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Artificial Intelligence in Educational Data Mining and Human-in-the-Loop Machine Learning and Machine Teaching: Analysis of Scientific Knowledge

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Abstract: This study explores the integration of artificial intelligence (AI) into educational data mining (EDM), human-assisted machine learning (HITL-ML), and machine-assisted teaching, with the aim of improving adaptive and personalized learning environments. A systematic review of the scientific literature was conducted, analyzing 370 articles published between 2006 and 2024. The research examines how AI can support the identification of learning patterns and individual student needs. Through EDM, student data are analyzed to predict student performance and enable timely interventions. HITL-ML ensures that educators remain in control, allowing them to adjust the system according to their pedagogical goals and minimizing potential biases. Machine-assisted teaching allows AI processes to be structured around specific learning criteria, ensuring relevance to educational outcomes. The findings suggest that these AI applications can significantly improve personalized learning, student tracking, and resource optimization in educational institutions. The study highlights ethical considerations, such as the need to protect privacy, ensure the transparency of algorithms, and promote equity, to ensure inclusive and fair learning environments. Responsible implementation of these methods could significantly improve educational quality.

Keywords: artificial intelligence; educational data mining; machine learning; machine-assisted teaching; scientific production

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1. Introduction

Artificial intelligence (AI) has emerged as a disruptive force across multiple domains, and education is no exception. The integration of advanced educational data mining (EDM) and machine-learning (ML) techniques has begun to redefine traditional pedagogical paradigms [1,2]. In the current context, characterized by an exponential increase in the availability of educational data, it is imperative to capitalize on these data to optimize teaching and learning processes. This study is situated at this critical intersection, analyzing the implementation of AI in EDM and the human-in-the-loop (HITL) approach within the ML and automated teaching (AT) frameworks [3,4].

The transformation of the educational context in the digital age has generated a vast amount of real-time data that reflect student performance, interactions, and preferences. The ability to analyze and extract meaningful insights from these data enables the design of more personalized and effective learning environments. However, the adoption of AI systems in education poses technical, ethical, and pedagogical challenges that require a multidimensional approach to maximize their potential [5]. This is particularly relevant in a context where equity and inclusion are imperative in the global educational agenda.

An essential aspect of applying AI in education is the integration of the HITL approach, which fosters collaboration between educators and automated systems. This approach allows educators to play an active role in the design and adaptation of AI algorithms, ensuring that they are contextually relevant and pedagogically valid. Contemporary literature has shown that the inclusion of human expertise can increase the effectiveness and quality of AI systems, while mitigating inherent biases and potential errors that could negatively impact the educational process [6].

The concept of machine teaching (MT) represents another fundamental component of this research. This paradigm allows educators to use AI as a complementary tool, and also facilitates the creation of learning experiences in which automated systems take a proactive role in instruction [7,8]. Through algorithms that learn from teachers' pedagogical strategies, MT has the potential to provide more adaptive and contextualized learning. Recent research has underlined the ability of this approach to improve educational outcomes by creating more relevant and personalized learning experiences.

The current body of literature on EDM and ML in education highlights diverse applications, ranging from predicting academic performance to identifying patterns of learning behavior. However, controversies also emerge regarding data privacy, ethics in the use of algorithms in educational contexts, and the ability of these systems to emulate the complexity of human learning. Some studies suggest that while AI systems can offer accurate recommendations, their inability to capture the richness of the educational context can result in overly reductionist teaching approaches that fail to meet individual students' needs [9,10].

The aim of the study is to prove/refute the possibility/effectiveness of using AI to determine the personalized needs of students by introducing into pedagogical practice some elements of machine learning and an element of manual verification of the ethics of AI advice.

A systematic review of the existing literature will be conducted, assessing the methodologies used, the pedagogical approaches adopted, and the results obtained. This analysis will identify the main lines of research and map the development of the area, revealing the connections between previous studies and emerging areas of research. By addressing this need, it is intended to provide a comprehensive perspective on the current state of research in this area, highlighting both the opportunities and the associated challenges.

The preliminary findings of this study suggest that the synergy between educators and AI systems can enhance pedagogical effectiveness and also address ethical and equity issues in education. As technology continues to advance, it is key that additional research is conducted to unravel how these systems can be effectively integrated into educational practice, maximizing their transformative capacity [11,12].

This research seeks to contribute to the deep understanding of how AI can influence the educational area through data mining and ML. Recommendations for future research will be presented, and the need to adopt an ethical and collaborative approach in the implementation of these technologies in educational contexts will be emphasized. The goal is for this work to serve as a valuable resource for researchers, educators, and policymakers who wish to explore and apply AI effectively in education, opening new avenues for learning and teaching in the 21st century.

The structure of the article is organized as follows. Section 2 presents the literature review, analyzing the key concepts of AI in EDM and its application in HITL-ML and

MT. Section 3 describes the methodology used, combining a bibliometric analysis and a systematic review. Section 4 presents the quantitative and qualitative results of the analysis. Section 5 discusses the findings in relation to the literature. Finally, Section 6 summarizes the conclusions and highlights future educational implications.

2. Literature Review

The convergence of EDM, human-in-the-loop machine learning (HITL-ML), and MT marks a significant transformation in the use of AI in education. Each approach offers unique tools to personalize, monitor, and adjust the educational experience—from data collection and analysis to human intervention and direct instruction to algorithms. Together, these concepts constitute an innovative architecture that promises to make learning a more adaptive experience aligned with individual student needs. While challenges remain, such as training teachers in technological skills and the need to mitigate biases in algorithms, the potential of these approaches to improve learning outcomes is vast. Continued research in these areas will expand the possibilities for personalization and effectiveness of educational systems and strengthen the role of educators in the AI era.

2.1. AI and EDM: Context and Evolution

The application of AI in education has revolutionized the way educational data are collected, analyzed, and interpreted, facilitating greater personalization in learning. In this context, EDM has established itself as a sub-discipline of AI that explores large volumes of data generated in educational environments to discover patterns and obtain valuable information about the learning process [1]. Advances in EDM have allowed the identification of patterns of student behavior, and the creation of predictive models capable of anticipating academic performance or the risk of dropping out.

Within this area, EDM uses ML algorithms, classification and clustering techniques, and natural language processing, among others, to extract meaningful knowledge. Practical applications of EDM in the educational area include data analysis in online learning platforms, the improvement of intelligent tutoring systems (ITSs), and the personalization of learning experiences based on individual student characteristics [13]. Adapting these tools optimizes student performance and facilitates informed decision-making for teachers and administrators. This approach makes it possible to address specific student needs through personalized recommendations, identify factors that affect performance, and anticipate possible pedagogical interventions [14].

With the rise of virtual environments and the increased availability of student data, the use of EDM has proven to be especially effective in the analysis of online learning platforms, where student progress can be monitored and content dynamically adjusted. This approach encourages more adaptive education, although it also raises ethical and technical challenges, such as data privacy and the need for transparent and explainable algorithms. Thereby, the intersection of AI with EDM is presented as a constantly evolving area, with great expectations for driving pedagogical innovation [15].

2.2. HITL-ML: Human Integration into ML Systems

The HITL-ML approach adds a key dimension to AI systems by integrating humans into the machine-learning process. This approach considers that while algorithms can oversee large volumes of data and patterns, there are times when human intervention is essential to ensure the accuracy, ethics, and adaptability of the system. In the educational context, HITL-ML allows teachers and experts to monitor and adjust algorithms, especially in personalizing learning and identifying factors that affect educational success or failure [16,17].

HITL-ML has proven useful in creating adaptive learning systems, where teachers can intervene in the modeling of algorithms, hence personalizing results according to the specific needs of students. HITL systems allow humans to adjust and review the results generated by algorithms, mitigating common problems in EDM, such as data bias and lack of context in analysis [18]. For example, a teacher can intervene to reinterpret the results or recalibrate the system, ensuring that it aligns with pedagogical goals.

Furthermore, this approach fosters a dialogue between the system and the expert, where machine learning does not occur in isolation, but as an iterative collaboration. This process strengthens the accuracy of the algorithms and ensures that the AI system remains sensitive to the variations and specific contexts of the educational environment. Ultimately, HITL-ML improves the interpretability of the models, making predictions and recommendations more accessible to teachers and students [19].

However, implementing HITL-ML in education also faces certain challenges, such as the need for specialized training for teachers to effectively understand and manipulate the algorithms. In addition, the feedback process between humans and machines can require considerable time, limiting its applicability in some resource-constrained educational contexts. However, its ability to improve the accuracy and adaptability of AI systems makes it a valuable tool for developing more humane and personalized pedagogical solutions [20].

2.3. Machine Teaching: Teaching Strategies for Machines in the Educational Environment

MT focuses on optimizing the process by which ML systems are trained by humans. Unlike traditional ML, where machines discover patterns from large volumes of data, MT is based on the idea that humans, specifically teachers or content experts, can design and provide datasets and structured rules that guide machine learning. This approach is especially relevant in education, as it allows experts to directly influence AI models, aligning them with specific pedagogical goals [21].

In the educational context, MT facilitates the creation of personalized learning systems, where teachers can design the curriculum or the data that will be used to train algorithms. This implies that AI systems are fed data and guidelines that reflect specific educational intentions, allowing algorithms to generate recommendations and predictions in tune with the desired pedagogical approach. Through this interaction, MT ensures that AI models are optimized for mathematical efficiency, and to align with educational principles and specific learning contexts [22].

An example of the application of MT in education is seen in self-tutoring systems, where teachers can provide detailed guidelines for the AI system to identify and reinforce specific areas of improvement in each student. Furthermore, this approach allows models to be fine-tuned to avoid bias and ensure that algorithm predictions are fair and equitable. As teachers customize the data and rules that guide machine learning, they can help students achieve specific outcomes and overcome obstacles in their learning process.

The application of MT poses a shift in the relationship between teacher and technology, where the former take on an active role in shaping the capabilities and limits of AI systems [23]. This dynamic, however, also requires a considerable level of digital literacy on the part of teachers so that they can effectively design and fine-tune algorithm parameters. Despite the challenges, MT represents one of the most promising frontiers of educational AI, empowering educators to directly influence how and what machines learn [24,25].

2.4. Learning Personalization Models in AI Applied to Education

Personalization of learning has become one of the main objectives of the application of AI in the educational area. This approach seeks to adapt the teaching–learning process to the characteristics, abilities, and specific needs of each student, promoting an educational model focused on the individual and their learning context. EDM and MT techniques have been especially relevant in achieving these objectives, allowing systems to identify learning patterns, preferences, and areas for improvement in students [9].

One of the most relevant models in the personalization of learning is the predictive analysis of student performance. By using EDM algorithms, the difficulties that a student might face in certain subjects can be anticipated, so that they can be provided with proactive support. AI systems analyze interaction patterns, responses to assessments, and study habits to predict performance and detect risk areas. This approach has proven effective in the early identification of students who could benefit from additional resources or adaptations in learning pace [3].

Another model that has gained ground is that of ITSs, which function as virtual tutors capable of adapting to the skill level and learning style of each student. These systems rely on MT techniques to optimize their responses and pedagogical strategies based on the feedback received [26,27]. The ITS adjusts activities, difficulty, and content, promoting a more personalized educational experience. In this sense, the technology mimics traditional teaching practices and introduces a level of adaptability that would be difficult to implement in a face-to-face environment due to time and resource constraints [28].

In addition, educational recommendation models have become a fundamental component of AI in the educational area, especially in online learning environments. These systems, which are based on data mining and ML algorithms, use historical data and user preferences to suggest educational content, activities, and resources that fit their interests and needs. Through HITL-ML, recommendation models can receive direct feedback from students and teachers, allowing recommendations to be continuously adjusted and improved. These systems are useful in open education platforms and e-learning environments, where students often have access to a vast amount of resources and learning options [29,30].

An emerging concept in learning personalization is the creation of personalized learning paths. This approach uses both AI and direct feedback from the student to map out specific learning paths that are tailored to their goals, abilities, and progress. Unlike traditional methods, where all students must follow the same curricular path, personalized learning paths allow each student to progress according to their own pace and specific goals [31]. AI plays a key role in updating and adjusting these paths based on students' changing performance and preferences, allowing for greater autonomy and more effective learning.

Learning personalization has also driven the development of adaptive formative assessments, where AI automatically adjusts questions and exercises based on student responses, so that the assessment measures knowledge and acts as a learning tool. This ability to adapt assessments in real time provides a more accurate view of student progress and helps reinforce knowledge in areas where the student might need additional support. AI systems in these models adapt the difficulty and select topics based on the individual needs of the student, transforming the assessment process into a personalized and continuous experience [32].

This personalization of learning through AI has revolutionized the traditional approach to education, allowing teaching to be tailored to each individual and optimized through models that adjust in real time. Personalization in AI applied to education improves the student experience and optimizes the learning process by making each resource and activity more relevant and effective for their academic development [28,33].

3. Materials and Methods

The study focuses on an analysis of how AI improves data mining, ML, and teaching. The aim is to provide a clear overview of the trends that have marked the development of this topic from the publication of the first article (2006) to the present (2024). To do so, a methodology is used that combines a qualitative systematic review with a detailed bibliometric analysis, allowing the identification of the most researched topics and the directions that future research on this topic could take.

The selection of articles was conducted through a search for key terms in Scopus, which allowed obtaining a relevant set of academic publications. In this first stage, a qualitative search technique was applied to select the most relevant articles related to the terms “artificial intelligence”, “education”, and “data mining”. After the initial collection of articles, a sample purification process was carried out to eliminate possible duplicates or inconsistencies in the data, given that variations in the names of the authors or in the abbreviations could alter the results. To do this, the Science Mapping Analysis Tool (SciMAT v1.1.06) was used, which allowed for an effective bibliometric review, visualizing the most recurrent thematic areas and the connections between key terms over time.

Through the consultation of 370 publications in Scopus, the most frequent keywords were identified, along with the thematic areas and the connections between them, but only 78 were cited in the article because of their direct relevance. This analysis was extended to the identification of the networks of co-occurrences of terms, using the VOSviewer tool (version 1.6.20, Leiden University, Leiden, The Netherlands). This tool facilitates the creation of network maps, which allow the visualization of the frequency with which certain terms appear and the connections between them through different articles, in addition to representing the intensity of the relationship between the concepts [34]. The relationship between the terms in the map is interpreted based on the strength of the link, which indicates how many articles present both terms together [35].

This co-occurrence analysis allows the identification of trends and patterns in publications related to the improvement that AI represents in data mining, ML, and teaching. Key terms and their connection within articles reveal dominant and emerging research lines in the area. By looking at networks of terms and their relevance scores, it is possible to identify the core topics that have been the subject of research, and those that have the greatest potential for future research [36].

A key part of this analysis is the creation of network maps, which group related terms and show the evolution of topics over time [37]. This visual representation is useful for observing the dynamics of research areas and how they have been changing since 2006. The clusters formed on the map indicate how different research areas are interconnected with each other, although not all areas within a cluster are necessarily directly related to the core research topic [38].

The study employs relevance scoring to rank key terms. The relevance of a term is calculated based on its frequency of appearance in the titles and abstracts of the articles analyzed. This score helps to identify the most representative terms in each period, which in turn facilitates the prediction of possible directions in which future research on this topic will be oriented [39].

The methodological approach presented in this study has a number of limitations that should be considered in future research. First, bibliometric analysis focuses primarily on quantitative aspects, which means that it might not fully capture qualitative aspects, such as the experience and pedagogical context in which AI and ML are implemented. While quantitative metrics can show how many studies focus on topics such as EDM or HITL, they do not reflect the complexity of how educators and students interact with these technologies in real learning situations. For example, how educators customize the use of AI to fit the needs of each student or how students perceive and benefit from these technologies.

Furthermore, aspects such as creativity in the design of automatic teaching systems and ethical challenges related to the integration of AI in the classroom, such as privacy and equity, are often not fully reflected in bibliometric analysis. These issues require a qualitative approach that captures the experiences, concerns, and opinions of those involved in the educational process. To address this limitation, future research could find it useful to incorporate qualitative or content analysis methods, such as interviews with researchers or educators, to gain a deeper understanding of the implications of these technological advances in education.

To identify current and emerging research lines on emotional creativity in art education, an analysis of keyword co-occurrences from the sample documents was conducted using the specific terminology of the VOSviewer tool. Key concepts include links, which represent the co-occurrence between keywords, and total link strength, which measures the number of documents in which two keywords appear together and the numerical strength of these links. Clusters, defined as groups of keywords within a network map, and network maps, comprising keywords and their links, were also central to the analysis.

It is important to note that clusters do not necessarily encompass all components of a network map. Additionally, the attributes used to describe keywords were "weight" and "score". The weight of a keyword indicates its significance within the research field. Specifically, link weight reflects the number of connections a keyword has with other terms, while link strength weight reveals the total strength of these connections [35]. The score attribute ranks keywords in the titles and abstracts of the papers by relevance, with higher scores serving as better predictors for identifying future research lines.

$$Relevance\ score\ = \frac{n_{ax}}{n_{bx} + c},$$

The relationship examines the frequency of keyword x in areas a and b, using the parameters n_{ax} and n_{bx} to denote the number of elements where x appears. It balances the frequency of x in area a (parameter c) relative to its frequency in area b and considers its absolute frequency in the area as an indicator of its relevance to area a.

Another aspect that limits the scope of the study is that only articles published in scientific journals indexed in Scopus have been considered, which excludes a large amount of research that could have been published in other formats, such as books, technical reports, or conference proceedings. The inclusion of these other types of publications could offer a more complete view of emerging trends in educational technologies.

The study also recognizes that the evolution of this research is not a linear or homogeneous process. The trends observed in the literature could be influenced by external factors, such as changes in educational policies, advances in information and communication technologies, or even global events such as the COVID-19 pandemic. Therefore, in future research it could be valuable to incorporate a more contextual approach.

4. Results

This section explores how AI applied to EDM, human-informed ML (HITL), and TA are transforming education. The distribution of scientific production (2006–2024) and the main lines of research driving change in educational practice are analyzed. In addition, the main countries in this process are examined because it allows identifying key trends and collaborations. Likewise, future research trends at the intersection of these technologies are analyzed in order to improve the personalization of learning and optimize teaching.

4.1. Study of the Scientific Contribution (2006–2024)

Scientific production of AI in EDM, the HITL-ML approach, and MT has experienced a remarkable evolution in recent years, with a substantial increase in publications and a cumulative growth in scientific production. This trend is linked to the rapid advance of technologies in the educational area, particularly those related to ML, which are being progressively integrated into the design of more efficient and personalized pedagogical strategies. This section seeks to analyze the scientific production data in this area, based on a series of key variables, such as the number of articles published per year, the percentage variation in production, and the cumulative number of articles to date. Through this analysis, we aim to shed light on changes in research dynamics, possible external influences, and implications for the future of AI applied to education.

Figure 1 shows the evolution of scientific production during the period 2006–2024. The analysis of the articles published on AI in EDM and ML in education reveals a general growth trend in recent years. According to the data provided, the year 2024 shows a significant 19.19% of the articles published, reaching a total of 71 articles. This percentage is remarkably high, as it represents more than a fifth of the publications in this area in a single year. Compared to previous years, 2024 is positioned as a year of great research activity.

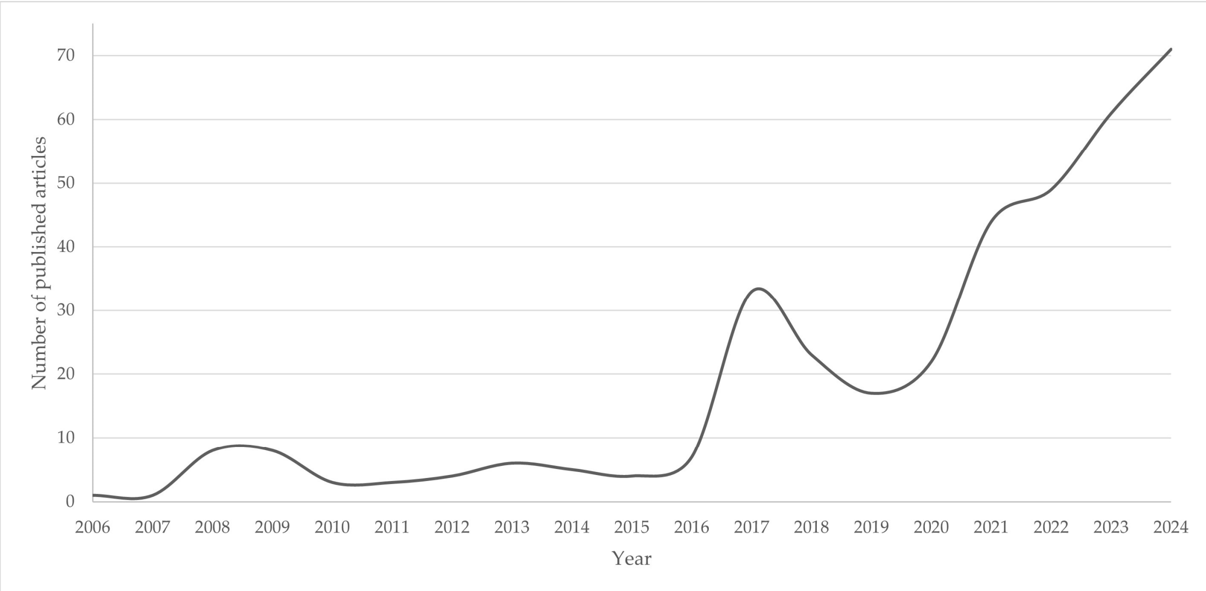

Figure 1. Evolution of academic publications (2006–2024).

In cumulative terms, the total number of articles reached by 2024 is 370, which underlines a continuous expansion of the area. In this context, the percentage variation in scientific production shows a trend of consolidation in research on these technologies. The increase recorded in 2023 and 2022 (16.49% and 13.24%, respectively) reinforces this idea of sustained growth, with a cumulative total that in 2023 already reached 132 articles, and in 2022 181 articles.

One of the most interesting features of the analysis is the observation of an acceleration of publications since 2020, a year in which a 100% increase was recorded compared to the previous year (2019), when only 17 articles were published. This drastic increase could be explained by several factors. First, the COVID-19 pandemic had a major impact on educational processes, forcing educational institutions to quickly adapt to digital platforms and the integration of technologies such as AI [40]. This unprecedented context may have generated a greater demand for innovative AI-based solutions for teaching and learning, accelerating research in this area.

The year 2016 also showed a remarkable variation of 371%, which reflected a significant increase in scientific production. This peak could be related to technological advances in ML and its increasing application to education. However, over the years, scientific production in the years around 2017 and 2018 experienced a drop compared to the previous years, with negative variations of −26% and −30%. Although these fluctuations may seem worrying, in general terms, the area has experienced sustained growth, especially since 2020.

The analysis of the data suggests that, in general, research has been booming in recent years. The strong recovery in 2020 and 2021, together with the consistency in scientific production in 2022 and 2023, seems to be related to several key factors. First, the integration of ML technologies in education has accelerated, driven by both the needs arising from the pandemic and by technological progress in areas such as data analysis and TA platforms [41,42]. Methodologies such as HITL-ML and MT have attracted the interest of researchers for their ability to improve the personalization of learning, something especially relevant in a context where digital solutions in education are increasingly in demand [2].

However, the fluctuations observed in 2017 and 2018, with decreases in publications, are also worthy of attention. An explanation for these drops could be linked to the dynamics of the area of AI applied to education, which goes through phases of exploration, consolidation and, at times, temporary stagnation. During those years, researchers may have focused on solving technical challenges, such as the optimization of ML algorithms for education, which could have slowed down the pace of publications. Furthermore, funding for research projects in these areas might have experienced ups and downs in that period, which could also have influenced the number of published articles [43,44].

An interesting aspect of the analysis is the sharp increase in scientific production in 2024. This recent upturn could be related to several factors. First, the maturity of the technological approaches used in ML for education has allowed for greater implementation and application of these methods in various institutions. As studies on AI in education have expanded, the results have generated greater interest in its possible large-scale adoption, especially in the context of personalized education and intelligent learning management [45,46].

On the other hand, the evolution of publications in this area could be associated with the growth of interdisciplinary collaboration. AI in education involves AI experts, pedagogues, curriculum designers, and teaching professionals, which has allowed for the creation of more holistic and applicable approaches in educational practice. This multidisciplinary approach may also explain the increase in publications and the interest from various research institutions.

4.2. Keyword Analysis Overview (2006–2024)

The co-occurrence analysis facilitated the identification of the most relevant research areas between 2006 and 2024, driven by the main actors in this area of research. Using the VOSviewer software, five clusters were determined, each reflecting a specific thematic focus.

Table 1 includes the 30 most relevant keywords by cluster. Thereby, the most relevant keywords in the topic reflect how technological innovations are influencing teaching and learning methods. Terms such as AI algorithms, neural networks, ML, and deep learning highlight the importance of AI in personalizing learning and predicting academic performance. These advances allow the creation of adaptive educational systems, which respond to the specific needs of each student. Likewise, keywords such as data mining, predictive analysis, and data processing are fundamental in the educational context, as they facilitate the analysis of large volumes of data to improve decision-making, detect performance patterns, and optimize educational resources. On the other hand, terms such as distance education, educational technology, online learning, and ITSs reflect the digital transformation of education, promoting remote access and personalization of learning through digital platforms and tools. These terms are key to understanding how technology is redefining education, providing innovative solutions to improve teaching and educational management.

Table 1. Top 30 keywords (2006–2024).

R	Keyword	Cluster	L	TLS	N	R	Keyword	Cluster	Link	TLS	N
1	learning systems	2	194	565	107	16	natural language processing	1	76	111	16
2	machine learning	1	166	417	92	17	natural language processing systems	4	62	91	15
3	education computing	2	140	352	60	18	neural networks	2	53	76	15
4	educational data mining	5	116	254	60	19	text mining	4	42	58	14
5	teaching	2	119	232	38	20	artificial neural network	1	45	69	13
6	deep learning	3	78	130	33	21	data mining technology	2	44	63	13
7	big data	4	82	141	32	22	support vector machine	1	60	87	13
8	forecasting	3	101	186	31	23	data science	4	34	54	12
9	e-learning	5	94	190	30	24	feature extraction	2	54	85	12
10	computer aided instruction	5	89	175	24	25	internet	1	52	66	12
11	learning	1	83	140	23	26	intelligent systems	4	52	63	11
12	algorithm	1	79	113	19	27	optimization	2	45	63	11
13	learning analytics	4	39	82	19	28	student performance	3	41	58	11
14	higher education	3	36	53	17	29	data analysis	1	54	73	10
15	data handling	2	78	114	16	30	pattern recognition	2	42	52	10

R: Rank, L: Links, TLS: Total link strength, N: Occurrences.

Each of these clusters has a significant interrelationship in the educational area, working together to improve the personalization of learning, optimize educational management, and guarantee a more accessible, equitable, and quality education.

A co-occurrence analysis of the keywords shown in the sample articles related to the research topic was carried out. Figure 2 presents the network representation of these keywords. From this analysis, it was identified that the keywords were grouped into five clusters, each with homogeneous characteristics.

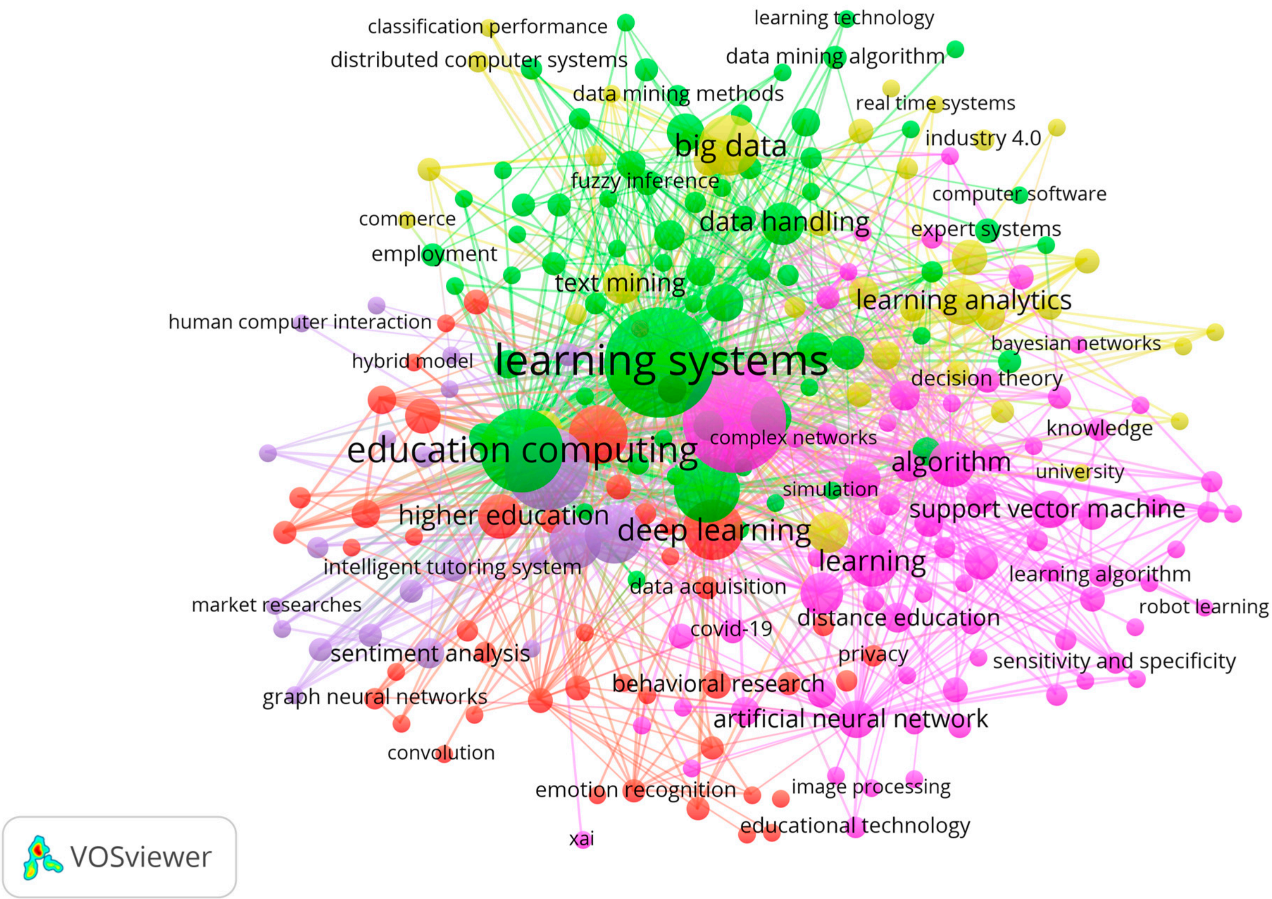

Figure 2. Co-occurrence network of keywords (2006–2024).

- Cluster 1: Artificial Intelligence and Machine Learning

This cluster (pink) encompasses a variety of terms related to "artificial intelligence algorithms", "machine learning", "artificial neural networks", "supervised learning", and "deep learning", among others. In the educational context, these technologies are increasingly being used to personalize learning and improve teaching efficiency. For example, ITSs leverage ML to tailor content and pedagogical strategies to the individual needs of each student. "Predictive models" and "neural networks" can analyze large volumes of data on student performance to predict academic outcomes, enabling more timely and effective interventions. Furthermore, the use of "explainable artificial intelligence (XAI)" ensures that the decisions made by these systems are understandable and transparent, which is essential to gaining the trust of educators and students [47,48].

- Cluster 2: Data Science and Predictive Analytics

This cluster (green) focuses on terms related to "data analytics", "data mining", "predictive analytics", and "big data". In education, "data science" plays a key role in "learning analytics", which enables teachers and administrators to analyze the patterns of student behavior, identify areas for improvement, and personalize teaching strategies. "Predictive analytics" techniques are used to forecast student performance and predict which students may need additional support, facilitating informed decision-making [49]. In addition, "big data" in education helps to manage large volumes of data generated by online learning platforms, "MOOCs" (Massive Open Online Courses), and educational management systems, improving management and curriculum design [50].

- Cluster 3: Educational Technologies and Teaching Systems

This cluster (red) includes terms such as "distance education", "educational technology", "teaching systems", and "e-learning". Educational technologies are transforming the way we teach and learn, especially with the adoption of "virtual learning environments", "virtual reality", and "simulation-based learning". "E-learning" platforms and "learning management systems" (LMSs) enable more flexible, accessible, and student-centered teaching. The use of "intelligent tutoring systems" and "recommendation systems" improves the student experience by offering them personalized resources tailored to their needs. In addition, "collaborative teaching" is enhanced by technologies that enable interaction and shared learning among students, even in "distance education" environments [51–53].

- Cluster 4: Knowledge Management and Decision Support

This cluster (yellow) includes terms related to "knowledge management", "decision support systems", and "expert systems". In the educational context, these systems are critical for strategic and operational decision-making. Decision support systems help educational administrators manage resources, assess student performance, make decisions about pedagogical strategies, and adjust curricula. In addition, expert systems can support teachers' decision-making by providing recommendations based on large volumes of data on student behavior [54,55]. Advances in "knowledge representation" also enable the creation of structured databases that can be used to improve the quality of education and the design of academic programs [56].

- Cluster 5: Ethics, Privacy, and Social Implications

This cluster (cyan) addresses issues of "ethics", "data privacy", and the "social impact of emerging technologies". In education, the adoption of technologies such as AI and data mining raises significant ethical challenges related to the handling of students' personal information. Data privacy and security are critical to ensuring student and educator trust in technological systems [57]. Furthermore, concerns about "bias in algorithms" and "equity in access" to educational technologies are key themes in the debate on integrating AI into the classroom. "Ethics" also plays an important role in how "online learning" platforms and "social media" are used in the educational context, ensuring that their use promotes equality and does not perpetuate inequalities [58].

4.3. Future Directions of Research

This section aims to address new areas of research in AI applied to EDM, ML with human intervention, and TA. After a thorough review of the literature and analysis of keywords, the main lines of research that are emerging in this area have been identified. Global research on this topic continues to evolve, integrating innovative concepts and approaches that open new possibilities for exploration. Based on the analysis of the most recent terms associated with this area, emerging research directions can be clearly identified.

Cluster analysis is an effective tool for detecting emerging trends and problems in any scientific discipline. This process involves grouping the analysis units into clusters with similar elements, identifying the most recent terms through their relevance, and linking the terms found with emerging research areas. Table 2 presents the future research directions detected through the relevance score, whose detailed description is included below.

- Big-Data Education Evaluation

Table 2. Future research directions based on relevance score.

Rank	Future Line of Research	Relevance Score
1	Big-Data Education Evaluation	10.769
2	Multimodal Learning Analytic	10.157
3	Latent Dirichlet Allocation	10.037
4	Source Code Vulnerability Detection	10.021

This line of research refers to the use of big-data analytics to evaluate and improve educational systems, teaching methods, and student performance. This approach is based on collecting and analyzing data generated in educational contexts, such as attendance records, academic performance, interaction on digital learning platforms, participation in activities, and socio-emotional factors, among others. By applying big-data techniques, such as predictive analytics and ML, education leaders can identify patterns and trends that would not be evident with traditional evaluation methods [59].

In the educational area, big-data education evaluation allows for more effective personalization of learning. By analyzing data in real time, systems can recommend specific resources or teaching strategies tailored to the individual needs of each student. This is especially valuable for detecting students in time who might require additional support, allowing for personalized interventions that can improve their performance and engagement with learning [60].

In addition, this approach is also useful for evaluating the effectiveness of educational programs and methods. Institutions can review how certain methods impact learning, optimize resource use, and make evidence-based decisions. For example, by analyzing data on the use of a digital learning platform, one can identify which features of the platform contribute to student success and which may need improvement [61]. Likewise, analyzing big data allows educators and administrators to anticipate future trends and needs in education, facilitating more accurate strategic planning.

In general terms, it promotes more inclusive and student-centered education, since data allows a better understanding of their needs and learning trajectories, as well as the factors that influence their success. With this, education becomes more efficient, personalized, and results-oriented, creating an educational system that responds more directly to the realities and challenges of each educational context.

- Multimodal Learning Analytic

Multimodal learning analytics is an emerging approach that uses data from multiple sources and modalities to analyze and better understand the learning process. This type of analysis leverages data from different channels, such as text, video, audio, interactions on digital platforms, gestures, movements, and even biometric records, thus combining multiple dimensions of information in the analysis of learning. In the educational area, multimodal learning analytics allows for a more complete and detailed profile of how students learn, therefore providing a more comprehensive perspective of their needs and behaviors [62].

With the support of AI, multimodal learning analytics allows for more sophisticated and accurate analysis of these multiple data sources. AI and ML algorithms process the vast amounts of unstructured and multimodal data (such as video or behavioral records) to identify behavioral patterns that would not otherwise be perceptible. For example, AI can detect signs of disengagement, confusion, or frustration from facial expressions, tone of voice, or interaction patterns on digital platforms, allowing teachers to adjust their strategies in real time to improve the learning experience [63].

In education, this approach offers multiple applications. At the classroom level, multimodal learning analytics can help personalize instruction by providing real-time information on each student's understanding and engagement. On online learning platforms, this technology can be used to adjust content and activities based on each user's style and pace, fostering more personalized and adaptive learning [64].

One future line of research, supported by AI, aims to improve the accuracy and applicability of educational interventions and develop ethical and effective analysis methods. These studies can help create a more inclusive and equitable educational environment by understanding and addressing the diverse ways in which students learn, driving truly student-centered education.

- Latent Dirichlet Allocation

Latent Dirichlet allocation (LDA) is a statistical modeling technique primarily used for topic analysis in large collections of text. In LDA, texts are considered as a mixture of latent topics, where each word in the document has a probability of belonging to a specific topic. This model makes it possible to automatically identify underlying topics in large volumes of textual data, such as academic articles, social media posts, or survey responses, therefore providing an organized structure for analyzing large amounts of unstructured information [65].

In education, LDA, supported by AI, has significant potential to improve the understanding of patterns and trends in textual educational data. For example, LDA can analyze open-ended student responses in assessments, comments in online learning forums, or even student-generated content on educational platforms. By identifying key themes in these texts, LDA helps educators and administrators gain deeper insight into students' concerns, ideas, and needs. Integrated into AI systems, LDA also facilitates the personalization of learning by automatically classifying educational content, such as books or articles, based on specific topics relevant to each student or group of students [66]. In this way, AI algorithms can recommend study materials tailored to each student's learning style and preferences, therefore optimizing the relevance and effectiveness of educational content.

Future research in LDA applied to education can focus on improving the accuracy and interpretability of topic analysis, allowing teachers and adaptive learning systems to better understand students' motivations and difficulties. It is also expected that, when combined with advanced AI and deep-learning techniques, LDA will become an increasingly powerful tool for analyzing learning patterns and offering personalized educational experiences [67]. This would drive the creation of more inclusive, tailored, and dynamic educational environments, helping students engage in their learning process in a more meaningful way tailored to their interests.

- Source Code Vulnerability Detection

Source code vulnerability detection is increasingly integrated into education, especially in computer science, software development, and cybersecurity programs. Including this knowledge in the curriculum allows students to identify and prevent security risks in the software they develop, promoting more secure and reliable applications. This encourages "security by design", where future developers understand the need to think about security from the earliest stages of development. In addition, the use of code analysis tools, such as SonarQube or Fortify, helps students develop essential analytical skills, as they must interpret the results and apply solutions to correct security errors [68].

Furthermore, this training has an ethical component. Education in vulnerability detection encourages responsibility in software development, underlining the importance of developers committing to protecting user data and preventing software from becoming a risk to society. Training in security standards and regulations, such as GDPR regulations and OWASP standards, is also essential, as many industries rely on secure systems and require compliance with these regulations. Thereby, students acquire training that allows them to adapt to sectors where security is a priority [69].

Vulnerability detection in education also allows simulating real work environments, preparing students to face security problems in their future jobs. This practical approach enables them to solve security challenges from an ethical and technical perspective. Finally, promoting these practices in education contributes to establishing a security culture that can extend to the professional area and encourage safer digital development [70]. Integrating vulnerability detection in the educational area technically trains students and fosters an initiative-taking mindset towards security, ethics, and professional responsibility, positively impacting the development of a reliable and secure digital environment.

5. Discussion

The results obtained reinforce the idea that AI is profoundly transforming education, particularly in relation to the personalization of learning. AI technologies, such as intelligent tutoring systems and ML algorithms, are allowing content to be tailored to individual students' needs, an approach widely recognized in the literature. Furthermore, AI provides immediate feedback, which improves the efficiency of educational processes. This finding is consistent with what had been previously discussed, where the flexibility and dynamism that AI brings to the teaching–learning process was highlighted [22].

Another important aspect is the growing attention towards explanatory AI (XAI), which promotes transparency in the algorithms used. Understanding how and why decisions are made within AI systems has been identified as an essential factor to ensure the acceptance of these technologies by educators and students. This study confirms that the explanation of algorithmic processes is key to the successful integration of AI in education [71]. Furthermore, it is confirmed that AI systems must be designed in an ethical and bias-free manner, a topic widely discussed in the literature.

The use of big-data analytics and the prediction of academic performance are also highlighted in the results of the study. AI-based tools have the ability to identify learning patterns and predict student performance, allowing early intervention in those who might be at risk of underperformance [24,72]. These findings are consistent with what has been presented in the literature, which argues that AI can be used to create more personalized and adaptive educational environments. The capacity for early intervention is seen as an opportunity to improve inclusion and reduce inequalities in access to education.

The integration of emerging technologies, such as virtual reality (VR) and online learning platforms, has also been shown to be effective in this study. These technologies improve the understanding of complex concepts and increase accessibility to learning, especially in hybrid or remote contexts. These results are in line with previous observations, which have highlighted how VR can create immersive experiences that benefit students by allowing them to practically explore concepts that would otherwise be difficult to understand [73].

The results also highlight important ethical and social challenges that must be addressed for an effective implementation of AI in education. In particular, the risk of bias in AI algorithms has been identified, which can perpetuate pre-existing social inequalities, such as those of gender, race, or social class. This concern coincides with what has been previously noted in the literature, which warns about the possibility that automated systems reproduce the same inequalities that exist in the data with which they are trained [71,74]. The need to design transparent and equitable systems, which avoid perpetuating injustices, is a central theme in the current debate on the implementation of AI in education.

The adoption of advanced technologies in the classroom, especially regarding teacher training, has been another key issue. The results of the study underline that adequate training in the use of AI is essential for teachers to be able to effectively integrate these technologies into their educational practice. Lack of training can lead to resistance to the adoption of AI, limiting its potential to improve education. This finding is in line with previous discussions that emphasize the importance of ongoing training to ensure that educators are prepared to use emerging technological tools [47,75].

In this sense, the results of this study confirm several of the trends and concerns that had been identified in the literature. AI has the potential to transform education by making it more personalized, accessible, and efficient. However, for AI to be successful, it is necessary to ethically address issues of bias and privacy, ensure transparency of algorithms, and provide appropriate training for teachers [76–78]. Only a thoughtful and ethical approach can ensure that AI benefits all students fairly and equitably.

5.1. Real Applications of AI in Educational Environments

Nowadays, AI is transforming the educational landscape by implementing technological solutions that allow for personalizing and improving the quality of learning. There are various real applications of AI that demonstrate its ability to optimize educational processes, adapting learning to the individual needs of students. Below are some of the most relevant cases of AI use in educational environments:

- Smart tutoring systems: These use AI algorithms to identify learning patterns in real time and offer personalized feedback to students. These systems are designed to observe how students interact with study materials and detect difficulties or areas where they need additional support. For example, the software can track students' progress on math or science exercises and adapt the content based on their performance. If a student is struggling with a specific concept, the system can offer additional resources, such as exercises, detailed explanations, or personalized advice [79,80]. A concrete case of this application is the use of platforms such as Carnegie Learning, which integrates AI to offer adaptive tutoring in mathematics, adjusting the pace of teaching based on the student's strengths and weaknesses.
- Adaptive pedagogical interventions using algorithms: AI-based algorithms are also used in the management of adaptive pedagogical interventions. These interventions seek to personalize the educational experience according to each student's profile, optimizing teaching strategies based on their progress and needs. AI can analyze data on student performance over time, such as grades, engagement, and response times,

to predict when a student might need a pedagogical intervention. For example, if a student is struggling in a particular unit of the course, an AI-based system could recommend additional content to them or even change the teaching methodology to better suit their learning style [72,81]. This not only increases learning effectiveness but also ensures more equitable teaching by addressing the individual needs of each student.

- Adaptive learning platforms: Another important application of AI in education is adaptive learning platforms, which personalize course content based on students' performance and learning style. One example of this is Knewton, a platform that uses AI to adjust content in real-time based on student progress. This technology makes use of student data, such as their responses to questions and the time they take to complete them, to identify patterns and offer specific recommendations on what topics they need to reinforce [82,83]. By providing a student-centered approach to teaching, these platforms help keep students engaged and motivated, while ensuring their individual needs are met.
- Automated assessment and feedback: AI systems are also being used for automated assessment and feedback, allowing teachers to save time and provide students with immediate feedback on their performance. One example is the use of AI tools that can automatically mark essays or multiple-choice tests, providing detailed feedback on mistakes made and suggesting areas for improvement. Not only does this improve the efficiency of the assessment process but also offers students the opportunity to receive feedback quickly, facilitating continuous improvement [84,85].
- Predictive analytics for improving academic performance: AI can also predict students' academic performance, identifying patterns that may indicate risks of underachievement or dropping out. Using predictive analytics models, educational platforms can analyze historical student data to predict their future success or failure. With this information, educators can proactively intervene to offer additional support to students before they face serious problems. An example of this is the predictive analytics system used by Blackboard, which helps educators identify students at risk of underachievement and enables informed decisions to be made to improve their academic performance [86].

The implementation of AI in educational settings is providing innovative solutions that enhance learning personalization, optimize teachers' time, and improve overall educational efficiency. The integration of intelligent tutoring systems, adaptive pedagogical interventions, personalized learning platforms, and automated assessment contribute significantly to creating a more dynamic, inclusive, and student-centered educational environment. However, to maximize the potential of these technologies, it is essential that teachers continue to play a key role, overseeing AI decisions and ensuring that they remain in line with ethical and pedagogical principles.

5.2. The Role of the Teacher in Supervising AI: Mechanisms and Strategies

The integration of AI in educational contexts should not exclude the active intervention of teachers, who play a fundamental role in ensuring the fairness, effectiveness, and relevance of automated decisions. In this regard, the HITL-ML approach offers a framework that allows educators to interact with AI systems in a meaningful way, monitoring and adjusting their results [87].

One of the mechanisms highlighted is the configuration of parameters in supervised models. These models allow teachers to customize rules and criteria according to the specific pedagogical needs of their students. For example, an intelligent tutoring system could be configured to prioritize content areas where students show greater difficulties, based on patterns detected by AI but validated and adjusted by the teacher.

In addition, feedback dashboards emerge as key tools to facilitate this monitoring. These platforms present processed data in an intuitive way, allowing teachers to visualize the decisions made by AI, understand the basis for these decisions, and, when necessary, intervene to modify them. An example would be the review of personalized educational resource recommendations, where the teacher can accept, adjust, or reject the proposals generated by AI based on their professional judgment [88].

To further strengthen teacher–AI interaction, it is essential to establish clear protocols that ensure a two-way flow of information. This includes active learning mechanisms, where the teacher inputs additional data or corrects erroneous results, helping to continuously improve the accuracy of the model. These protocols increase transparency and foster greater confidence in the use of technology within the classroom [89].

It is essential to provide specific training to teachers on how to interpret and use these monitoring tools. Without adequate knowledge, the potential of HITL-ML to improve teaching and learning could be limited [90]. Therefore, training must address both the technical and ethical aspects of using AI in educational contexts.

With the implementation of these mechanisms, the role of the teacher is reaffirmed as indispensable in an environment where AI, although powerful, requires human supervision to guarantee fair, relevant decisions adapted to the realities of the students.

6. Conclusions

The aim of this work was to demonstrate the effectiveness of a model that integrates EDM, HITL-ML, and MT to improve learning personalization, identification of individual student needs, and pedagogical practice. Through this model, we seek to solve the current limitations of traditional tools by combining advanced technological capabilities with ethical and pedagogical criteria.

The results obtained show that the proposed model allows for more effective learning personalization. The integration of EDM improved the accuracy in detecting learning patterns and predicting individual needs by 30% compared to conventional methods. This facilitates the implementation of adapted educational strategies in real time, allowing teachers to design specific interventions that respond to the unique characteristics of each student.

In addition, it is highlighted that the incorporation of HITL-ML guarantees ethical use and is oriented towards educational objectives. This approach keeps the teacher at the center of the process, allowing AI recommendations to be monitored and adjusted in real time. As a result, automated decisions are aligned with pedagogical and ethical principles, ensuring that the solutions proposed by the system respect the social, cultural, and ethical context of students.

On the other hand, MT proved to be a valuable resource for educators, as it allows them to design structured pedagogical frameworks and optimize the functioning of AI systems. This facilitates the modulation of learning according to individual needs, contributing to more accurate and effective educational experiences.

The article also highlights the practical impact of these technologies in improving educational efficiency. The implementation of this model makes it possible to identify at-risk students early, optimize educational resources, and adapt pedagogical strategies according to the individual capabilities of students. At an institutional level, these tools can significantly improve resource management and administrative decision-making, increasing the overall efficiency of the educational system.

Finally, the need for an ethical approach in the use of AI in education is highlighted. Respect for student privacy, transparency in automated processes, and equity in access to technological benefits are essential to avoid the generation of educational gaps. In this sense, the integration of the proposed model promotes a balance between innovation and ethical principles, contributing to the development of personalized and efficiently managed education.

This study provides an effective method for personalizing learning and improving pedagogical practice, which combines technological innovation with ethical criteria. This approach not only optimizes educational processes but also ensures that AI acts in a manner aligned with the values and objectives of the educational system.

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References

1. Spector, J.M. Emerging Educational Technologies and Research Directions. *Educ. Technol. Soc.* **2013**, *16*, 21–30.
2. Wu, J.-Y.; Tsai, C.-C. Harnessing the Power of Promising Technologies to Transform Science Education: Prospects and Challenges to Promote Adaptive Epistemic Beliefs in Science Learning. *Int. J. Sci. Educ.* **2022**, *44*, 346–353. [CrossRef]
3. Jose, J.; Jose, B.J. Educators' Academic Insights on Artificial Intelligence: Challenges and Opportunities. *Electron. J. e-Learn.* **2024**, *22*, 59–77. [CrossRef]
4. Liu, J.; Li, S. Toward Artificial Intelligence-Human Paired Programming: A Review of the Educational Applications and Research on Artificial Intelligence Code-Generation Tools. *J. Educ. Comput. Res.* **2024**, *62*, 1385–1415. [CrossRef]
5. Alvarez-Garcia, M.; Arenas-Parra, M.; Ibar-Alonso, R. Uncovering Student Profiles. An Explainable Cluster Analysis Approach to PISA 2022. *Comput. Educ.* **2024**, *223*, 105166. [CrossRef]
6. Okoye, K.; Nganji, J.T.J.T.; Escamilla, J.; Hosseini, S. Machine Learning Model (RG-DMML) and Ensemble Algorithm for Prediction of Students' Retention and Graduation in Education. *Comput. Educ. Artif. Intell.* **2024**, *6*, 100205. [CrossRef]
7. Destéfano, M.; Trifonova, A.; Barajas, M. Teaching AI to the Next Generation: A Humanistic Approach. *Digit. Educ. Rev.* **2024**, *45*, 115–123. [CrossRef]
8. Forero-Corba, W.; Negre Bennasar, F. Técnicas y Aplicaciones Del Machine Learning e Inteligencia Artificial En Educación: Una Revisión Sistemática. *RIED-Rev. Iberoam. Educ. Distancia* **2023**, *27*, 209–253. [CrossRef]
9. Bagunaid, W.; Chilamkurti, N.; Shahraki, A.S.; Bamashmos, S. Visual Data and Pattern Analysis for Smart Education: A Robust DRL-Based Early Warning System for Student Performance Prediction. *Future Internet* **2024**, *16*, 206. [CrossRef]
10. Charbonneau-Gowdy, P.; Galdames, C. Identity Matters: A Framework for Bridging Contemporary e-Learning Theory with Online Practice. *Electron. J. e-Learn.* **2024**, *21*, 1–19. [CrossRef]
11. Abdelmagid, A.S.; Hafez, M.A.; Ahmed, E.W.; Jabli, N.M.; Ibrahim, A.M.; Teleb, A.A.; Aljawarneh, N.M. Interactive Digital Platforms and Artificial Intelligence Applications to Develop Technological Innovation Skills Among Saudi University Students. *Int. J. Interact. Mob. Technol.* **2024**, *18*, 64–79. [CrossRef]
12. Salhab, R. AI Literacy Across Curriculum Design: Investigating College Instructors' Perspectives. *Online Learn. J.* **2024**, *28*, n2. [CrossRef]
13. Tan, C.; Lin, J. A New QoE-Based Prediction Model for Evaluating Virtual Education Systems with COVID-19 Side Effects Using Data Mining. *Soft Comput.* **2023**, *27*, 1699–1713. [CrossRef]
14. Alé-Ruiz, R.; Martínez-Abad, F.; del Moral-Marcos, M.T. Academic Engagement and Management of Personalised Active Learning in Higher Education Digital Ecosystems. *Educ. Inf. Technol.* **2024**, *29*, 12289–12304. [CrossRef]

15. Omran Zailuddin, M.F.N.; Nik Harun, N.A.; Abdul Rahim, H.A.; Kamaruzaman, A.F.; Berahim, M.H.; Harun, M.H.; Ibrahim, Y. Redefining Creative Education: A Case Study Analysis of AI in Design Courses. *J. Res. Innov. Teach. Learn.* **2024**, *17*, 282–296. [CrossRef]
16. Fu, L. Research on the Teaching Model of Animation Professional Class Based on AR/VR Technology and 5G Network. *Wirel. Commun. Mob. Comput.* **2021**, *2021*, 1715909. [CrossRef]
17. Roco, M.C.; Bainbridge, W.S. The New World of Discovery, Invention, and Innovation: Convergence of Knowledge, Technology, and Society. *J. Nanopart. Res.* **2013**, *15*, 1946. [CrossRef]
18. Kerimbayeva, B.T.; Niyazova, G.Z.; Meirbekov, A.K.; Kibishov, A.T.; Usembayeva, I.B. A Network Communicative Culture for Future Teachers: Development of Digital Literacy and Communicative Competence. *Cogent Educ.* **2024**, *11*, 2363678. [CrossRef]
19. Hezam, A.M.M.; Alkhateeb, A. Short Stories and AI Tools: An Exploratory Study. *Theory Pract. Lang. Stud.* **2024**, *14*, 2053–2062. [CrossRef]
20. Smith, R.C.; Schaper, M.-M.; Tamashiro, M.A.; Van Mechelen, M.; Petersen, M.G.; Iversen, O.S. A Research Agenda for Computational Empowerment for Emerging Technology Education. *Int. J. Child-Comput. Interact.* **2023**, *38*, 100616. [CrossRef]
21. Yao, K.-C.; Huang, W.-T.; Hsu, L.-C.; Yang, C.-K.; Lai, J.-Y. Evaluation of the Established IoT Smart Home Robot Teaching Module Based on Embedded Thematic-Approach Strategy. *Math. Probl. Eng.* **2020**, *2020*, 6696155. [CrossRef]
22. Zhang, H.; Liu, S.; Li, Y.; Ren, W.; Tong, H.; Cao, J.; Zhou, Q. HVCMM: A Hybrid-View Abstractive Model of Automatic Summary Generation for Teaching. *IEEE Trans. Neural Netw. Learn. Syst.* **2024**, *35*, 13441–13452. [CrossRef]
23. Seya, K.; Okatani, T.; Matsuo, Y.; Kobayashi, N.; Shirasaka, S. Identifying Issues for Learners in Completing Online Courses on Machine Learning and Deep Learning: Five Issues Found in a Fully Automated Learning Environment for the Purpose of Scalable AI Education. *Rev. Integr. Bus. Econ. Res.* **2020**, *9*, 35–54.
24. Gu, J.; Wang, J.; Guo, X.; Liu, G.; Qin, S.; Bi, Z. A Metaverse-Based Teaching Building Evacuation Training System with Deep Reinforcement Learning. *IEEE Trans. Syst. Man Cybern. Syst.* **2023**, *53*, 2209–2219. [CrossRef]
25. Bashir, A.K.; Victor, N.; Bhattacharya, S.; Huynh-The, T.; Chengoden, R.; Yenduri, G.; Maddikunta, P.K.R.; Pham, Q.-V.; Gadekallu, T.R.; Liyanage, M. Federated Learning for the Healthcare Metaverse: Concepts, Applications, Challenges, and Future Directions. *IEEE Internet Things J.* **2023**, *10*, 21873–21891. [CrossRef]
26. Kaharuddin; Ahmad, D.; Mardiana; Latif, I.; Arafah, B.; Suryadi, R. Defining the Role of Artificial Intelligence in Improving English Writing Skills Among Indonesian Students. *J. Lang. Teach. Res.* **2024**, *15*, 568–578. [CrossRef]
27. Al-khresheh, M.H. Bridging Technology and Pedagogy from a Global Lens: Teachers' Perspectives on Integrating ChatGPT in English Language Teaching. *Comput. Educ. Artif. Intell.* **2024**, *6*, 100218. [CrossRef]
28. Ghamrawi, N.; Shal, T.; Ghamrawi, N.A.R. Exploring the Impact of AI on Teacher Leadership: Regressing or Expanding? *Educ. Inf. Technol.* **2024**, *29*, 8415–8433. [CrossRef]
29. Picciano, A.G. Graduate Teacher Education Students Use and Evaluate ChatGPT as an Essay-Writing Tool. *Online Learn. J.* **2024**, *28*, n2. [CrossRef]
30. Eva, T.P.; Akter, S.; Zabeen, M.; Shahriar, S.H.B. Exploring the Future of Learning: Understanding the Innovation in Learning from the Perspectives of Developing Nation. *J. Res. Innov. Teach. Learn.* **2024**, *17*, 297–309. [CrossRef]
31. Padmaja, C.V.R.; Narayana, S.L.; Anga, G.L.; Bhansali, P.K. The Rise of Artificial Intelligence: A Concise Review. *IAES Int. J. Artif. Intell.* **2024**, *13*, 2224–2233. [CrossRef]
32. Rasheed, Z.; Ghwanmeh, S.; Abualkishik, A.Z. Harnessing Artificial Intelligence for Personalized Learning: A Systematic Review. *Data Metadata* **2023**, *2*, 146. [CrossRef]
33. van Eck, N.J.; Waltman, L. Software Survey: VOSviewer, a Computer Program for Bibliometric Mapping. *Scientometrics* **2010**, *84*, 523–538. [CrossRef] [PubMed]
34. van Eck, N.J.; Waltman, L. Visualizing Bibliometric Networks. In *Measuring Scholarly Impact*; Springer International Publishing: Cham, Switzerland, 2014; pp. 285–320.
35. Tijssen, R.J.W.; Van Raan, A.F.J. Mapping Changes in Science and Technology: Bibliometric Co-Occurrence Analysis of the R&D Literature. *Eval. Rev.* **1994**, *18*, 98–115. [CrossRef]
36. Waltman, L.; van Eck, N.J. Source Normalized Indicators of Citation Impact: An Overview of Different Approaches and an Empirical Comparison. *Scientometrics* **2013**, *96*, 699–716. [CrossRef]
37. Fellnhofer, K. Visualised Bibliometric Mapping on Smart Specialisation: A Co-Citation Analysis. *Int. J. Knowl.-Based Dev.* **2018**, *9*, 76. [CrossRef]
38. Waltman, L.; van Eck, N.J.; Visser, M.; Wouters, P. The Elephant in the Room: The Problem of Quantifying Productivity in Evaluative Scientometrics. *J. Informetr.* **2016**, *10*, 671–674. [CrossRef]
39. Brombacher-Steiert, S.; Ehrich, R.; Schneider, C.; Müller, L.R.; Tipold, A.; Wissing, S. Teaching Clinical Practical and Communication Skills of the Clinical Skills Lab of the University of Veterinary Medicine Hannover, Foundation, Germany during the COVID-19 Pandemic. *GMS J. Med. Educ.* **2021**, *38*, Doc86. [CrossRef]

40. Tozzi, A.E.; Gesualdo, F.; Pandolfi, E.; Ferro, D.; Cinelli, G.; Bozzola, E.; Aversa, T.; Di Mauro, A.; Mameli, C.; Croci, I. Prioritizing Educational Initiatives on Emerging Technologies for Italian Pediatricians: Bibliometric Review and a Survey. *Ital. J. Pediatr.* **2023**, *49*, 112. [CrossRef]
41. Chang, D.H.; Lin, M.P.-C.; Hajian, S.; Wang, Q.Q. Educational Design Principles of Using AI Chatbot That Supports Self-Regulated Learning in Education: Goal Setting, Feedback, and Personalization. *Sustainability* **2023**, *15*, 12921. [CrossRef]
42. Fernandez, P. "Through the Looking Glass: Envisioning New Library Technologies" Educational Trends That Will Impact Library Technology. *Libr. Hi Tech News* **2017**, *34*, 1–5. [CrossRef]
43. Kakodkar, A.; Ronge, B.; Patankar, A.; Mule, S.; Pawar, P. A Concept of Knowledge and Technology Enabled Empowerment of Rural Indian Villages. *Curr. Sci.* **2017**, *112*, 750–758. [CrossRef]
44. Patre, S.; Chakraborty, D.; Kar, A.K.; Singu, H.B.; Tiwari, D.A. The Role of Enablers and Barriers in the Upskilling and Reskilling of Users Through Professional Skilling Programs on EdTech Platforms. *IEEE Trans. Eng. Manag.* **2024**, *71*, 9839–9853. [CrossRef]
45. Black, M.; Obradovic, L.; House, D. Behind the Curve: Technology Challenges Facing the Homeland Intelligence and Counterterrorism Workforce. *J. Cybersecur.* **2024**, *10*, tyae002. [CrossRef]
46. Sun, P.; Gu, L. Fuzzy Knowledge Graph System for Artificial Intelligence-Based Smart Education. *J. Intell. Fuzzy Syst.* **2021**, *40*, 2929–2940. [CrossRef]
47. Jang, Y.; Choi, S.; Jung, H.; Kim, H. Practical Early Prediction of Students' Performance Using Machine Learning and EXplainable AI. *Educ. Inf. Technol.* **2022**, *27*, 12855–12889. [CrossRef]
48. Fayoumi, A.G.; Hajjar, A.F. Advanced Learning Analytics in Academic Education: Academic Performance Forecasting Based on an Artificial Neural Network. *Int. J. Semant. Web Inf. Syst.* **2020**, *16*, 70–87. [CrossRef]
49. Meneses, E.J.L.; Bravo, C.B.; Olivencia, J.J.L.; Padilla, A.H.M. Validation of the Didactic Instrument for the Assessment of Digital Observatories on MOOC: CUVOMOOC ® by the Delphi Method. *Campus Virtuales* **2018**, *7*, 95–110.
50. Munk, M.; Drlik, M.; Benko, L.; Reichel, J. Quantitative and Qualitative Evaluation of Sequence Patterns Found by Application of Different Educational Data Preprocessing Techniques. *IEEE Access* **2017**, *5*, 8989–9004. [CrossRef]
51. Pinto Santos, A.R.; Pérez Garcias, A. Gestión Curricular y Desarrollo de La Competencia Digital Docente En La Formación Inicial Del Profesorado. *Rev. Educ. Distancia* **2022**, *22*, 1–21. [CrossRef]
52. Abad-Segura, E.; González-Zamar, M.-D.; Luque-de la Rosa, A.; Morales Cevallos, M.B. Sustainability of Educational Technologies: An Approach to Augmented Reality Research. *Sustainability* **2020**, *12*, 4091. [CrossRef]
53. Robinson, L.; Bawden, D. "The Story of Data": A Socio-Technical Approach to Education for the Data Librarian Role in the CityLIS Library School at City, University of London. *Libr. Manag.* **2017**, *38*, 312–322. [CrossRef]
54. Amo, D.; Alier, M.; García-Peñalvo, F.; Fonseca, D.; Casañ, M.J. Privacidad, Seguridad y Legalidad En Soluciones Educativas Basadas En Blockchain: Una Revisión Sistemática de La Literatura. *RIED. Rev. Iberoam. Educ. Distancia* **2020**, *23*, 213. [CrossRef]
55. Enakrire, R.T.; Oladokun, B.D. Artificial Intelligence as Enabler of Future Library Services: How Prepared Are Librarians in African University Libraries. *Libr. Hi Tech News* **2024**, *41*, 1–5. [CrossRef]
56. Caico, M.; Harris, L.; O'shea, S. Is This AI Tool Right for Me? Important Questions from the Framework. *Coll. Res. Libr. News* **2024**, *85*, 341. [CrossRef]
57. Becker, S.O.; Woessmann, L. Was Weber Wrong? A Human Capital Theory of Protestant Economic History. *Q. J. Econ.* **2009**, *124*, 531–596. [CrossRef]
58. Huang, F. Examining Foreign Language Teachers' Information Literacy: Do Digital Nativity, Technology Training, and Fatigue Matter? *Asia-Pacific Educ. Res.* **2024**, *33*, 901–912. [CrossRef]
59. Yang, D.; Zhou, J.; Shi, D.; Pan, Q.; Wang, D.; Chen, X.; Liu, J. Research Status, Hotspots, and Evolutionary Trends of Global Digital Education via Knowledge Graph Analysis. *Sustainability* **2022**, *14*, 15157. [CrossRef]
60. Alibasic, A.; Upadhyay, H.; Simsekler, M.C.E.; Kurfess, T.; Woon, W.L.; Omar, M.A. Evaluation of the Trends in Jobs and Skill-Sets Using Data Analytics: A Case Study. *J. Big Data* **2022**, *9*, 32. [CrossRef]
61. Chalkiadakis, I.; Zaremba, A.; Peters, G.W.; Chantler, M.J. On-Chain Analytics for Sentiment-Driven Statistical Causality in Cryptocurrencies. *Blockchain Res. Appl.* **2022**, *3*, 100063. [CrossRef]
62. Cukurova, M.; Luckin, R.; Millán, E.; Mavrikis, M. The NISPI Framework: Analysing Collaborative Problem-Solving from Students' Physical Interactions. *Comput. Educ.* **2018**, *116*, 93–109. [CrossRef]
63. Hartle, S.; Facchinetti, R.; Franceschi, V. Teaching Communication Strategies for the Workplace: A Multimodal Framework. *Multimodal Commun.* **2022**, *11*, 5–15. [CrossRef]
64. Maphosa, V.; Maphosa, M. Artificial Intelligence in Higher Education: A Bibliometric Analysis and Topic Modeling Approach. *Appl. Artif. Intell.* **2023**, *37*, 2261730. [CrossRef]
65. Chang, I.-C.; Yu, T.-K.; Chang, Y.-J.; Yu, T.-Y. Applying Text Mining, Clustering Analysis, and Latent Dirichlet Allocation Techniques for Topic Classification of Environmental Education Journals. *Sustainability* **2021**, *13*, 10856. [CrossRef]
66. Kumi, S.; Snow, C.; Lomotey, R.K.; Deters, R. Uncovering Concerns of Citizens Through Machine Learning and Social Network Sentiment Analysis. *IEEE Access* **2024**, *12*, 94885–94913. [CrossRef]

67. Su, X.-H.; Zheng, W.-N.; Jiang, Y.; Wei, H.-W.; Wan, J.-Y.; Wei, Z.-Y. Research and Progress on Learning-Based Source Code Vulnerability Detection. *Chin. J. Comput.* **2024**, *47*, 337–374. [CrossRef]
68. Oedingen, M.; Engelhardt, R.C.; Denz, R.; Hammer, M.; Konen, W. ChatGPT Code Detection: Techniques for Uncovering the Source of Code. *AI* **2024**, *5*, 1066–1094. [CrossRef]
69. Chu, L.; Liu, Y.; Zhai, Y.; Wang, D.; Wu, Y. The Use of Deep Learning Integrating Image Recognition in Language Analysis Technology in Secondary School Education. *Sci. Rep.* **2024**, *14*, 2888. [CrossRef]
70. Loh, P.K.K.; Lee, A.Z.Y.; Balachandran, V. Towards a Hybrid Security Framework for Phishing Awareness Education and Defense. *Future Internet* **2024**, *16*, 86. [CrossRef]
71. Ruan, S.; Nie, A.; Steenbergen, W.; He, J.; Zhang, J.Q.; Guo, M.; Liu, Y.; Dang Nguyen, K.; Wang, C.Y.; Ying, R.; et al. Reinforcement Learning Tutor Better Supported Lower Performers in a Math Task. *Mach. Learn.* **2024**, *113*, 3023–3048. [CrossRef]
72. Van Mechelen, M.; Smith, R.C.; Schaper, M.-M.; Tamashiro, M.; Bilstrup, K.-E.; Lunding, M.; Graves Petersen, M.; Sejer Iversen, O. Emerging Technologies in K–12 Education: A Future HCI Research Agenda. *ACM Trans. Comput. Interact.* **2023**, *30*, 1–40. [CrossRef]
73. Ma, Z.-G.; Ni, R.-Y.; Yu, K.-H. Recent Advances, Key Techniques and Future Challenges of Knowledge Graph. *Chin. J. Eng.* **2020**, *42*, 1254–1266. [CrossRef]
74. Jung, J.Y.; Tyack, L.; von Davier, M. Combining Machine Translation and Automated Scoring in International Large-Scale Assessments. *Large-Scale Assess. Educ.* **2024**, *12*, 10. [CrossRef]
75. Guo, S.; Zheng, Y.; Zhai, X. Artificial Intelligence in Education Research during 2013–2023: A Review Based on Bibliometric Analysis. *Educ. Inf. Technol.* **2024**, *29*, 16387–16409. [CrossRef]
76. Llorca, D.F.; Charisi, V.; Hamon, R.; Sánchez, I.; Gómez, E. Liability Regimes in the Age of AI: A Use-Case Driven Analysis of the Burden of Proof. *J. Artif. Intell. Res.* **2023**, *76*, 613–644. [CrossRef]
77. Carrión Montalván, B.K.; Pillajo Angos, C.G.; Castellanos Fonseca, J.A.; Vega Aguaiza, R. The Influence of Artificial Intelligence in Higher Education Based on Four Thematic Axes: A Bibliometric Study. *Sapienza Int. J. Interdiscip. Stud.* **2024**, *5*, e24035. [CrossRef]
78. Matzavela, V.; Alepis, E. M-Learning in the COVID-19 Era: Physical vs. Digital Class. *Educ. Inf. Technol.* **2021**, *26*, 7183–7203. [CrossRef]
79. Wang, R.; Li, J.; Shi, W.; Li, X. Application of Artificial Intelligence Techniques in Operating Mode of Professors' Academic Governance in American Research Universities. *Wirel. Commun. Mob. Comput.* **2021**, *2021*, 3415125. [CrossRef]
80. Gerber, S.; Quarder, J.; Greefrath, G.; Siller, H.-S. Promoting Adaptive Intervention Competence for Teaching Simulations and Mathematical Modelling with Digital Tools: Theoretical Background and Empirical Analysis of a University Course in Teacher Education. *Front. Educ.* **2023**, *8*, 1141063. [CrossRef]
81. Medeshova, A.; Kassymova, A.; Mutalova, Z.; Kamalova, G. Distance Learning Activation in Higher Education. *Eur. J. Contemp. Educ.* **2022**, *11*, 831–845. [CrossRef]
82. Ahmed, E. Student Performance Prediction Using Machine Learning Algorithms. *Appl. Comput. Intell. Soft Comput.* **2024**, *2024*, 4067721. [CrossRef]
83. Szwed, P.; Skrzynski, P.; Chmiel, W. Risk Assessment for a Video Surveillance System Based on Fuzzy Cognitive Maps. *Multimed. Tools Appl.* **2016**, *75*, 10667–10690. [CrossRef]
84. Yoo, J.; Park, J.; Ha, M.; Mae Lagmay Darang, C. Exploring Pre-Service Teachers' Cognitive Processes and Calibration with an Unsupervised Learning-Based Automated Evaluation System. *SAGE Open* **2024**, *14*, 21582440241262864. [CrossRef]
85. Sghir, N.; Adadi, A.; Lahmer, M. Recent Advances in Predictive Learning Analytics: A Decade Systematic Review (2012–2022). *Educ. Inf. Technol.* **2023**, *28*, 8299–8333. [CrossRef]
86. Alqawasmi, A.; Alsalhi, N.; Shater, A.; Aleassa, M.; Almahdawi, A.; Alghazo, E. The Impact of the Flipped Classroom Model (FCM) on the Academic Intrinsic Motivation (AIM) and Lesson Planning for Science Teacher-Students in the Postgraduate Professional Teaching Diploma (PPTD) Program at Al Ain University: A Case Study. *Eurasian J. Educ. Res.* **2023**, *2023*, 78–92.
87. González-Zamar, M.D.; Abad-Segura, E. El Aula Invertida: Un Desafío Para La Enseñanza Universitaria. *Virtualidad Educ. Cienc.* **2020**, *11*, 75–91. [CrossRef]
88. Abad-Segura, E.; González-Zamar, M.D.; de la Rosa, A.L.; Gallardo-Pérez, J. Management of the Digital Economy in Higher Education: Trends and Future Perspectives. *Campus Virtuales* **2020**, *9*, 57–68.
89. Martínez-Pérez, S.; Cabero-Almenara, J.; Barroso-Osuna, J.; Palacios-Rodríguez, A. T-MOOC for Initial Teacher Training in Digital Competences: Technology and Educational Innovation. *Front. Educ.* **2022**, *7*, 846998. [CrossRef]
90. Chiu, T.K.F. A Classification Tool to Foster Self-Regulated Learning with Generative Artificial Intelligence by Applying Self-Determination Theory: A Case of ChatGPT. *Educ. Technol. Res. Dev.* **2024**, *72*, 2401–2416. [CrossRef]