table 2, Zhai, X., Nehm, R. H., Huang, X., Xie, C., and Cooper, G. stand out as prolific authors who have made significant contributions to the knowledge base in this field. Cooper, G., in particular, is the most cited researcher with 529 citations across three articles. Zhai, X., Boone, W. J., Nehm, R. H., Chin, D. B., Dohmen, I. M., and Schwartz, D. L. are among the other most cited researchers in the field.

Keyword Analysis

Author keywords from the WoS dataset were analyzed using VOSviewer, and the resulting co-occurrence network is shown in Figure 6. Keywords that appeared at least twice were included to create a co-occurrence network. Out of 575 keywords, 24 met this criteria. Network analysis indicating the most frequently used keywords as "science education" (Occurrences: 46; TLS: 41), "computer science education" (21; 19), "machine learning" (19; 20), "artificial intelligence" (14; 19), "assessment" (10; 11), 'chatgpt' (9; 11), and "learning analytics" (9; 10). Figure 6 shows that the author's keyword network analysis reveals a structure made up of five clusters, each representing a different research theme. Cluster 1 (7 items, red) includes keywords such as computational thinking, computer science education, STEM education, engineering education, and educational technology.

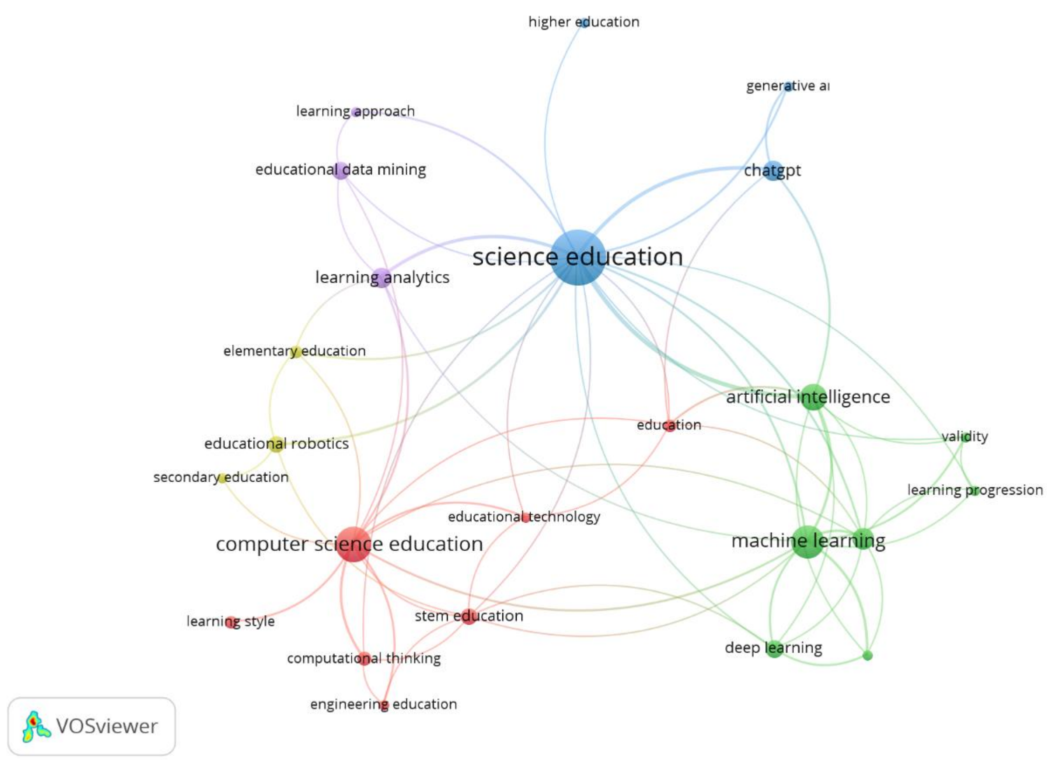

Figure 6. Co-occurrence network of the author's keywords

This cluster concentrates on incorporating AI-related tools into STEM and computer science education, with a special focus on developing students' computational thinking skills. Cluster 2 (7 items, green) features keywords such as artificial intelligence, machine learning, deep learning, natural language processing, assessment, learning progression, and validity. It emphasizes research on measurement, evaluation, and learning analysis in science education using AI. Cluster 3 (4 items, dark blue) contains keywords ChatGPT, generative AI, higher education, and science education, indicating that new technologies, including generative AI and large language models, are being integrated into science education, especially at the higher education level. Cluster 4 (3 items, yellow) mainly centers on AI in science education for early age groups and robotic applications, with keywords including educational robotics, elementary education, and secondary education. Finally, Cluster 5 (3 items, purple) includes keywords such as learning analytics, educational data mining, and learning approach. This cluster encompasses studies in science education that utilize AI to monitor learning processes, conduct data-driven analysis, and evaluate learning approaches.

Structural and Thematic Development

The evolution of keywords for each specified analysis period provides information about the overlap level of keywords. An upward slanted arrow indicates keywords eliminated in the next period; a downward slanted arrow shows keywords included in the new period; the horizontal arrow pointing to the right signifies keywords overlapping between periods. The circles represent the keywords of a period. Figure 7 shows the evolution of keywords across different time periods. The time periods were determined based on the number of published articles and the developmental stages of the research field. Three distinct periods were examined: 1985–2010, 2011–2018, and 2019–2024.

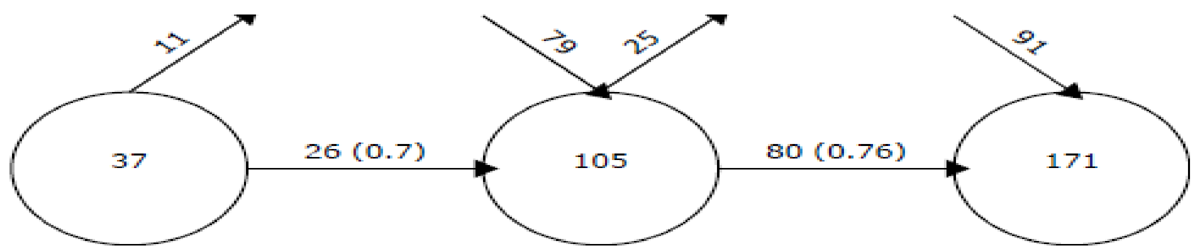

Figure 7. Continuity of keywords between intervals

As shown in Figure 7, the overlap level of keywords between periods is above 70%. These data highlight the thematic consistency of artificial intelligence research in science education across successive periods, while also indicating a dynamic change in terminology, particularly in the most recent period. The themes for each sub-period have been visualized using strategic diagrams to reveal changes in trends related to AI research in science education over time.

Period 1 (1985-2010)

The 16 articles published in first period between the years 1985 and 2010 were examined, and the analysis identified five key strategic themes. Details about these themes are provided in Figure 8.

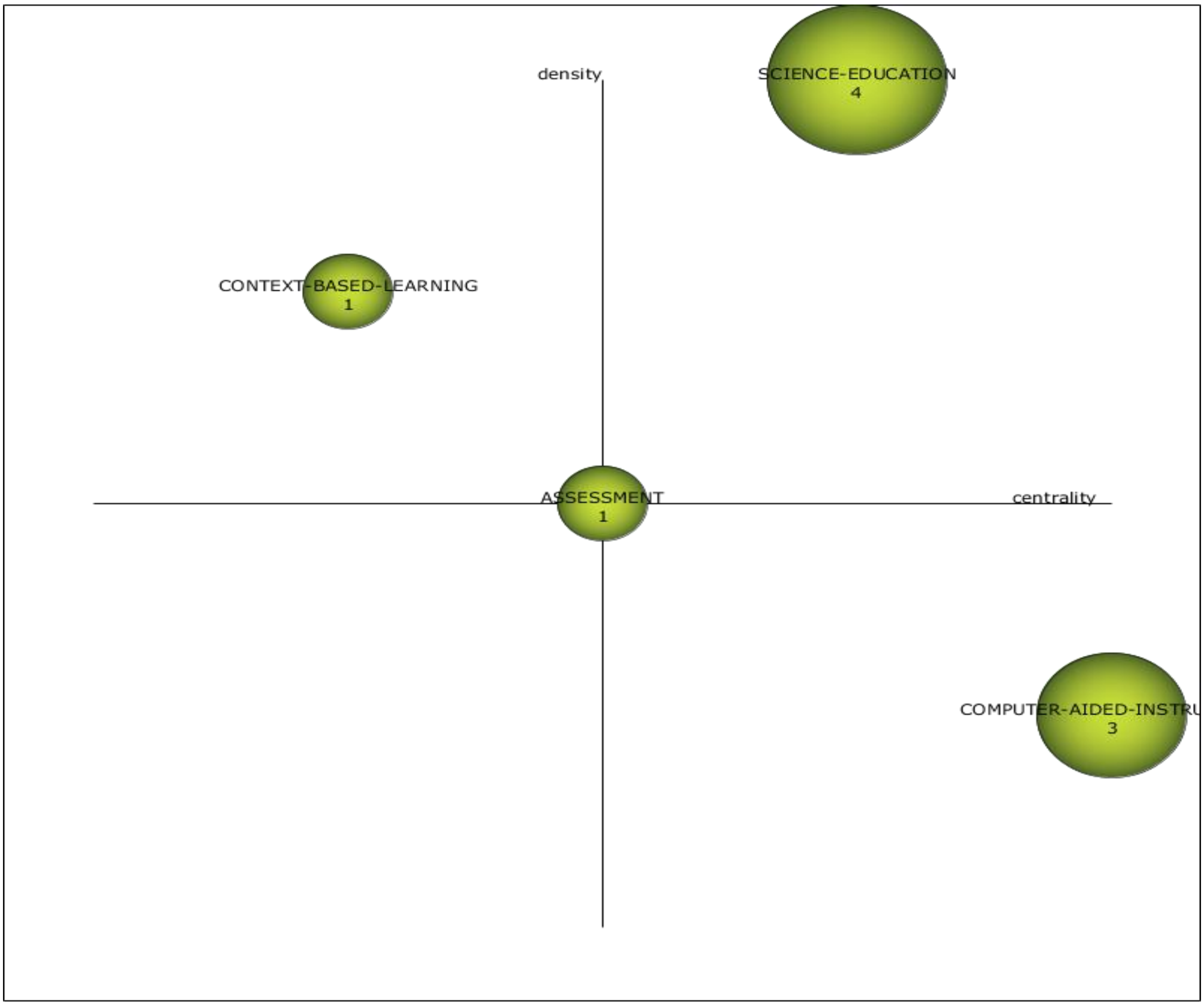

Figure 8. Period 1 (1985–2010) strategic diagram (h-index)

As shown in Figure 8, the theme with the highest bibliometric value is "science education," followed by the theme "computer-aided instruction." Since the "science education" theme is located in the upper right quadrant, it stands out as the primary driving or pioneering theme of the period. "Context-based learning" appears as a highly developed and isolated theme, whereas "computer-aided instruction" is a basic and transversal theme. Moreover, the "assessment" theme suggests that measurement and evaluation applications in AI-supported learning environments were also addressed during this period. A comprehensive analysis of the "science education" motor theme and related sub-themes are presented in the thematic network structure in Figure 9.

As shown in Figure 9, the cluster network of the "science education" theme is connected to the sub-themes "ability," "achievement," "self-efficacy," "classroom," "instruction," "instructional-design," "inquiry," "motivation," "perceptions," "personalized-learning," "machine learning," and "automated-assessment." Therefore, it can be concluded that research on AI in science education during this period mainly focused on the technological aspects, assessment systems, and the integration of various pedagogical processes.

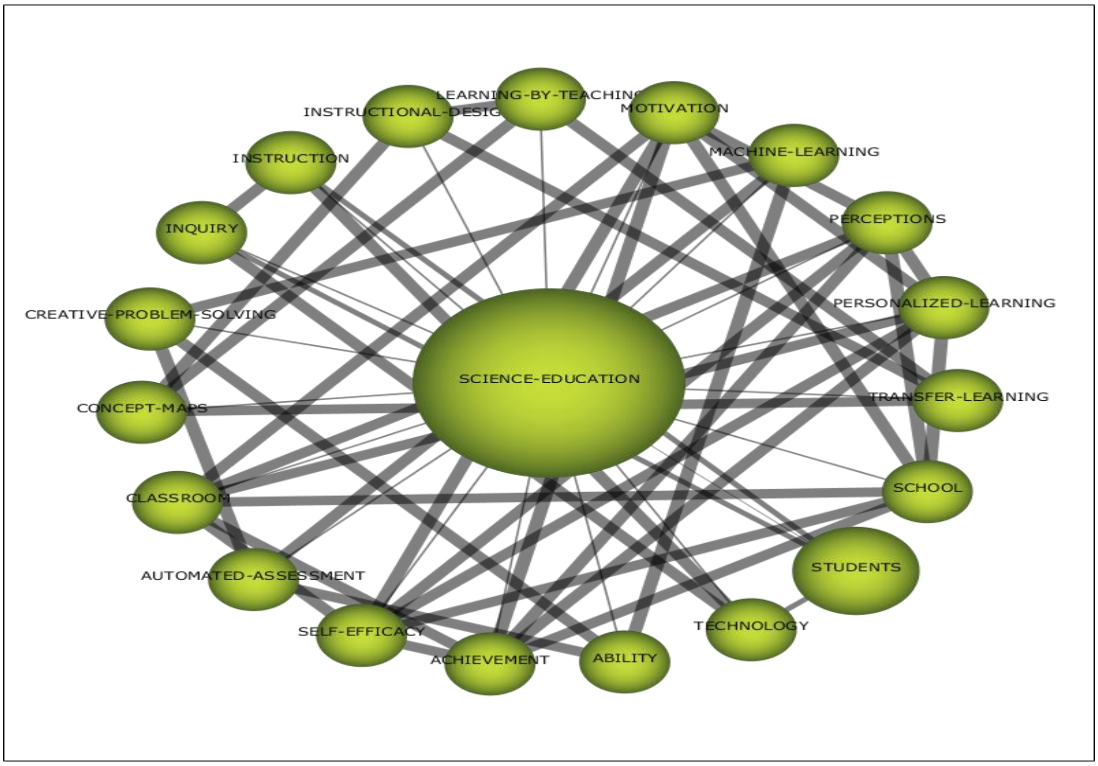

Figure 9. Thematic network structure of the motor theme in Period 1

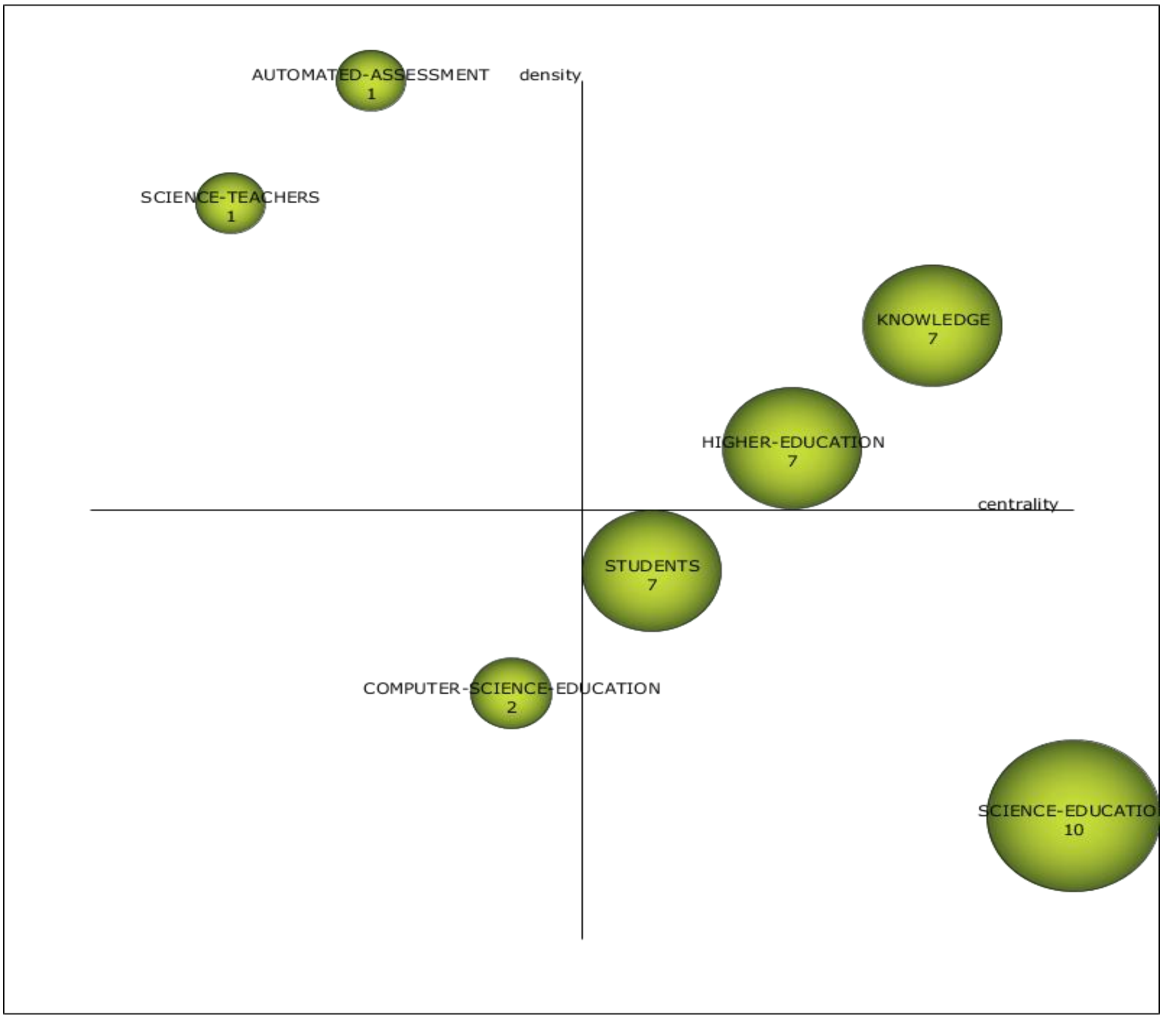

Figure 10. Period 2 (2011-2018) strategic diagram (h-index)

Period 2 (2011-2018)

The second period encompasses 43 articles published between 2011 and 2018, and the analysis identified seven strategic themes. Details about these themes are shown in Figure 10. In the second period (2011–2018), the theme with the highest bibliometric value is again "science education." This is followed by the themes "students," "knowledge," and "higher education." The motor themes of this period are "knowledge" and "higher education." "Automated assessment" and "science teachers" are highly developed and isolated themes. "Science education" and "students" are basic and transversal themes. Studies conducted in the field of science education on AI during this time period indicate that higher education is the educational level most strongly influenced by this technology. The thematic network structures of the two motor themes identified in Period 2 are presented in Figure 11.

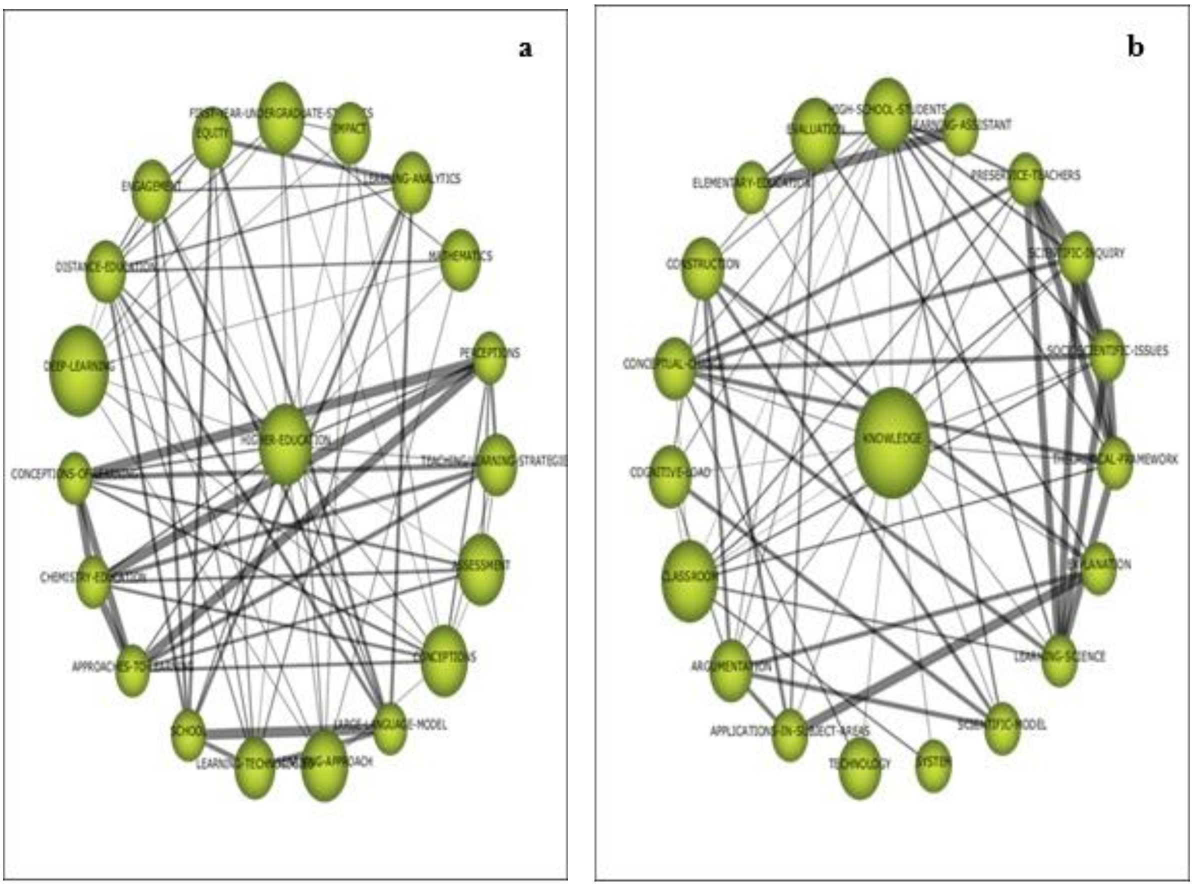

Figure 11. Thematic network structures of period 2 motor themes; (a) higher education and (b) knowledge

When examining the cluster network in Figure 11, it can be seen that the theme of "higher education" is associated to "impact," "learning analytics," "mathematics," "perceptions," "teaching/learning strategies," "assessment," "conceptions," "approaches to learning," "large language model," "learning technologies," "school," "distance education," "equality," "participation," "learning concepts," and "chemistry education." The theme of ''knowledge'' is associated to "learning assistant," "teacher candidates," "scientific inquiry," "socio-scientific issues," "theoretical framework," "explanation," "applications in subject areas," "argument," "construction," "learning science," "scientific model," "technology," "classroom," "system," and "primary education." During this period, research primarily focused on integrating AI into higher education for knowledge building, automatic assessment, smart/interactive learning environments, and personalized learning.

Period 3 (2019-2024)

In the third period, from 2020 to 2024, the number of articles published increased to 110, and analysis of the metadata identified 10 themes. Details on these themes are shown in Figure 12. In the third and final period, the theme found to have the highest bibliometric value was "learning analytics," followed by ''students'' and "science education." The motor themes contributing to the development of the research field in this final period were "computational thinking (CT)," "classroom," "knowledge," and "model." The themes "cognitive load" and "learning style" are found to be highly developed and isolated themes. The themes "students" and "learning analytics" were among the basic and transversal themes. These themes are not yet sufficiently developed, indicating potential for growth in the coming periods and a broad scope for improvement. Finally, themes such as "ChatGPT" and "science education" are emerging and declining themes suggesting either an increasing attention from academic circles or areas that have not yet been sufficiently developed. The thematic network structures of the four motor themes identified in Period 3 are presented in Figure 11.

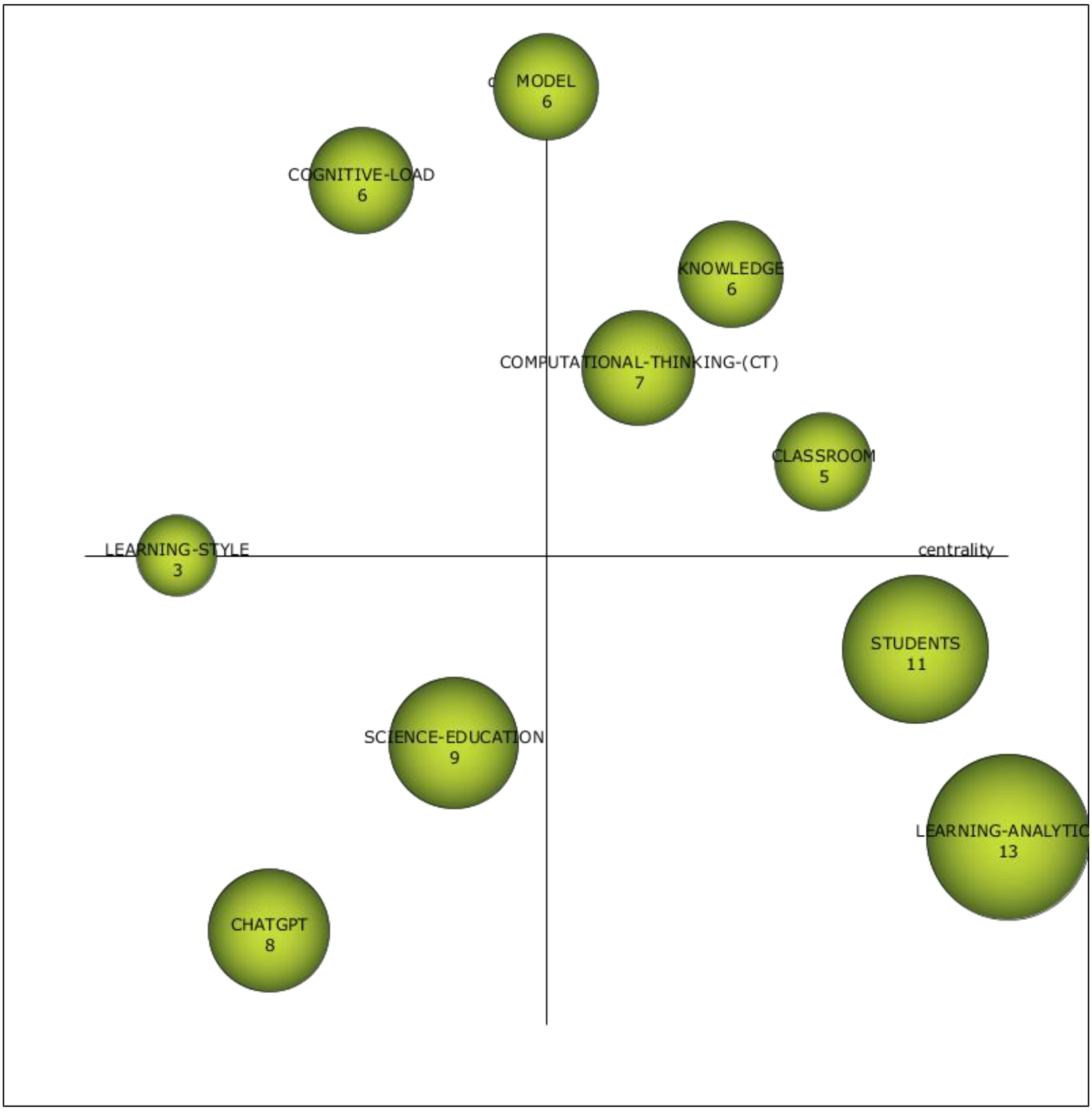

Figure 12. Period 2 (2018-2024) strategic diagram (h-index)

As shown in Figure 13, the "classroom" theme relates to sub-themes such as "school," "ethical AI," "learning outcomes," "engagement," "feedback," "interest," "online learning," "personalized learning," "algorithms," "cultural," and "children." These theme-subtheme connections demonstrates that the main application of AI in science education is within the classroom setting, where it is examined alongside pedagogical, technological, socio-cultural, and ethical aspects. The "knowledge" theme connects to sub-themes such as "meaningful assessment," "reflective assessment," "language processing," "deep learning," "video," "perceptions," "scientific inquiry," "scientific model," "professional vision," and "teachers' reflections." These data highlight that the "knowledge" theme is closely associated with AI assessment techniques, teacher development, and technological tools. The "model" theme is associated with "system," "technology," "abductive reasoning," "anatomy education," "argumentation," "attitudes," "digital education," "formative assessment," "improve," "information," "learning management system," "scaffolding," "technology acceptance model (TAM)," "undergraduate biology," "virtual reality," and "user acceptance.'' This theme- subtheme network shows that artificial intelligence research in science education enhances modeling.

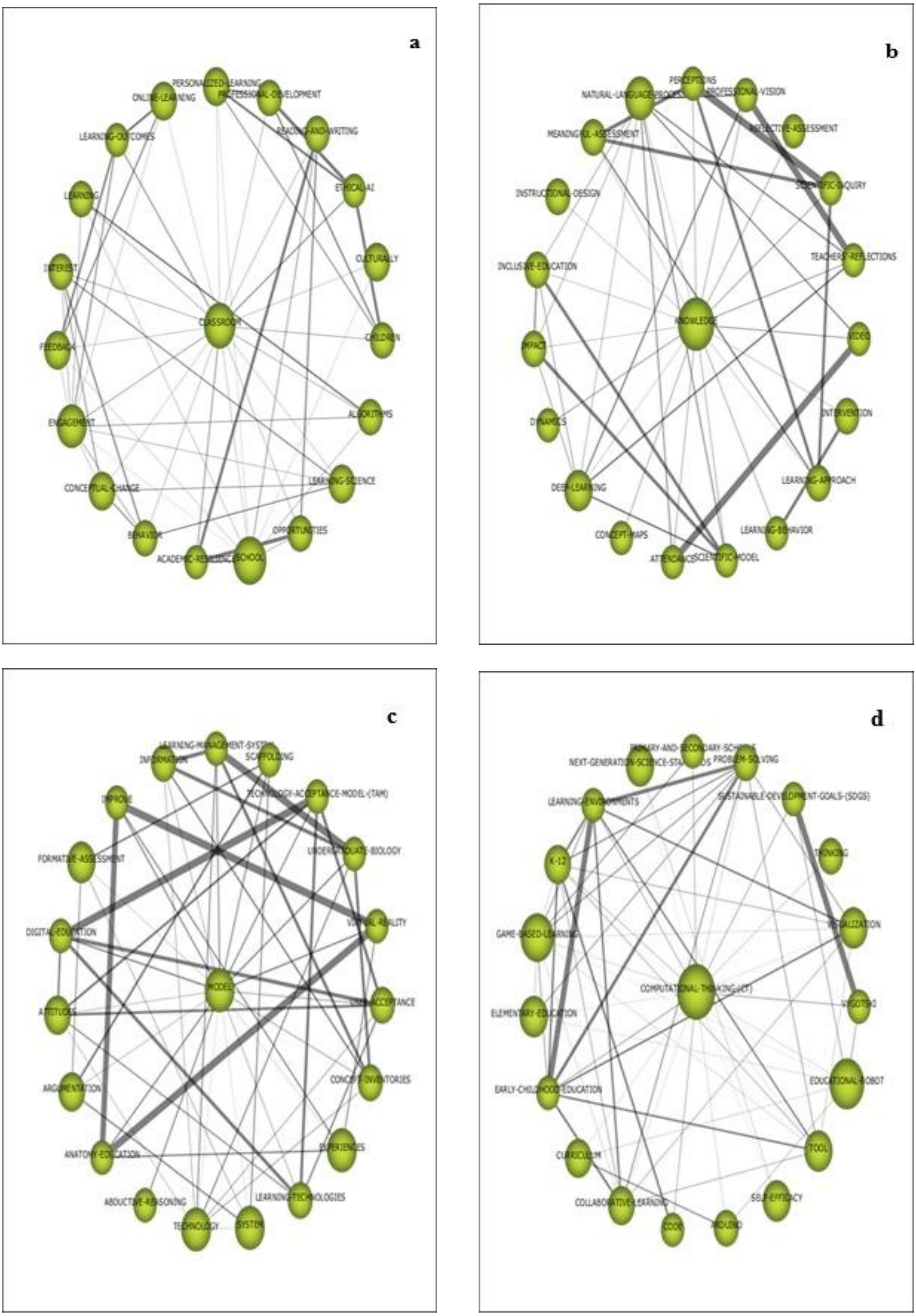

Figure 13. Thematic network structures of Period 3 motor themes; (a) classroom, (b) knowledge, (c) model, and (d) computational-thinking-(ct)

The “computational thinking (CT)” theme relates to “educational robot,” “code,” “game-based learning,” “tool,” “collaborative learning,” and “problem solving.” This shows that computational thinking is reinforced through practical applications. The theme is also connected to “primary and secondary schools,” “K-12,” and “early-childhood education,” indicating that computational thinking is being explored across various educational levels.

Thematic Evolution Analysis

The thematic evolution map, created to examine all three analysis periods as a whole and to see their evolution over time more clearly, is presented in Figure 14.

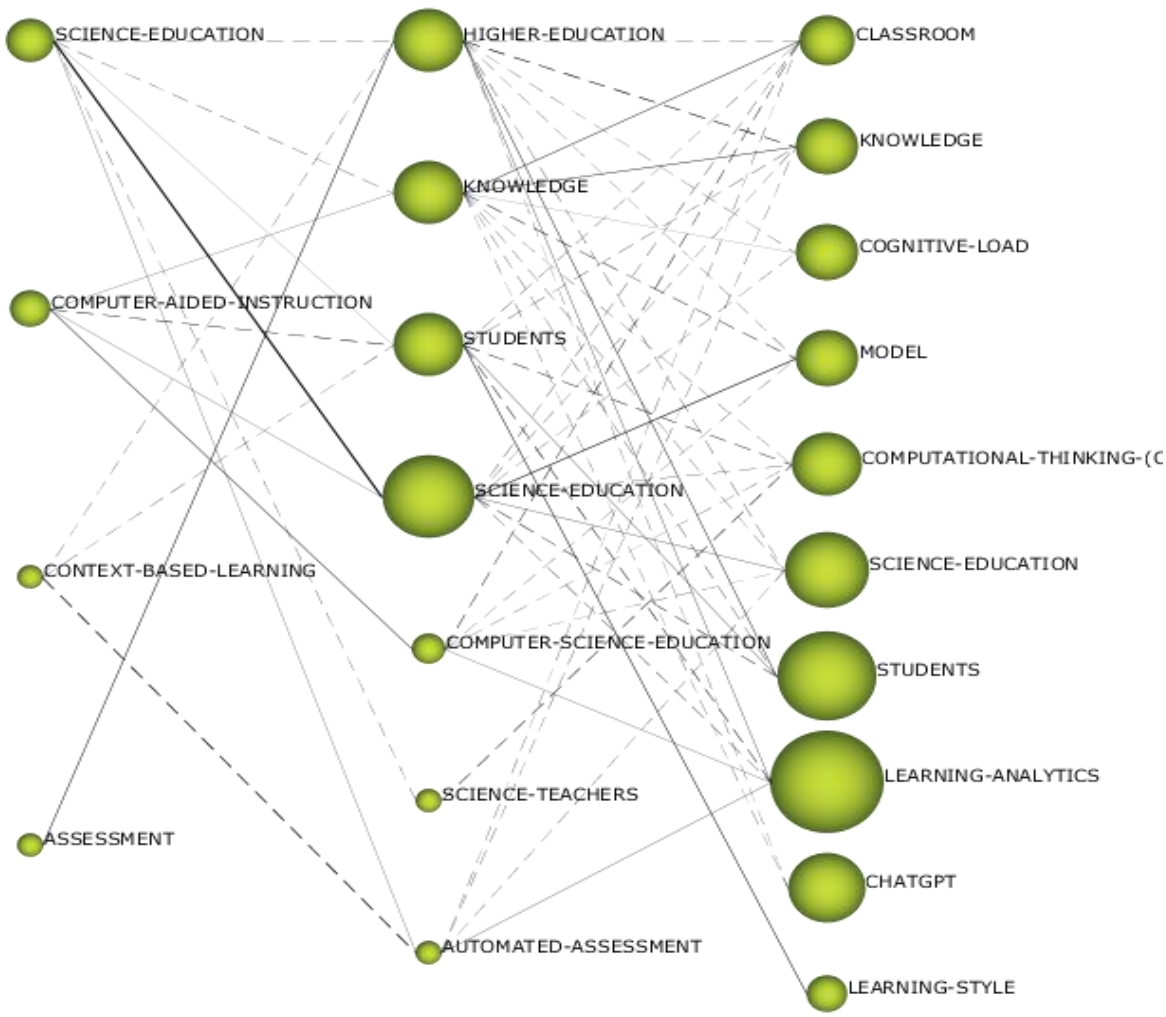

Figure 14 Thematic evolution by h-index

As shown in Figure 14, four themes emerged during the first period. While the theme “science education” was present across all three time periods, the other three themes, computer- aided instruction, context-based learning and assessment were seen to evolve into different themes in subsequent periods. The theme “computer-aided instruction” was also found to be related to “knowledge,” “computer science education,” “students,” and “science education” during the second period. Similarly, “context-based learning” was associated with “higher education,” “students,” and “automated assessment” during the second period. The ‘‘assessment’’ theme was likewise linked to the “higher education” at this stage. New themes appeared in the second period, and the themes of “science education,” “students,” and “knowledge” persisted into the third period, while the remaining themes evolved into others. During this period, "higher education" was connected to “students,” “learning analytics,” and ‘‘ChatGPT,” whereas ‘‘knowledge’’ theme was associated with “classroom,” “cognitive load,” “model,” and “ChatGPT” in the third period. The “students” theme was closely linked to “learning-style,” “learning-analytics,” and “classroom,” whereas the “computer science education” theme relates to “learning-analytics” and “model.” The “science-teachers” theme demonstrated a relationship with “computational-thinking,” while the “automated-assessment” theme is connected to “learning-analytics” and “science-education” during the third period. The "science-education" theme maintained its continuity in the third period and was linked to themes such as "model," "classroom," "learning analytics," and "knowledge." This stage represents the point at which AI research in science education become most diversified with ten themes emerging. In the final period, research interest shifted toward a data-driven, competency-based approach that included "learning analytics," "cognitive load," "model," "computational thinking (CT)," and "ChatGPT.''

Conclusion, Discussion, and Recommendations

Recent technological innovations have become an integral part of today's social life and are having a global impact, particularly in the fields of economics, health, and education. AI technologies, with a growing interest, have become one of these innovations being incorporated into teaching and learning processes. This article provides a comprehensive overview of research on AI in science education. For this purpose, 169 English-language articles published between 1985 and 2025 in the WoS database were analyzed.

An examination of publication trends shows that scientific output on AI in science education began in 1985 and has since exhibited irregular growth. Three time periods were observed based on the trends of publications. From 1985 to 2009, publication levels remained low and between 2010 and 2018, scientific production stayed relatively stagnant. However, after 2019, a notable increase was observed, reaching its peak in 2024. This pattern suggests a growing interest in this field in recent years. Similarly, the rise in the citations counts also reflects this growing interest. This upwards trend can be attributed to the rapid advancement of AI technologies, their improved accessibility, the expansion of potential application areas in science education, and growing interest and investment in AI-driven educational technologies. The COVID-19 pandemic, which began in late 2019, also appears to have accelerated this process (Ayuni et al., 2024; Heeg & Avraamidou, 2023).

Regarding countries, the United States stands out as the leading contributer to research in this field which is consistent with findings of previous bibliometric studies on AI research in science education (Akhmadieva et al., 2023; Ayuni et al., 2024). Australia, China, and Germany were the other countries following the United States with their significant contribution to the research. Policies promoting the integration of technology in educational settings, different levels of research infrastructure, and substantial funding sources may be responsible for the observed increase in the numbers of publications in these countries (Arıcı, 2024; Ekin et al., 2025). The analysis of international collaboration reveals that the United States has the highest frequency of cooperation, while the participation of developing countries is limited. This finding illuminates the need to support for the integration of AI in science education settings in low-income/disadvantaged communities and countries as well research and strengthening international cooperation

The distribution of publications across journals indicates that research on AI in science education has primarily been published in the Journal of Science Education and Technology, Frontiers in Education, and the Journal of Research in Science Teaching. This finding suggests that the current body of research is predominantly published in multidisciplinary journals that address topics at the intersection of science education and technology. These journals offer academics and practitioners involved in AI in science education opportunities to access research findings and explore emerging trends.

In terms of autorship, Zhai, X., and Nehm, R. H., stand out as the most prolific authors. Additionally, Cooper, G., and Zhai, X. are among the leading authors. These researchers play a significant role in mentorship and collaboration, guiding and shaping AI-related research within the field of science education. The findings of the current study agree with those of Atmaca Aksoy and Irmak (2024), who identify Zhai, X., as the most prolific author in artificial intelligence research in science education.

The keyword network analysis revealed that the most frequently occurring keywords were "science education," "computer science education," "machine learning," "artificial intelligence,'' ''assessment," "ChatGPT," and "learning analytics." Similarly, the bibliometric study conducted by Atmaca Aksoy and Irmak's (2024) identified these keywords as the most significant ones in AI-related science education research.

Regarding the evolution of keywords, it has been found that there is a high level of overlap between adjacent periods, indicating an agreement on the established line of research on this subject. In terms of thematic performance, it is evident that the number of studies and themes was quite limited in the first period from 1985 to 2010 which was a limitation. The theme of "science education" is at the forefront during this period. Research conducted during this period indicates that the integration of AI into science education has primarily progressed through the theme of "computer-aided instruction." The focus of studies was observed to broaden in the second period, covering years between 2011 and 2018. “Knowledge” and “higher education” were the motor themes of this period, and the focus was on integrating AI into higher education to support knowledge building, automatic assessment, innovative and interactive learning environments, and personalization. Indeed, Moreno-Guerrero et al. (2020) also stated that AI applications were most commonly used in higher education among all levels. Subsequently, related studies have become increasingly diverse between 2018 and 2024. The motor themes of this third period include ‘‘computational thinking (CT),’’ ‘‘classroom,’’ ‘‘knowledge,’’ and ‘‘model.’’ Additionally, the presence of themes such as "learning analytics" and ‘‘ChatGPT’’ suggests that this field of study is still in its early stages of exploration. This indicates that current research trajectories are being shaped around the development of students' computational thinking skills, the rising applications of ChatGPT and generative AI, learning analytics, personalization, cognitive design, and knowledge construction and learning. These findings are also supported by studies conducted by Jia et al. (2024) and Arıcı (2024). Furthermore, AI applications in teacher education, potential risks, as well as ethical and practical implications of AI integration in science education are areas that have not yet been sufficiently explored in existing studies. Future research could focus on teacher training, large language models, the ethical and theoretical foundations for advancing AI in science education, and the long-term impacts of AI technologies on learning and teaching processes in actual Keard–12 classroom settings.

In terms of thematic evolution based on the specified time periods, a conceptual progression was observed even though different themes emerged in each period. This is primarily due to the persistent presence of the theme “science education” throughout all three periods. Research on AI in science education, which initially conducted at an experimental and conceptual level, has recently evolved into a more interactive and data-driven framework that addresses students' changing needs, fosters computational thinking, and transforms the learning experience. In conclusion, this comprehensive bibliometric analysis provides both theoretical and practical insights into AI-supported science education and to the evolving research landscape. It reveals clear evidence that interest in this subject has grown significantly, particularly since 2019. Advancing the field of AI in science education requires interdisciplinary collaboration among stakeholders, including computer scientists, educators, researchers, funders, and policymakers. Such collaboration is essential to fostering innovation, addressing the challenges of AI integration into contemporary teaching practices, and meeting the demands of an increasingly dynamic technological environment in education.

Limitations

Like any research study, this research has certain limitations. The most evident limitation is that it only includes studies published in English and indexed in the WoS database. A second limitation of this study is the exclusion of studies published in 2025, as the calender year has not yet concluded. Given the growing interest in AI-related research within science education, this exclusion may prevent the identification of emerging publication trends. Finally, although the time periods were determined based on the number of articles and the developmental trajectory of the field, the selection of specific intervals of time periods may also represent a limitation limitation.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest

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