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Review

Learning Analytics and Educational Data Mining in Augmented Reality, Virtual Reality, and the Metaverse: A Systematic Literature Review, Content Analysis, and Bibliometric Analysis

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Abstract: This study aims to examine the combination of educational data mining and learning analytics with virtual reality, augmented reality, mixed reality, and the metaverse, its role in education, and its impact on teaching and learning. Therefore, a systematic literature review, a bibliometric and scientific mapping analysis, and a content analysis are carried out based on 70 relevant documents identified from six databases, namely, ACM, ERIC, IEEE, ScienceDirect, Scopus, and Web of Science (WoS) following the PRISMA framework. The documents were separated into the following three categories, (i) Theoretical and Review studies, (ii) Proposal and Showcase studies, and (iii) Experimental and Case studies and were examined from different dimensions through an in-depth content analysis using both quantitative and qualitative approaches. The documents were further analyzed using scientometric tools, such as Bibliometrix and VOSviewer and topic modeling through Latent Dirichlet Allocation (LDA). The most prominent topics, areas, and themes were revealed and the outcomes regarding the influence of this combination on learning and teaching were summarized. Based on the results, this combination can effectively enrich education, positively affect learning and teaching, offer deep and meaningful learning, and support both students and teachers. Additionally, it can support different educational approaches and strategies, various learning styles, and special education and be utilized in both formal and informal learning environments. The real-time identification, tracking, monitoring, analysis, and visualization of multimodal learning data of students' behavior, emotions, cognitive and affective states and the overall learning and teaching processes emerged as a significant benefit that contributes greatly to the realization of adaptive and personalized learning. Finally, it was revealed that the combination of extended reality technologies with learning analytics and educational data mining can support collaborative learning and social learning, improve students' self-efficacy and self-regulated learning, and increase students' learning gains, academic achievements, knowledge retention, motivation, and engagement.

Keywords: extended reality; augmented reality; virtual reality; metaverse; learning analytics; educational data mining; immersive learning; virtual learning environments; learning technologies; artificial intelligence; technology-enhanced learning; education; review

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1. Introduction

There is an ever increasing need to integrate data science into educational contexts to further enhance learning and teaching [1]. Via educational data science, educational processes can be tailored to each individual's requirements, needs, and preferences [2]. Among the various methods and approaches used in the domain of data science in education, learning analytics and educational data mining are the most widely used [3,4]. Educational data hold a lot of value and meaning [5] and can be used in many ways, including analyzing students' performance [6]. Therefore, and due to the potential benefits that they can bring in the educational domain, research into educational data mining [7] and learning analytics [8] is continuously increasing. It should be noted that despite their sharing similarities and their being applied at all educational levels, there are distinct differences between the two [2,9]. Specifically, learning analytics evaluate the educational process and learning theories using existing models in a top–down approach, while educational data mining strives to create new models and identify new patterns in data in a bottom–up approach [10,11]. Additionally, there are several other differences regarding the methods, adaptations, techniques, personalization strategies, origins, and approaches used between the two [12,13]. As a result, it can be inferred that learning analytics put an emphasis on addressing educational challenges, while educational data mining puts an emphasis on the technical ones [14].

Specifically, learning analytics is an interdisciplinary scientific field that is increasing in popularity since learning analytics can enrich current education models [12,14]. Learning analytics focuses on analyzing data, commonly deriving from educational environments, to enhance the overall quality of teaching and learning, to improve personalization, and to overcome existing barriers and challenges [15,16]. Hence, learning analytics involves the processes of collecting, processing, analyzing, and visualizing data to better understand teaching and learning processes to further improve educational experiences and environments [3,13,14,17,18]. Learning analytics can support both teachers and students, help meet their needs, and positively influence teachers' performance and students' progress [19,20]. Hence, learning analytics can be utilized to comprehend and optimize the educational process and the environment in which it occurs [21]. Several systematic literature reviews have examined the role and use of learning analytics in educational settings [21–26]. These studies highlight the positive effect that they can have on learning and teaching practices, point out the educational outcomes that can be yielded, and comment upon the fact that this area of study is still in its infancy. Another fact that derives from these studies is the drastic need to further explore how multi-modal data can be used in the context of learning analytics to increase learning outcomes.

Simultaneously, educational data mining is also gaining ground [3]. Based on the "International Educational Data Mining Society", educational data mining is "an emerging discipline, concerned with developing methods for exploring the unique and increasingly large-scale data that come from educational settings and using those methods to better understand students, and the settings which they learn in" [27]. Hence, it constitutes an interdisciplinary study field that capitalizes on statistics, machine learning, deep learning, information retrieval, and artificial intelligence [5]. Specifically, this specialized data mining form aims to process information, analyze data, develop models, and identify patterns within data to address educational challenges, improve institutional effectiveness, and enhance learning outcomes and experiences [2,11,28]. Due to the nature and scope of educational data mining, several systematic literature reviews have been conducted to examine its use in educational contexts [5,22,28–30]. The outcomes of these studies highlight the capabilities of educational data mining to enrich learning and teaching and comment upon the increasing need to capitalize on educational data and explore how to effectively identify and extract meaning from it.

Through extended reality technologies, valuable data can be generated which can reveal additional key aspects when examined within educational settings. Specifically, extended reality refers to new reality formats that are provided through mixed reality, virtual reality, and augmented reality technologies [31]. Augmented reality involves users' physical environment enrichment with digital objects and virtual information that are interactive and can be perceived through users' senses [32–34]. Virtual reality involves fully virtual environments that perceptually surround users and simulate their physical presence within them [35–37] to create "all-inclusive, sensory illusion of being present in another environment" [38]. These environments provide high immersion, involvement, immediacy, and interaction [39–42] and capitalize on psychological and social aspects to be perceived by users as real [43]. In the context of the "reality-virtuality continuum", somewhere in the middle between the real and virtual environments lies a mixed reality in which real and virtual contexts co-exist [44]. Within this continuum, virtual reality is nearer to the virtual environment, whereas augmented reality is nearer to the physical world [44]. Owing to their interactivity and immersiveness, these technologies are more widely utilized in educational settings across levels and subjects. The outcomes of systematic literature reviews that have examined both theoretical and experimental studies and focused on both augmented reality [45–48] and virtual reality [49–52] technologies have highlighted the benefits and the positive influence that their integration into the educational domain can bring about. Additionally, extended reality technologies can be combined with different approaches, such as gamification, and other technologies (e.g., artificial intelligence) to further increase learning outcomes and offer personalized learning experiences [53]. Due to their unique nature, additional data to that generated within traditional classrooms or when using traditional teaching means can be generated. By examining this data meaningful insights that can further increase our understanding of learning could be yielded.

According to the aforementioned information, it is evident that by combining these technologies and methods, personalized learning environments that are characterized by high engagement and immersiveness can be created. The relationship among extended reality technologies, learning analytics, and educational data mining is presented in Figure 1. Specifically, through extended reality technologies, interactive, secure, and immersive learning environments that foster experiential learning can be created, which, in turn, can render the collection of multimodal data feasible. Using advanced algorithms and computational techniques in the context of educational data mining, the educational data can be analyzed to predict learners' behaviors, discover patterns, create predictive models, and offer meaningful recommendations to improve teaching and learning. Additionally, through learning analytics, the educational data can be systematically collected, processed, analyzed, visualized, and interpreted to optimize the overall educational process.

However, despite the existing studies that have focused on these topics, there has not been any study, to the best of our knowledge, which explores how learning analytics and educational data mining are used within extended reality environments. Hence, there is a clear gap in the literature regarding the examination of the role and use of learning analytics and educational data mining within extended reality environments and the representation of the existing state of the art. Given the potential benefits that their combination can bring and to address this literature gap, this study aims to explore the role and use of educational data mining and learning analytics within augmented reality and virtual reality learning environments and the metaverse. Specifically, the goal of this study is to showcase the state of the art, to highlight the impact that the combination of these technologies and methods has on teaching and learning activities, and to suggest future research directions to help shape this novel field of study based on the existing literature. Hence, the main research questions of this study are how educational data mining and learning analytics can be used within virtual reality and augmented reality learning environments as well as the metaverse and how they impact the processes of teaching and learning. To meet the objective of this study and address the research question set, a systematic literature review following the "Preferred Reporting Items for Systematic Reviews and Meta-Analyses" (PRISMA) [54] framework and an in-depth content analysis was conducted. Additionally, topic modeling using Latent Dirichlet Allocation (LDA) [55] was also used and Bibliometrix (v.4.3.0) [56] and VOSviewer (v.1.6.20) [57] tools were adopted to further examine the document collection.

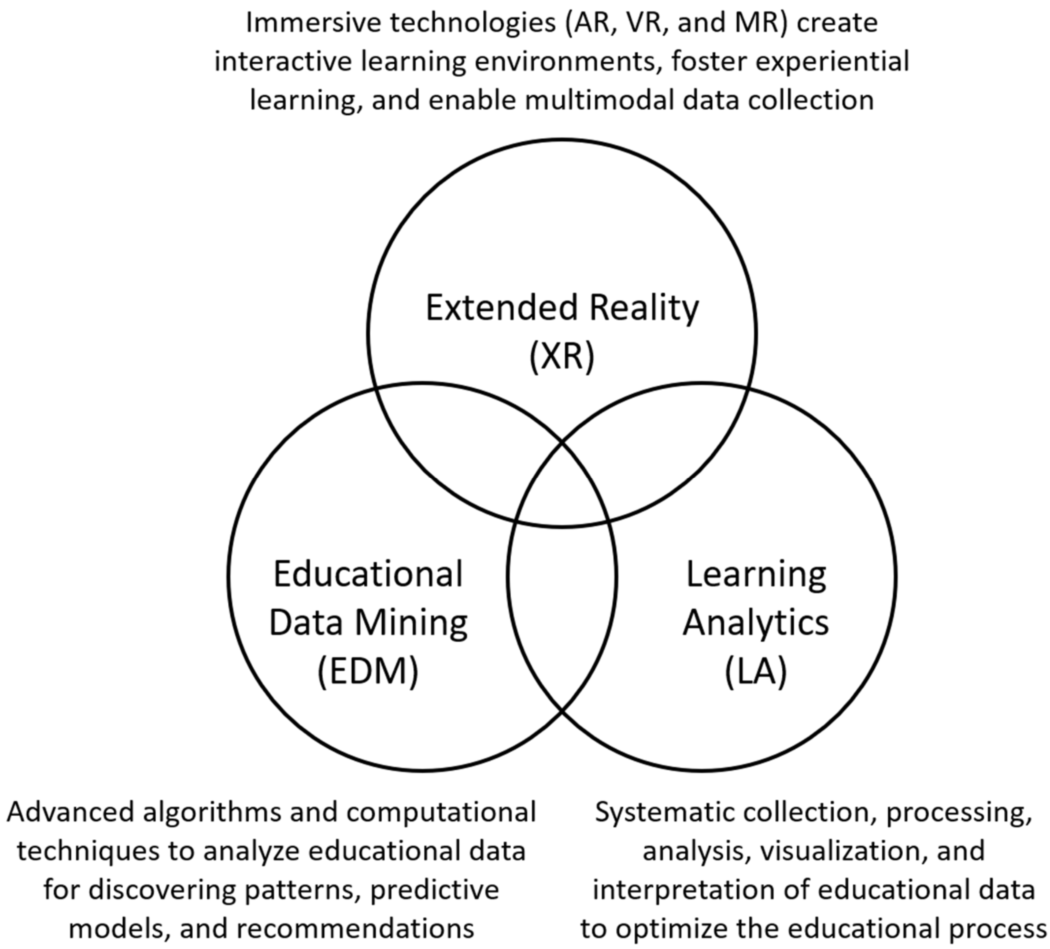

Figure 1. The relationship among extended reality technologies, educational data mining, and learning analytics.

This study contributes to the existing literature by providing an in-depth analysis of this emerging field of study. Specifically, it presents findings from theoretical, proposal, and experimental studies and synthesizes their outcomes. Additionally, it provides a content analysis of the experimental and case studies to identify key aspects in the realization of learning analytics and educational data mining within augmented reality and virtual reality environments. Furthermore, this study also contributes through its bibliometric analysis and scientific mapping of the existing literature as well as the identification of emerging topics and limitations within the literature. Finally, this study also highlights future research directions and areas. The remainder of this study explores related works (Section 2) and presents the methodology used in detail so as to provide clarity, transparency, and reproducibility (Section 3). Moreover, it presents the data analysis and the related results (Section 4) and focuses on analyzing the document collection as a whole (Section 4.1) as well as each different document type separately following a mixed-method approach (Sections 4.2–4.4). The findings are further examined, synthesized, and analyzed and implications are provided (Section 5). In Section 6, the conclusions arisen are presented, the study limitations are discussed, and future research directions are provided.

2. Related Work

Given the scope of this study and the main topics examined, some relevant literature review studies are presented. The study of Mangaroska et al. [21] focused on examining the intersection between learning design and learning analytics to improve learning. Their study analyzed 43 papers from 2010 to 2017 and highlighted the synergies between learning analytics and learning design. Additionally, emphasis was placed on the pedagogical contexts, data analysis and collection methods, and the learning settings and objectives reported. Finally, the study highlighted the need to theoretically ground learning analytics for the field to further mature. Avella et al. [23] explored the challenges, benefits, and methods of integrating learning analytics in higher education. Their work highlighted the personalization of learning, the improvement of the curriculum, the identification of suitable material and courses, as well as the improvement of students' and instructors' performance as the main benefits yielded through the adoption of learning analytics. Additionally, the study pointed out the challenges associated with data tracking, collection, and analysis, with effective evaluation, environment optimization, and privacy and ethical considerations. Larrabee Sønderlund et al. [24] put an emphasis on the efficacy of learning analytics intervention within higher education settings by analyzing 11 related studies. The study highlighted the potentials of learning analytics but simultaneously showcased the need for more evidence-based research to be conducted to solidify the effectiveness, generalizability, and feasibility of learning analytics interventions. Leitner et al. [26] also focused on the use of learning analytics in higher education and, in their literature review study, examined 101 related papers. Their study revealed the various techniques used within the studies (e.g., prediction, clustering, outlier detection, etc.) and commented on the short-term and long-term trends and future research directions.

Furthermore, some studies focused on both learning analytics and educational data mining. For example, the study of Aldowah et al. [22] explored their use in the context of 21st century higher education. Their work examined 402 studies from 2000 to 2017 and focused on computer-supported learning analytics, visualization analytics, predictive analytics, and behavioral analytics. Their findings reveal the beneficial role that these approaches can play in creating effective student-focused teaching strategies. Papamitsiou and Economides [25] analyzed 40 documents from 2008 to 2013 to examine the practical implementations of learning analytics and educational data mining using non-statistical methods. Their study revealed key implications, commented upon the added value of learning analytics and educational data mining research, and suggested future research questions aiming at addressing both technical and pedagogical considerations.

Other studies focused exclusively on the use of educational data mining in educational settings. Romero and Ventura [5] carried out a review regarding the state of the art of educational data mining to present the most relevant to the field studies, describe key aspects, such as user groups, environment types, and data types, and explored the most commonly used tasks. Specifically, the user groups were divided into: "Learners/Students/Pupils, Educators/Teachers/Instructors/Tutors, Course Developers/Educational Researchers, Organizations/Learning Providers/Universities/Private Training Companies, and Administrators/School District Administrators /Network Administrators/System Administrators". The data/environment types were divided into: "Traditional Education, Web-based Education/E-learning, Learning Management Systems, Intelligent Tutoring Systems, Adaptive Educational Systems, Tests/Questionnaires, Texts/Contents, and Others". Finally, the study highlighted the importance of this field and its close relationship with other well-established fields. In their review, Dutt et al. [28] highlighted the need for more sophisticated data mining techniques and approaches to analyze educational data. Their work focused on clustering algorithms and examined documents from 1983 to 2016. The study highlighted the provision of pertinent insights and of students' learning style-based models. Finally, it pointed out the need to carefully select the most suitable approaches and algorithms. In another study, Mohamad and Tasir [29] highlighted the ability of educational data mining to be used to identify and track students' learning behaviors within online learning environments. The study focused on revealing the latest trends on using data mining in education in the context of online learning. Additionally, they examined potential challenges and commented upon its use to engage students in collaborative learning. Baker and Yacef [30] reviewed the history, advancement, and trends in the early years of educational data mining. Among the different educational data mining methods, "predictions, discovery with models, clustering, human judgement, and relationship mining" were the ones most widely used. The study also revealed key applications, mapped the existing literature, and provided recommendations for future research directions.

Regarding the use of extended reality technologies, several literature review studies have been carried out that explored the use of augmented reality and virtual reality in education. For example, Akçayır and Akçayır [45] focused on identifying the challenges and advantages of integrating augmented reality in education. Their work analyzed 68 documents and highlighted the increased interest in the field. The improvement of students' learning achievements arose as the main benefit, while technical problems and usability considerations emerged as the main drawbacks. Their study further expanded upon the implications of applying augmented reality in education and the existing gaps in the literature. Chen et al. [46] reviewed 55 studies from 2011 to 2016 regarding the use of augmented reality in education. Their work focused on presenting the state of the art regarding the adoption and integration of augmented reality and revealed future trends and visions for research opportunities to further advance the specific field of study. Garzón [47] provided an overview of the use of augmented reality in teaching and learning activities by examining studies from 1996 to 2019. The study explored the different stages and trends of augmented reality in education, commented upon the pending issues, such as usability, accessibility, and dissemination issues and pedagogical considerations, and provided insights into how these issues could be addressed. In a more recent study, Lampropoulos et al. [48] explored the use of augmented reality and gamification in education. The study analyzed 113 documents that were published until 2022. The work focused on addressing 15 research questions and revealed the benefits and challenges associated with the integration of augmented reality in education. The study also revealed the diverse nature of augmented reality which enables it to be used in conjunction with other technologies, approaches, and methods to enrich the educational process.

Furthermore, studies also focused on exploring the educational use of virtual reality. In their literature review study, Freina and Ott [49] explored the state of the art regarding the use of immersive virtual reality in education. In their work, they highlighted the main challenges and potentials of using virtual reality in teaching and learning activities. They defined interaction, engagement, and immersion as the key principles behind the advantages that immersive virtual reality can bring in the field of education. Finally, the study focused on different groups of students and how their needs can be met. Radianti et al. [50] explored the design elements associated with immersive virtual reality applications that are targeted at the educational domain. Their work focused on mapping the existing literature to determine the most commonly used design elements and learning theories, on identifying the domain structure of the learning content, and on defining the foundations that render the virtual reality-based education successful. Additionally, the study revealed 18 potential application domains for virtual reality in education, which further highlights the significant influence that it can have. Kavanagh et al. [51] focused on educators' motivation for integrating virtual reality in education, explored relevant applications, and examined the associated issues and problems reported in the literature. Based on their findings, most studies put an emphasis on increasing students' intrinsic motivation and the design elements of the interventions were limited. The study also went over the existing drawbacks and issues regarding the adoption of virtual reality in education and suggested techniques and actions to potentially address them. Lampropoulos and Kinshuk [52] explored the use of virtual reality and gamification in education by analyzing 112 documents until August 2022. The study addressed 15 research questions, followed a mixed-methods approach, and evaluated the quality of the studies using the Mixed Methods Appraisal Tool (MMAT). The study discussed the combination of virtual reality with gamification and revealed the main advantages and disadvantages associated with their integration in educational settings. Through its content analysis, the study presented the state of the art regarding gamification and virtual reality in education.

Based on the aforementioned, it is evident that extended reality technologies, learning analytics, and educational data mining can positively influence the educational process. However, the studies conducted have not focused on the role and use of learning analytics and educational data mining within augmented reality and virtual reality environments. Additionally, most of the studies that have been carried out do not involve the analysis of recently published documents. Given the potential that their combination can bring about in the educational domain, this study seeks to bridge this research gap by focusing on how educational data mining and learning analytics can be combined within extended reality environments and how this combination can influence teaching and learning practices by providing a thorough representation of the existing state of the art, identifying the main benefits that can be yielded, and suggesting future research directions.

3. Materials and Methods

Due to this study's scope and to address the research question defined and meet its aim, a systematic literature review was conducted. A systematic literature review should be transparent, reliable, valid, and reproducible [58]. Hence, given its rigorous rules, its ability to add transparency and offer comprehensive insights, and it being widely used and validated in educational settings [59–61], the PRISMA framework [54] was adopted. Besides an in-depth content analysis, topic modeling using LDA [55] was conducted and the document collection was further examined using Bibliometrix [56] and VOSviewer [57]. Specifically, PRISMA constitutes a set of guidelines to effectively report the process of a systematic literature review and was used as the framework of this study. Additionally, LDA is a probabilistic model which was used for topic modeling, and Bibliometrix and VOSviewer are tools used to analyze the scientific literature focusing on the visualization of networks and on the analysis of metadata and were used to further examine the document collection. Manual content analysis was also carried out based on the full text of the documents.

To identify the most relevant documents, a thorough combination of keywords was used as the query to search in 6 databases. In particular, ACM, ERIC, IEEE, ScienceDirect, Scopus, and Web of Science (WoS) were used to find suitable studies. The most accurate results were reported from the Scopus and WoS databases, which further verifies their being highly regarded and appropriate to be used to carry out literature review, bibliometric analysis, and scientific mapping studies as was already indicated in the literature [62,63].

Systematic Literature Review Process

Different combinations of keywords were used to find the most relevant documents. The final query used consisted of a combination of keywords relevant to the main topics explored in this study and was as follows: "("augmented reality" OR "virtual reality" OR "extended reality" OR "mixed reality" OR "metaverse" OR "ar" OR "vr" OR "xr" OR "mr") AND ("learning analytics" OR "educational data mining" OR "edm")". This query was selected as it yielded the most relevant documents. Although the abbreviations can identify additional related documents, their use also results in the identification of documents that are not related to the topic. For example, "mr" and "edm" are also acronyms for different things besides mixed reality and educational data mining. However, it was deemed more appropriate to be included not to miss any related document. Hence, a large volume of documents was omitted during the initial screening. Additionally, the search query did not have any limitations regarding the year of publication and publication type. However, only English documents were considered and examined in this study. The relevant documents were searched on a topic level, namely the document title, document abstract, and document keywords.

The final search was performed in December 2024 and resulted in the identification of 773 documents. Specifically, 404 documents returned from Scopus, 184 from WoS, 102 from IEEE, 37 from ScienceDirect, 22 from ERIC, and 19 from ACM. Given that most highly regarded outlets are indexed in a combination of these databases, 259 documents emerged as duplicates based on their title and were removed. Throughout the process of assessing the eligibility of the documents, the authors worked independently and cross-checked their results. In the cases where there was a different outcome, the related document was further discussed. The values reported reflect the final outcomes of the procedure. Therefore, 514 documents were then screened manually according to their title and abstract for eligibility. For a study to be included in this review, 4 inclusion criteria were set and had to be met. Specifically, the study had to (i) involve extended reality technologies; (ii) involve educational data mining and learning analytics methods; (iii) focus on or be applied in educational settings; and (vi) focus on the combination of learning analytics and/or educational data mining with extended reality technologies. Hence, only studies that met these inclusion criteria were included in the document collection.

Through the initial screening, 422 documents were omitted since they did not satisfy the inclusion criteria. This number can be justified based on the strict criteria set, as well as the use of multiple abbreviations within the search query. However, we deemed that it would be better to eliminate more documents that are not suitable than miss some documents because abbreviations were not used in the search query. Hence, 92 documents remained and were sought for retrieval. Since all documents were retrieved, all potentially relevant documents were manually assessed for eligibility by examining the documents' full text. Taking the inclusion criteria into account, 22 more documents were excluded because they did not satisfy one or more of the criteria specified. Particularly, 14 documents were removed because they did not focus on the combination extended reality technologies with learning analytics and/or educational data mining, 3 documents were excluded because they did not involve educational settings, 3 documents were removed because they did not focus on educational data mining or learning analytics, and 2 documents were excluded as they were not related to extended reality technologies. As a result, 70 studies satisfied the criteria set and were included in the document collection examined. The complete process of document identification, processing, and selection, which followed the PRISMA framework, is showcased in Figure 2.

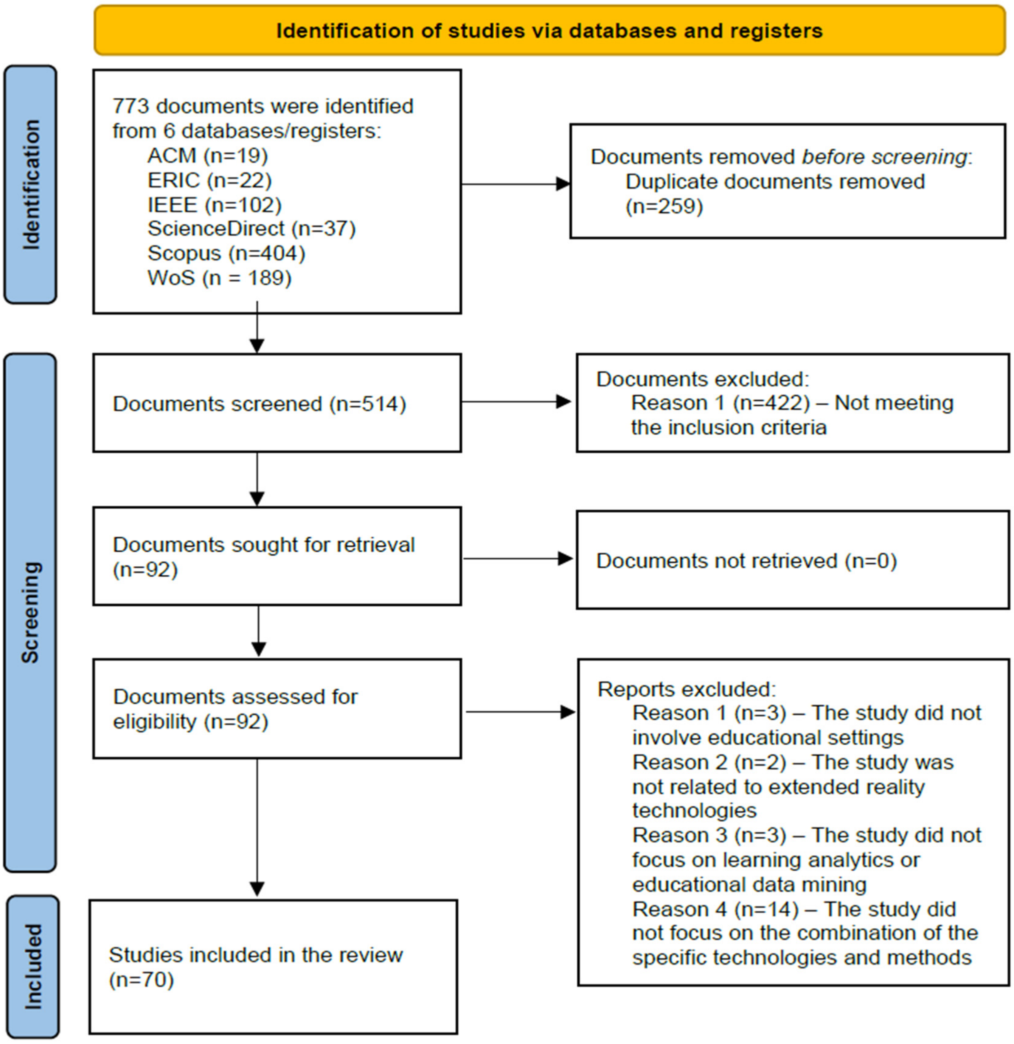

Figure 2. PRISMA flow diagram.

4. Result Analysis

To better understand how educational data mining and learning analytics are used in extended reality learning environments and the metaverse, the documents were organized into the following three categories: (1) Theoretical and Review studies: documents that explored the use of these technologies but did not showcase any relevant application and did not apply them in educational settings or did not carry out an experiment. (2) Proposal and Showcase studies: documents that presented indicative examples of applications or the combination of these technologies but did not apply them in educational settings or did not carry out an experiment. (3) Experimental and Case studies: documents that have carried out experiments and case studies using the specific technologies in combination. The categorization of documents follows that of existing published systematic literature reviews [48,52] and distinguishes the documents into three categories based on their nature and content so that they can be accordingly analyzed.

Additionally, the following subsections go over the result analysis for each of these categories and focus on the analysis of the document collection. Specifically, in the document collection analysis in Section 4.1, the results represent all documents of the collection, whereas in the following three sections (Sections 4.2–4.4), the results presented reflect only the documents of each corresponding document type. Section 4.2 analyzes the Theoretical and Review studies, while Section 4.3 examines the Proposal and Showcase studies. Finally, Section 4.4 presents the content analysis which was carried out for the Experimental and Case studies.

4.1. Analysis of the Document Collection

The collection of documents analyzed in this systematic literature review comprised of 70 documents and its details are presented in the following subsections. Specifically, the data analysis of the document collection is divided into the following parts:

- Document and Study type analysis (Section 4.1.1).
- Document collection analysis (Section 4.1.2).
- Document publication frequency analysis (Section 4.1.3).
- Sources analysis (Section 4.1.4).
- Country analysis (Section 4.1.5).
- Analysis of the technologies and methods used in the studies (Section 4.1.6).

4.1.1. Document and Study Type Analysis

According to Figure 3, most documents were published as conference papers (n = 41, 58.6%), followed by journal articles (n = 26, 37.1%) and book chapters (n = 3, 4.3%). Based on Figure 4, most documents were categorized into Experimental and Case studies (n = 36, 51.5%), followed by Proposal and Showcase studies (n = 19, 27.1%) and Theoretical and Review studies (n = 15, 21.4%).

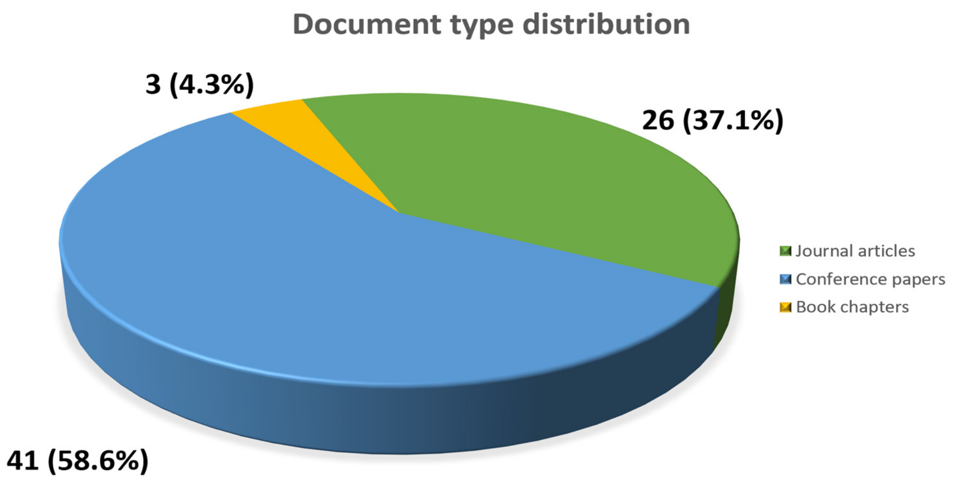

Figure 3. Document type distribution.

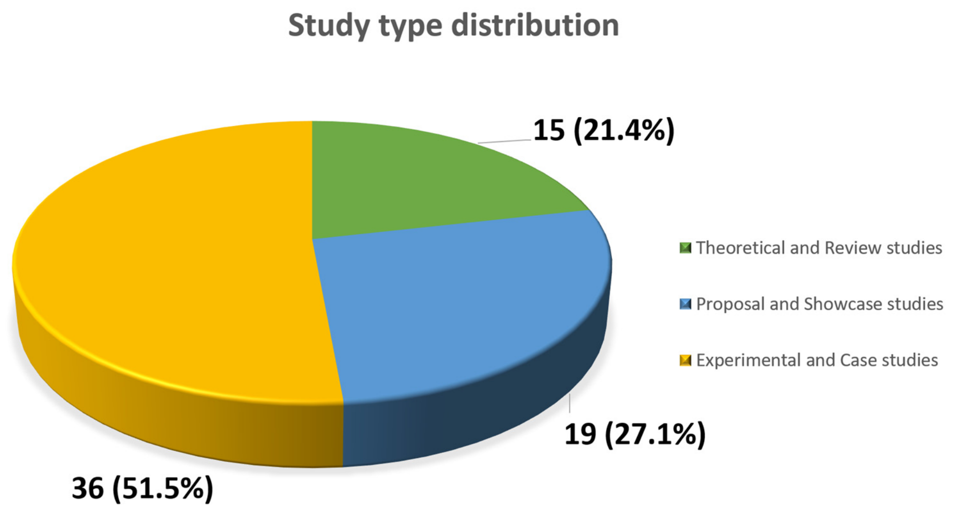

Figure 4. Study type distribution.

4.1.2. Document Collection Analysis

Furthermore, the main characteristics of the 70 documents which were published during the period of 2013-2024 in 46 different sources (e.g., journals, conferences, edited books, etc.) are summarized in Table 1. The documents were written and published by 642 authors from 28 countries and had 3.99 co-authors on average. Of the 70 documents, only five documents (7.1%) were single-authored. An annual growth rate of 25.35% is observed, with documents being citable for 2.79 years on average and receiving 8.5 citations on average. Additionally, the number of documents which authors have contributed to was examined using Lotka's law. Specifically, only one author (0.45) has contributed to six documents, while three authors have contributed to five documents. Most authors have contributed to one study (84.82). Given the specifications of the Bibliometrix tool, the authors' unique names were manually checked. Figure 5 depicts the related outcomes.

Table 1. Document collection information.

Description	Results	Description	Results
Main information about data		**Document types**	
Timespan	2013:2024	Journal article	27
Sources	46	Book chapter	3
Documents	70	Conference/Proceedings paper	40
Annual Growth Rate %	25.35		
Document Average Age	2.79	**Authors**	
Average Citations per Document	8.5	Authors	642
References	2332	Authors of single-authored docs	32
Document contents		**Authors collaboration**	
Keywords Plus	482	Single-authored docs	5
Author's Keywords	198	Co-authors per doc	3.99

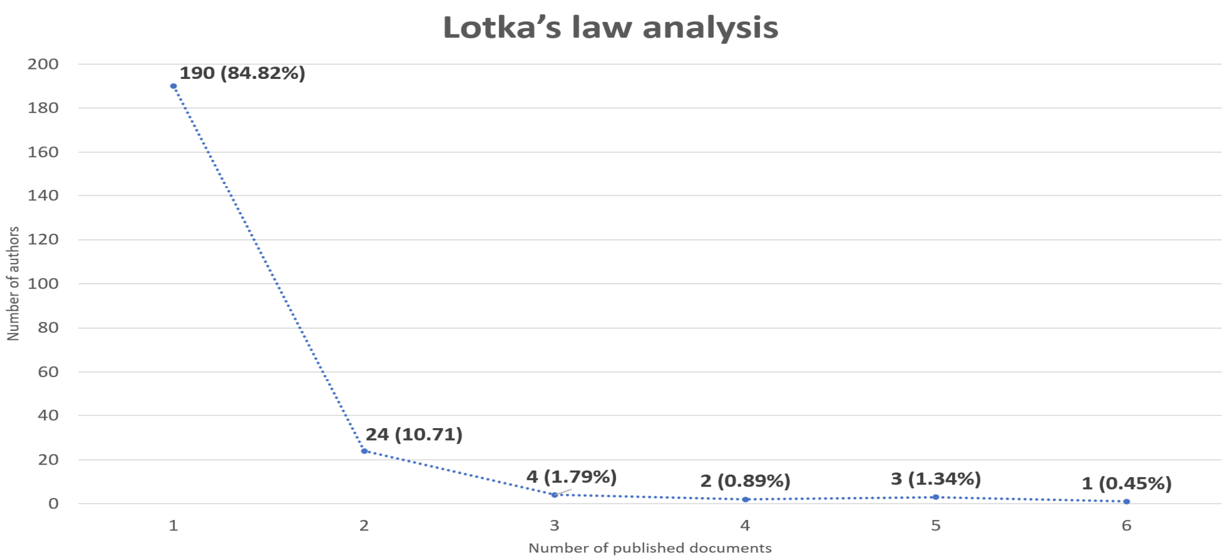

Figure 5. Information regarding the document collection.

4.1.3. Document Publication Frequency Analysis

Figure 6 depicts the annual scientific production. Based on the annual growth rate (25.35%), an increased interest in the specific topic is observed. The year 2023 was the one with the most published documents, followed by 2024. Even though there is a slight decrease in the documents published in 2024, due to the emergence of these technologies and methods and their being more accessible and more widely used, it is expected that the research around them will increase in the near future as the topic is still in its infancy.

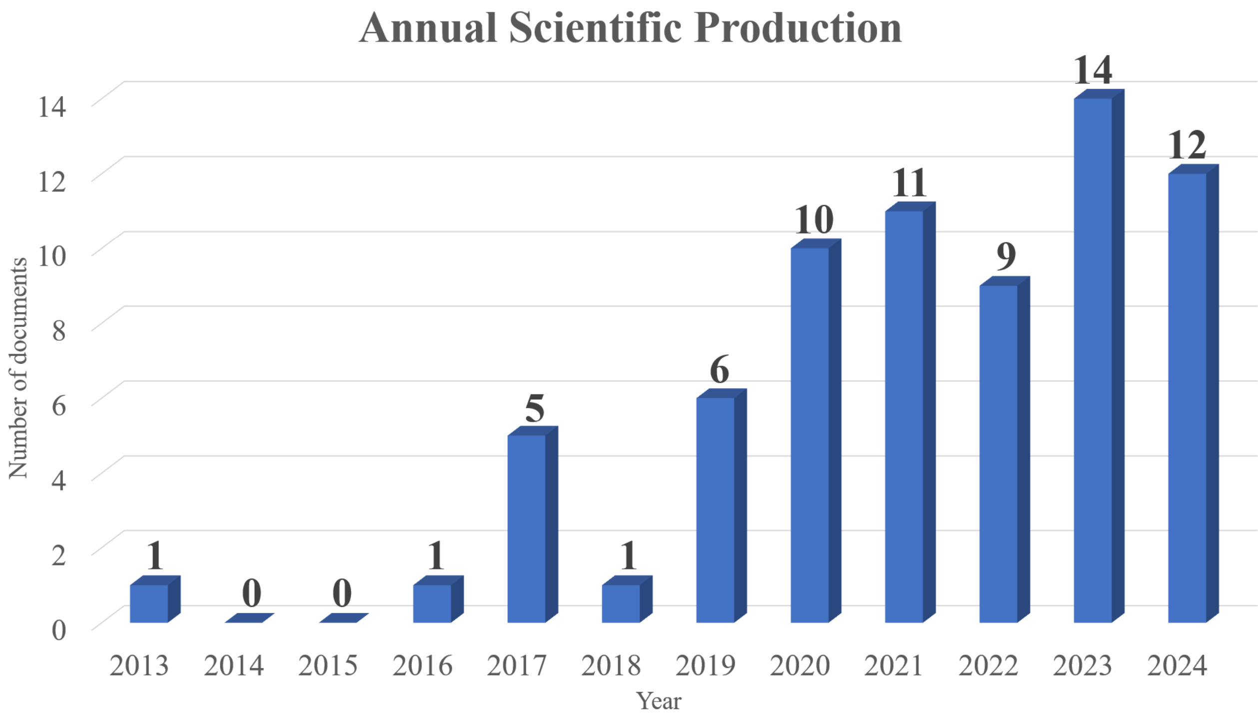

Figure 6. Annual distribution of published studies.

4.1.4. Sources Analysis

The 70 documents were published in 46 different sources. Bradford's law was used to better comprehend the impact and quality of the sources used. Three clusters (Cluster 1–3) were created to categorize the documents, with Cluster 1 having the most relevant sources. Particularly, 7 sources (15.2%) that published 25 documents (35.7%) comprised Cluster 1, 16 sources (34.8%) that published 22 documents (31.4%) comprised Cluster 2, and 23 sources (50.0%) that published 23 documents (32.9%) comprised Cluster 3. Table 2 presents the sources of the first cluster, where "Source" is the name of the source, "Rank" is the overall rank of the source, "Freq." is the volume of documents published in the specific source, "cumFreq." is the cumulative volume of published documents, and "Cluster" represents the cluster in which each source was categorized in. Based on the outcomes of applying Bradford's law, "IEEE International Conference on Advanced Learning Technologies (ICALT)" (rank = 1 and freq. = 6), "ACM International Conference Proceeding Series" (rank = 2 and freq. = 5), "CEUR Workshop Proceedings" (rank = 3 and freq. = 4), "IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)" (rank = 4 and freq. = 3), "Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)" (rank = 5 and freq. = 3), "British Journal of Educational Technology" (rank = 6 and freq. = 2), "Communications in Computer and Information Science" (rank = 7 and freq. = 2), "British Journal of Educational Technology" (rank = 8 and freq. = 2), and "Communications in Computer and Information Science" (rank = 9 and freq. = 2) were the top sources.

Table 2. Most relevant sources of the document collection according to Bradford's law.

Source	Rank	Freq.	cumFreq.	Cluster
"IEEE International Conference on Advanced Learning Technologies (ICALT)"	1	6	6	1
"ACM International Conference Proceeding Series"	2	5	11	1
"CEUR Workshop Proceedings"	3	4	15	1
"IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)"	4	3	18	1
"Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)"	5	3	21	1
"British Journal of Educational Technology"	6	2	23	1
"Communications in Computer and Information Science"	7	2	25	1
"British Journal of Educational Technology"	6	2	23	1

4.1.5. Country Analysis

Moreover, the documents were published by authors from 28 different countries based on the country of the corresponding author or the first author, in case no corresponding author was specified. The distribution of the documents in the three aforementioned categories and the number of published documents of each country are presented in Figure 7. Specifically, Germany and Greece were the countries which published the most documents with each having published nine documents (12.86%). Japan, Hong Kong, and the United States followed with seven published documents each (10.00%). Hence, Germany, Greece, Japan, Hong Kong, and the United States were the countries which published the most documents. When considering the different categories of documents, Germany contributed the most Theoretical and Review studies (n = 5), Greece and Japan contributed the most Proposal and Showcase studies (n = 3), and Hong Kong and the United States contributed the most Experimental and Case studies (n = 7). However, meaningful and impactful contributions have been made from several other countries as well. Based on the results presented in Figure 7, the significance of the topic is highlighted due to the global interest it receives and the fact that countries from different continents, predominantly Europe, Asia, and North America, contribute to developing both the theoretical and practical aspects of the field.

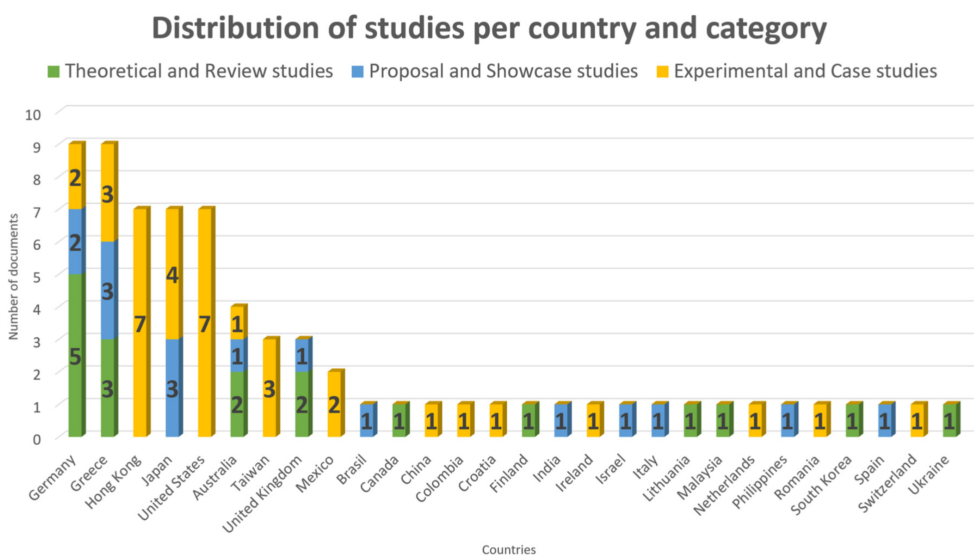

Figure 7. Distribution of studies per country and category.

Moreover, among the 70 documents examined, 65 documents (92.86%) were authored by an average of 3.99 authors, while only five documents (7.14%) were single-authored. Despite this fact and the number of countries involved, there was a clear lack of global collaborations. Specifically, among the 70 documents examined, only 14 (20.00%) involved authors of multiple countries, while the vast majority of studies (n = 56, 80.00%) involved only authors from the same country and/or institute. Even among these 14 global collaborations, most involved the same set of authors. Hence, more efforts should be placed in laying the foundations for more global collaborations to occur.

4.1.6. Analysis of the Technologies and Methods Used in the Studies

Furthermore, since this study investigates the utilization of extended reality technologies and their combination with educational data mining and learning analytics, the frequency of the documents that put an emphasis on these technologies and methods was explored. Based on Figure 8, it can be stated that most studies focused on virtual reality technology (n = 43, 61.4%), followed by augmented reality technology (n = 27, 38.6%). Only a few studies (n = 3, 4.3%) examined using educational data mining and learning analytics in mixed reality settings. Thes outcomes are in line with the results of previous studies, which showcase that although still at its early stages, virtual reality is more mature and more widely examined when compared to augmented reality and mixed reality. Another reason that has led to virtual reality being more widely studied is the related equipment (e.g., virtual reality head-mounted devices) that are more advanced and developed in comparison to augmented reality devices, as well as the fact that developing fully virtual environments is more streamlined than the development of mixed reality environments. However, given the fact that the integration of augmented reality has showcased positive learning outcomes when integrated into classrooms and given the advances in the field, it is expected that more emphasis will also be placed on augmented reality in the future. It should be noted that 2 studies examined both augmented reality and virtual reality and 1 study focused on both mixed reality and virtual reality. Hence, the total document number presented in Figure 8 adds up to 73 and not to 70 which is the total number of documents.

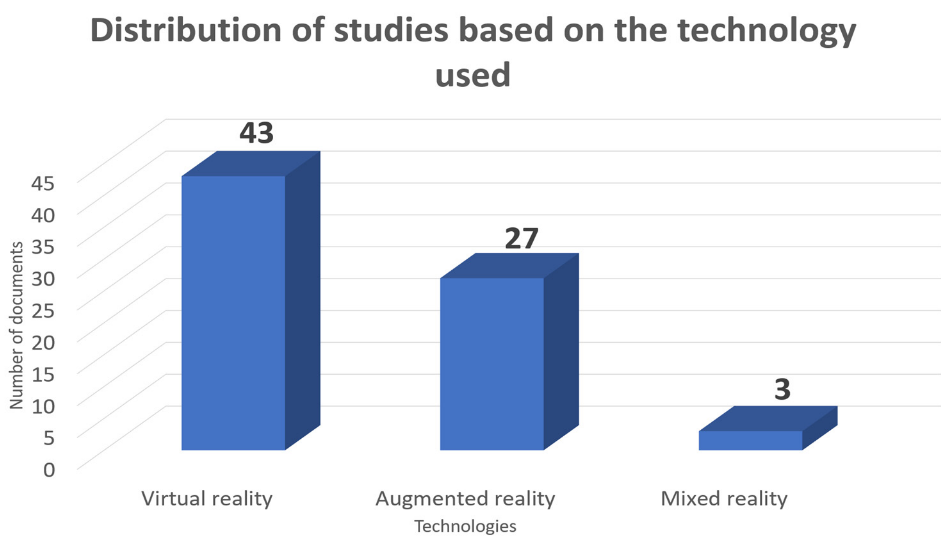

Figure 8. Distribution of studies based on the technology used.

According to the findings presented in Figure 9, most studies put an emphasis on exploring using learning analytics within extended reality environments (n = 66, 94.29%), while only 11 studies (15.71%) focused on using educational data mining. It should be mentioned that seven studies explored using both educational data mining and learning analytics. Hence, the total number of documents presented in Figure 9 adds up to 77 and not to 70, which is the number of documents examined. Based on the findings, it can be inferred that due to the data generated through extended reality experiences utilizing learning analytics is more widely and frequently used to provide meaningful inputs to both teachers and students. However, more recent studies have also started to focus on capitalizing on using educational data mining to create more adaptive and personalized learning experiences by trying to investigate the meaning behind the raw data. Another reason that has led to this significant change in the number of studies that focus on learning analytics and educational data mining is the fact that studies mostly utilized raw data deriving from the applications and/or platforms used to examine students' performance and actions and did not apply more advanced techniques to identify patterns, create effective predictive models, and develop more efficient recommendation systems. Additionally, based on the outcomes of Figure 9, it is evident that more emphasis should be put on examining the implications of educational data mining within extended reality environments to capitalize on the multimodal data generated within them.

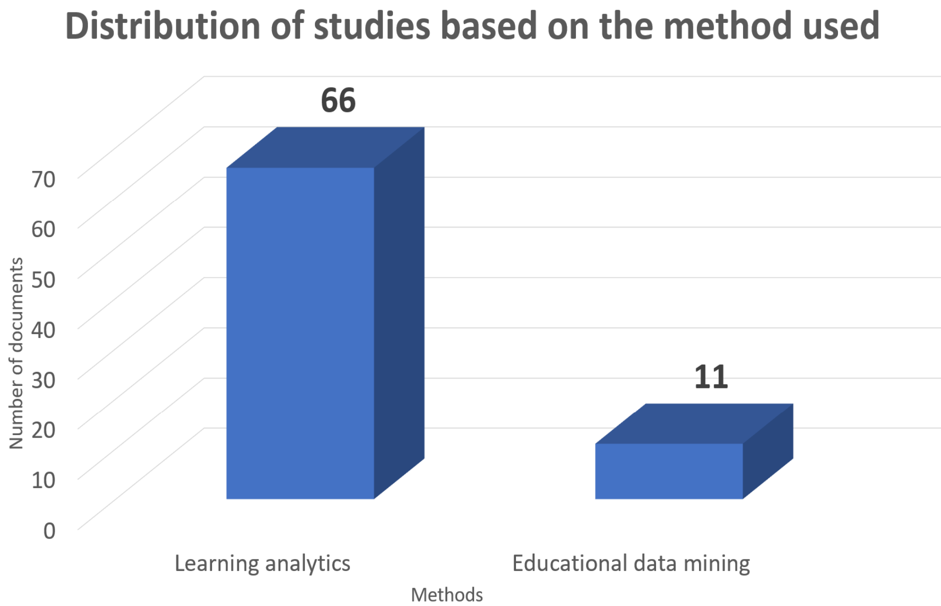

Figure 9. Distribution of studies based on the method used.

4.2. Theoretical and Review Studies

Of the 70 documents examined, 15 (21.43%) were classified within the Theoretical and Review studies category. Although these studies did not present a specific application or carried out a case study or an experiment, they added value to the field through their theoretical contributions and analyses of these technologies. The Theoretical and Review studies are presented in Table 3.

Table 3. Theoretical and Review studies.

Reference	Title	Year
[64]	Towards evaluating and modelling the impacts of mobile-based augmented reality applications on learning and engagement	2013
[65]	A study on capturing learning data from virtual and mixed reality contents through data collection API	2017
[66]	Learning Analytics in Augmented Reality: Blueprint for an AR / xAPI Framework	2019

Table 3. *Cont.*

Reference	Title	Year
[67]	A Learning Analytics Theoretical Framework for STEM Education Virtual Reality Applications	2020
[68]	Theoretical Foundations of Virtual and Augmented Reality-Supported Learning Analytics	2020
[69]	Virtual Reality Application Integrated with Learning Analytics for Enhancing English Pronunciation: A Conceptual Framework	2020
[70]	What are the risks of Virtual Reality data? Learning Analytics, Algorithmic Bias and a Fantasy of Perfect Data	2023
[71]	ARLEAN: An Augmented Reality Learning Analytics Ethical Framework	2021
[72]	A Learning Analytics Conceptual Framework for Augmented Reality-Supported Educational Case Studies	2021
[73]	On Top-Down Versus Bottom-up Personalisation and Evaluation of Augmented Reality Learning Systems	2021
[74]	An Architecture for Capturing and Presenting Learning Outcomes using Augmented Reality Enhanced Analytics	2022
[75]	A Modularity Approach in Design Science Research for Mixed Reality Learning Artifacts	2023
[76]	Augmented Reality User's Experience: AI-Based Data Collection, Processing and Analysis	2023
[77]	Towards using the xAPI specification for Learning Analytics in Virtual Reality	2024
[78]	Virtual, augmented reality and learning analytics impact on learners, and educators: A systematic review	2024

The study of Kazanidis et al. [72] provided a conceptual framework for using learning analytics within augmented reality applications. Their framework focused on providing suggestions regarding appropriate design elements and instructional strategies to use when creating augmented reality applications. Na et al. [69] presented a conceptual framework that focused on integrating learning analytics into virtual reality applications. The study also provided implications and suggestions for designing virtual reality applications and capitalizing on learning analytics. Christopoulos and Pellas [68] provided some initial theoretical foundations for augmented- and virtual reality learning analytics, which were then further expanded in follow-up studies. Christopoulos et al. [67] also presented a theoretical framework which focused on learning analytics and virtual reality applications. Their framework consisted of four dimensions and proposed a set of structural elements that can be used when prototyping such systems or applications. In another study, Christopoulos et al. [71] presented an ethical framework for using learning analytics within augmented reality applications. Their framework takes into account the unique traits of augmented reality applications and focuses on provided guidelines to designers on how to integrate learning analytics within their practices to support learners.

Son and Cho [65] focused on the use of data collection API to capture learning data from mixed reality and virtual reality contents that can then be analyzed through the use of appropriate learning analytics techniques. The study showcased a method of extracting learning data that was generated from virtual environments. The possibility to offer learners customized learning paths and provide them with interesting and attractive learning activities was highly regarded. Hensen [75] examined a modularity approach for mixed reality learning artifacts. In the proposed open-source toolkit, solutions to integrate different technologies within mixed reality environments and agents were presented and the use of learning analytics to capitalize on the generated data was highlighted. Görzen et al. [77] focused on using xAPI to examine the use of learning analytics within virtual reality settings. Their work presented different data-tracking technologies and approaches for integrating xAPI for learning analytics. They reported that implementing learning analytics in virtual reality learning environments can yield several benefits; however, there are requirements and limitations that need to be considered.

Singh et al. [74] also explored how to capture, analyze, and present learning data that derived from augmented reality applications. In their work, they presented a system architecture for mobile devices and applications which consisted of various parts, such as data collection, aggregation, and storage, process metrics, analytics presentation, learning outcomes, and affective factors analytics. The ability to support teachers in offering personalized learning experiences to students through the use of such applications was highlighted. Sakr and Abdullah [78] examined the use of learning analytics within augmented reality and virtual reality environments. Specifically, they reported that these technologies can support educators and increase students' performance. Finally, they commented upon the need for institutions and industrial organization to adopt these technologies.

Poitras et al. [64] explored theoretical and practical frameworks regarding the use of educational data mining techniques and their use in mobile-based augmented reality applications. Their work highlighted that designing learning activities should follow the theories of learning and instruction and aimed at modeling and evaluating the impacts of design parameters on students' learning and engagement. Secretan et al. [66] presented an xAPI framework to combine learning analytics and augmented reality educational experiences. The study also presented key design considerations and investigated system requirements. Focusing on the use of learning analytics and educational data mining techniques, Kurilovas [73] examined top–down and bottom–up approaches for personalizing and evaluating augmented reality learning systems. The study also presented different methods of identifying students' preferences and explored different techniques to analyze the generated data to offer personalized learning.

Sulema et al. [76] put an emphasis on the use of artificial intelligence tools to collect, process, and analyze learning data deriving from augmented reality applications. Specifically, besides the use of application-related data, they commented on the use of feedback and interaction as a means of multimodal learning analytics that takes students' motoric and physiological behavior into consideration to capture the social, situational, and environmental contexts in which they are engaged. The study also showcased related tools, sensors, and techniques to gather and present such data. Carter and Egliston [70] focused on examining important issues related to the data that is generated from virtual reality experiences. Specifically, their study focused on the use of learning analytics and investigated the concept of algorithmic bias. They highlighted the need to regulate and standardize the application of learning analytics to virtual reality generated data.

Based on the aforementioned studies, it is observed that efforts have been made to propose and present relevant frameworks regarding learning analytics and their use in augmented reality and virtual reality applications. However, little is known regarding the adoption of educational data mining within these environments. To define effective frameworks, it is important to consider the unique traits of extended reality technologies, the characteristics of learning analytics and educational data mining, design options, and ethical considerations. Additionally, studies have mentioned the use of appropriate APIs to aid in the identification, tracking, and monitoring of the data to offer personalized learning and customized learning paths. Efforts have also been made to present system architectures to develop applications that integrate these technologies and approaches and are capable of capturing, analyzing, and visualization learning data in real time and, in turn, aid both students and teachers. The studies also highlighted the need to carefully examine the influence of design elements on students' interaction and learning performance and to establish relevant learning and instruction theories and approaches. Artificial intelligence also arose as a key technology that can facilitate and improve the combination of extended reality technologies with learning analytics and educational data mining. Finally, the studies indicated that through the use of appropriate sensors, multimodal data generated from extended reality environments can effectively be identified, processed, and analyzed to provide students with interactive, immersive, adaptive, and personalized learning.

4.3. Proposal and Showcase Studies

In total, 19 (27.14%) studies were classified as Proposal and Showcase studies. Although these studies did not carry out a case study or an experiment, they added value by describing their prototype applicates and systems and going over design and development considerations. The Proposal and Showcase studies are showcased in Table 4.

Table 4. Proposal and Showcase studies.

References	Title	Year
[79]	Immersive Community Analytics for Wearable Enhanced Learning	2019
[80]	MAGIS: mobile augmented reality games for instructional support	2019
[81]	MAGES 3.0: Tying the knot of medical VR	2020
[82]	Learning analytics: Virtual reality for programming course in higher education	2020
[83]	Integrating xAPI in AR applications for Positive Behaviour Intervention and Support	2021
[84]	Towards design guidelines for virtual reality training for the chemical industry	2021
[85]	Web-Based 3D and 360° VR Materials for IoT Security Education and Test Supporting Learning Analytics	2021
[86]	Web-Based 3D and 360° VR Materials for IoT Security Education Supporting Learning Analytics	2021
[87]	COVID-19—VR Strikes Back: Innovative medical VR training	2021
[88]	Usage of Visual Analytics to Support Immigration-Related, Personalised Language Training Scenarios	2022
[89]	Systematic Design for Effective Learning in Virtual Reality	2022
[90]	Augmented Reality Enhanced Analytics to Measure and Mitigate Disengagement in Teaching Young Children	2022
[91]	Learning Analytics and Classroom Management in Specialized Environments: Enhancing the VR Classroom for CS Teacher Education	2023
[92]	Teaching the basics of computer graphics in virtual reality	2023
[93]	cleAR: an interoperable architecture for multi-user AR-based school curricula	2023
[94]	Learning analytics in VR: What if we can collect learning logs in VR classroom	2023
[95]	EduVR: Towards an Evaluation Platform for User Interactions in Personalized Virtual Reality Learning Environments	2023
[96]	A Learning Analytics Dashboard to Investigate the Influence of Interaction in a VR Learning Application	2024
[97]	Towards Learning Analytics for Student Evaluation in the Metaversity	2024

Heinemann et al. [89] showcased a pilot system design for achieving effective learning in virtual reality using learning analytics. In follow-up studies, Heinemann et al. [91,92] examined the use of learning analytics and classroom management within virtual reality environments. Their proposed system focused on computer science and capitalized on virtual reality to offer immersive and interactive experiences and on learning analytics to assist learners' reflections. In another study, Heinemann et al. [96] showcased a learning analytics dashboard that can be used within the context of a virtual reality application. Using their proposed system, they aimed to evaluate the efficiency of interactive tasks and other aspects of virtual reality experiences. Their system used xAPI, focused on transferability, and tracked user behaviors.

Singh et al. [90] explored how augmented reality-enhanced analytics can be used to measure young learners' engagement. Their proposed system uses various learning analytics components and integrates them into an augmented reality application. Their focus is to evaluate students' disengagement when compared to traditional ways of teaching and learning. Masneri et al. [93] presented an architecture for multi-user augmented reality-based school curricula. The study also explored the related literature and carried out a survey to analyze the most suitable design objectives and architecture requirements for their application based on teachers' perspectives. The provision of customization, the interactive experiences, the accessibility from different devices, and the collection of data emerged as the most impactful features. Finally, they highlighted the use of data analytics and commented upon the use of artificial intelligence-based module to undertake this task.

Using xAPI, Farella et al. [83] explored the use of learning analytics to track learners' behaviors in augmented reality applications. Their proposed application will follow the positive behavior intervention and support methodology and will be able to support behavioral lessons while also capitalizing on the benefits that augmented reality applications bring. To support the educational process, Vidal et al. [80] proposed a framework for developing augmented reality mobile applications. Using the suggested framework, they developed an augmented reality application and integrated analytics to determine learners' engagement and performance. Winer and Geri [97] explored the integration of learning analytics into virtual reality environments to assess students' experiences and performance. They highlighted the significance of learning analytics to assist in developing, managing, and operating teaching and learning within virtual environments. Their proposed system follows the theory of constraints and uses different assessment methods.

Fracaro et al. [84] focused on presenting design guidelines for training industrial stakeholders within virtual reality settings. Although the study explored different design considerations, learning analytics emerged as one of the most impactful approaches to enhance the effectiveness of training and learning in virtual reality. Antzoulatos et al. [88] investigated the use of data analytics within virtual reality environments to support language learning. Their application enabled learners to interact with virtual agents and for meaningful information to be collected. Shi et al. [85,86] explored the use of learning analytics within web-based 3D and 360-degree virtual reality environments. Specifically, they presented a framework for creating e-learning material and quizzes that used linked data. Additionally, they presented a prototype system that uses visual analyzing tools and collects and analyzes data from learners' activities.

Papagiannakis et al. [81] and Zikas et al. [87] demonstrated two virtual reality applications for medical training, which also integrated aspects of real-time data analytic through the use of supervised machine learning. Their work highlighted the potential of these technologies to offer training opportunities even in unprecedented events, such as the COVID-19 pandemic. In their study, Viol et al. [95] presented their evaluation platform for assessing user interactions in virtual learning environments. Specifically, they focused on integrating learning analytics to personalize the overall experience through the integration of xAPI. Klamma et al. [79] focused on examining the use of immersive learning analytics to support different training scenarios. Their approach demonstrates how collaborative immersive community analytics could be achieved when using wearable devices to support learning.

ShengKai et al. [94] looked into the usefulness of learning logs in the context of virtual reality classrooms. They highlighted the significance of learning analytics to identify and track issues encountered by most students and to provide meaningful visualized information to assist teachers. Srimadhaven et al. [82] explored the use of learning analytics in the context of a virtual reality-based computer science course. The study goes over the applicability of learning analytics within virtual reality environments and emphasizes their use in supporting learners' self-regulated learning and self-efficacy, as well as learners' affective and cognitive behaviors. The potential of supporting all learners despite their learning performance was highly commented.

The studies examined highlighted the applicability of this approach to be integrated into different educational levels and contexts. The studies emphasized the importance of evaluating learners' interaction with the applications and systems, their actions within the virtual environments, and their performance. Additionally, the ability to support diverse learners by identifying and tracking issues and challenges that they face and by monitoring their actions, preferences, and behaviors was highlighted. The studies also commented upon the need to define suitable design guidelines and objectives, to emphasize realism and interactivity, and to compare the effectiveness of this approach with traditional teaching and learning approaches. Through the pilot applications, the ability to offer teachers meaningful visualized information and assist them to more effectively manage and coordinate their classrooms was revealed. However, the need to develop appropriate learning material and resources was also highlighted. The specific studies highlighted the need to monitor learners' engagement, interactions, experiences, and performance within virtual learning environments and highly regarded the use of artificial intelligence and virtual agents to enhance the provision of personalized learning.

4.4. Experimental and Case Studies

Of the 70 documents, 36 documents (51.43%) were classified as Experimental and Case studies. These studies involved the related technologies and either developed and applied a system or an application or applied an existing one and evaluated its effect. The related documents are presented in Table 5. Given the nature of these studies, a more in-depth content analysis was carried out.

Table 5. Experimental and Case studies.

References	Title	Year
[98]	Augmented reality crossover gamified design for sustainable engineering education	2016
[99]	Evaluating a mixed reality 3D virtual campus with big data and learning analytics: A transversal study	2016
[100]	Analyzing heterogeneous learning logs using the iterative convergence method	2017
[101]	Bringing Abstract Academic Integrity and Ethical Concepts into Real-Life Situations	2017
[102]	Data-Driven Construction of a Student Model Using Bayesian Networks in an Electrical Domain	2017
[103]	A virtual reality game for teaching graph theory: A study of its effectiveness in improving outcomes and encouraging autonomy	2018
[104]	Assessing the Efficacy of VR for Foreign Language Learning Using Multimodal Learning Analytics	2019
[105]	Beyond Reality-Extending a Presentation Trainer with an Immersive VR Module	2019
[106]	Exploring the treatment integrity of virtual reality-based social skills training for children with high-functioning autism	2019
[107]	The Role of Active Engagement of Peer Observation in the Acquisition of Surgical Skills in Virtual Reality Tasks for Novices	2019
[108]	Biosensor Real-Time Affective Analytics in Virtual and Mixed Reality Medical Education Serious Games: Cohort Study	2020
[109]	Development of engineering educational support system for manufacturing using Augmented Reality	2020
[110]	Emotional characterization of children through a learning environment using learning analytics and AR-Sandbox	2020
[111]	Learning analytics for student modeling in virtual reality training systems: Lineworkers case	2020
[112]	The development and evaluation of an augmented reality learning system for Japanese compound verbs using learning analytics	2020

Table 5. *Cont.*

References	Title	Year
[113]	Can you Escape from Dr. Tom Cat's Lab? Educational Escape Rooms with Scientists, Riddles and Serious Games as Learning Tools	2021
[114]	Effect of Collaboration Mode and Position Arrangement on Immersive Analytics Tasks in Virtual Reality: A Pilot Study	2021
[115]	A Distance Learning VR Technology Tool for Science Labs	2022
[116]	Learning Analytics Enabled Virtual Reality Content Creation Platform: System Design and Preliminary Evaluation	2022
[117]	Needs Analysis and Prototype Evaluation of Student-facing LA Dashboard for Virtual Reality Content Creation	2022
[118]	The design and evaluation of an AR-based serious game to teach programming	2022
[119]	Towards Multi-modal Evaluation of Eye-tracked Virtual Heritage Environment	2022
[120]	A study on learning analytics of using mobile augmented reality application to enhance cultural competence for design cultural creation in higher education	2023
[121]	An Empirical Evaluation of Educational Data Mining Techniques in a Dynamic VR Application	2023
[122]	Automated Analysis of Text in Student-created Virtual Reality Content	2023
[123]	Experience the Theory: New Perspectives Through VR Learning Environments for Photography Education	2023
[124]	Learning Analytics for Assessing Hands-on Laboratory Skills in Science Classrooms Using Bayesian Network Analysis	2023
[125]	Using Deep Learning to Track Representational Flexibility Development of Children with Autism in a Virtual World	2023
[126]	Using learning analytics to investigate learning processes and behavioural patterns in an augmented reality language learning environment	2023
[127]	A Platform for Analyzing Students' Behavior in Virtual Spaces on Mozilla Hubs	2024
[128]	Applying multimodal data fusion to track autistic adolescents' representational flexibility development during virtual reality-based training	2024
[129]	Approximating eye gaze with head pose in a virtual reality microteaching scenario for pre-service teachers	2024
[130]	In-game performance: The role of students' socio-economic status, self-efficacy and situational interest in an augmented reality game	2024
[131]	Unveiling Synchrony of Learners′ Multimodal Data in Collaborative Maker Activities	2024
[132]	Utilizing augmented reality for embodied mental rotation training: A learning analytics study	2024
[133]	Learning Analytics for Collaboration Quality Assessment during Virtual Reality Content Creation	2024

Most of the documents of this category were published in 2023 (n = 8, 22.2%), followed by 2022 (n = 7, 19.4%). Additionally, most documents were published in conferences/proceedings (n = 19, 52.8%), 16 documents (55.4%) were published in journals, and only one document (2.8%) was published in an edited book. Hong Kong (n = 7, 19.4%) and the United States (n = 7, 19.4%) contributed the most documents, followed by Japan (n = 4, 11.1%), Greece (n = 3, 8.3%), and Taiwan (n = 3, 8.3%). The remaining 12 documents were published by 12 different countries.

Furthermore, all studies involved face-to-face learning. As no study focused on online learning, there is a need to further explore the use of these technologies and methods in online learning settings as well. Additionally, studies were conducted in both formal and informal settings, highlighting the applicability of this approach. Studies mostly put an emphasis on higher education (66.7%) and to a lesser extent on secondary education (16.6%) and primary education (11.1%). Two of the studies (5.6%) involved diverse participants (e.g., ages, expertise, etc.) and were not categorized into any of these education levels Table 6. The vast majority of the studies involved only students (88.9%), while two studies involved both students and teachers (5.55%), and two studies involved various participants (5.55%), as can be seen in Table 7. On average, each study involved 108 participants. Hence, the emphasis on students is highlighted.

Table 6. Education-level distribution.

Education Level	Freq.	Perc.	References
Primary Education	4	11.1%	[100,106,110,116]
Secondary Education	6	16.6%	[98,109,124,125,128,130]
Higher Education	24	66.7%	[99,101–104,107,108,111–115,117–120,122,123,126,127,129,131–133]
Included various participants	2	5.6%	[105,121]

Table 7. Participant distribution.

Participants	Freq.	Perc.	References
Students	32	88.9%	[98,100–104,106–115,117–120,122–133]
Students and teachers	2	5.6%	[99,116]
Various	2	5.6%	[105,121]

Furthermore, the technology and the method which the studies focused on were also explored. Most studies put an emphasis on virtual reality (n = 22, 61.1%) and, to a lesser extent, on augmented reality (n = 13, 36.1%). Only one study focused on mixed reality (2.8%), as can be seen in Table 8. Additionally, significantly more emphasis was put on learning analytics (n = 28, 77.8%) than educational data mining (n = 3, 8.3%). However, five studies (13.9%) explored both learning analytics and educational data mining. The related information is presented in Table 9.

Table 8. Technology distribution.

Technology	Freq.	Perc.	References
Virtual reality	22	61.1%	[102–108,111,114–117,119,121–123,125,127–129,131,133]
Augmented reality	13	36.1%	[98,100,101,109,110,112,113,118,120,124,126,130,132]
Mixed reality	1	2.8%	[99]

Table 9. Method distribution.

Method	Freq.	Perc.	References
Learning analytics	28	77.8%	[98–100,103–109,111–120,123,126,127,129–133]
Learning analytics and educational data mining	5	13.9%	[101,110,122,124,128]
Educational data mining	3	8.3%	[102,121,125]

Table 10 presents the distribution of the systems used within the studies. Based on the outcomes, most studies focused on virtual learning environments (n = 17, 47.2%), followed by mobile applications (n = 9, 25.0%) and digital games (16.7%). Only 3 studies (8.3%) focused on platforms and a single study (2.8%) adopted a sandbox in their experiments. However, little information was given regarding the tools and approaches used to develop the specific systems as the vast majority of studies did not report the platform or the tools they used during the development process. Of the ones that did, Unity arose as the most popular development platform [105,115,121,123,129], followed by Mozilla Hubs [127]. Similarly, in the case of educational data mining, only a few studies specified the techniques used. It should also be noted that a lack of information regarding machine learning and deep learning approaches was observed in the documents examined. Among the ones that did, machine learning and deep learning techniques, models, and approaches such as Bayesian networks [102,121,124], DBSCAN algorithm [110], supervised machine learning using multilayer perceptron (MLP) [125], and support vector machines (SVM), decision trees, and random forest under multimodal and unimodal approaches [128] were used. Lastly, a lack of information was observed regarding the equipment used during the experiment process. Of the 36 studies, only six (16.67%) reported the exact equipment used. Meta Quest 2 (n = 3) [121,123,129], Oculus Rift (n = 3) [103,104,114], and Microsoft Hololens (n = 2) [105,108] were mostly used.

Table 10. System distribution.

System	Freq.	Perc.	References
Virtual learning environments	17	47.2%	[99,102,104,105,107,111,114–117,119,122,123,125,127–129]
Mobile applications	9	25.0%	[98,100,101,109,112,120,124,126,132]
Digital games	6	16.7%	[103,108,113,118,121,130]
Platforms	3	8.3%	[106,131,133]
Sandbox	1	2.8%	[110]

Focusing on the research approaches adopted by the studies, the research methods used, the variables examined, and the experimental designs were examined. Specifically, and given the nature of the data generated, most studies adopted a quantitative research methodology (n = 27, 75.0%), while only a single study (2.8%) followed a qualitative research methodology. A total of eight studies (22.2%) adopted a mixed-method research approach. The related information is presented in Table 11. Although some studies focused on the collection and analysis of log files as well as application, system, or game-related data (50.0%), other studies also used other data collection tools (e.g., surveys, questionnaires, interview, observations, etc.) (50.0%). Most of the studies that used additional data collection tools opted for ad hoc tools. However, few studies also integrated existing tools, such as those presented in [134–138]. Table 12 presents the related data.

Table 11. Research methods.

Research method	Freq.	Perc.	References
Quantitative	27	75.0%	[100,102,105,107–116,119,121–133]
Mixed	8	22.2%	[98,99,101,103,104,106,118,120]
Qualitative	1	2.8%	[117]

Table 12. Data collection.

Data Collection	Freq.	Perc.	References
Data from the application	18	50.0%	[100,102,107,108,110,111,113,115,121,122,124–129,131,133]
Data from the application and other means (questionnaires, surveys, observations, interviews, etc.)	18	50.0%	[98,99,101,103–106,109,112,114,116–120,123,130,132]

Finally, the experimental design adopted was also explored, as can be seen in Table 13. Specifically, the majority of studies (n = 29, 80.6%) focused solely on an experimental group, while seven (19.4%) studies used both an experimental and a control group in their experiments. Given the ability to collect data in several stages of the experimental process, due to the technologies and methods used, studies focus on collection data, before, during, and after the interventions. Most studies capitalized on the data generated during the use of the applications, systems, or games and the ability to analyze them in real time and as a result, the studies focused on collecting data during the intervention. Finally, the variables that were mostly examined in the studies are summarized below:

- Performance, score, and time.
- Decisions, choices, and responses.
- Number of correct and wrong responses, number of tries, and amount of assistance received.
- Time-on-task, dropout rate, task completion rate, and overall completion rate.
- Usefulness, satisfaction, enjoyment, and realism.
- Ease of learning and ease of use.
- Learners' knowledge, skills perspectives, and progression.
- Behavioral, cognitive, and affective states.
- Learners' actions, engagement, experiences, focus, and stress.
- Learning gains, learning effectiveness, and learning behaviors.
- Movement and position.
- Head-, hand-, and eye-tracking, visual attention, and regions of interest.
- Interactions with virtual content, virtual objects, and educational material.

Table 13. Experimental design.

Experimental Design	Freq.	Perc.	Data Collection	Freq.	Perc.	References
Experimental group	29	80.6%	After the intervention	2	6.9%	[107,117]
			Before and after the intervention	3	10.3%	[112,118,119]
			Before, during, and after the intervention	2	6.9%	[98,109]
			During and after the intervention	7	24.1%	[99,101,103,105,116,123,130]
			During the intervention	15	51.7%	[100,102,106,108,110,113,115,121,122,124,125,127–129,131]
Experimental group and control group	7	19.4%	Before and after the intervention	2	28.6%	[126,132]
			Before, during, and after the intervention	1	14.3%	[114]
			During and after the intervention	2	28.6%	[104,120]
			During the intervention	2	28.6%	[111,133]

5. Discussion

Augmented reality and virtual reality are more widely being adopted in educational settings. Additionally, studies have showcased the benefits that can be yielded when integrating learning and analytics and educational data mining within extended reality environments. To identify the most prominent topics and areas of research, as well as directions for future research, the 70 documents were further analyzed. Specifically, the author keywords and the keywords plus/indexed keywords were used as they both can efficiently present the knowledge structure of the documents [139].

In Figure 10, the most commonly used keywords plus/indexed keywords are presented, while the most frequently used author keywords are displayed in Figure 11. "Virtual reality", "learning analytics", "e-learning", "augmented reality", "students", "learning systems", "computer-aided instruction", "engineering education", "eye-tracking", "computing education", "educational data mining", "teachers" were the most common keywords plus/indexed keywords, while "learning analytics", "virtual reality", "augmented reality", "education", "machine learning" "multimodal learning analytics", "educational data mining", "technology-enhanced learning", "evaluation", "eye-tracking", "language learning", "mobile learning" were the most frequently used keywords by the authors.

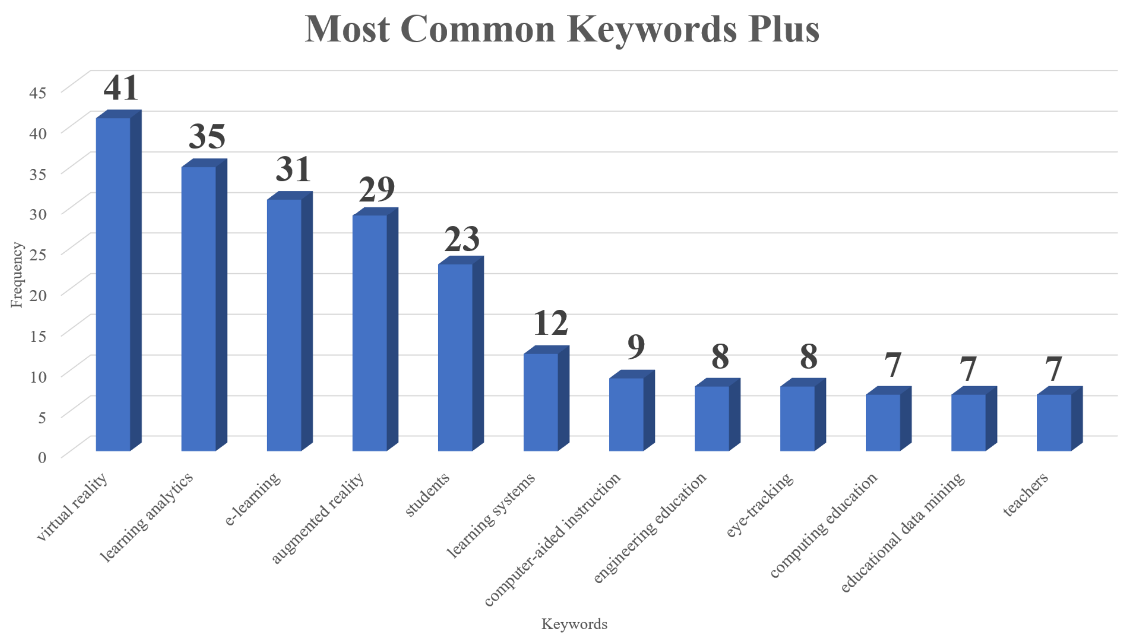

Figure 10. Keywords plus/Indexed keywords.

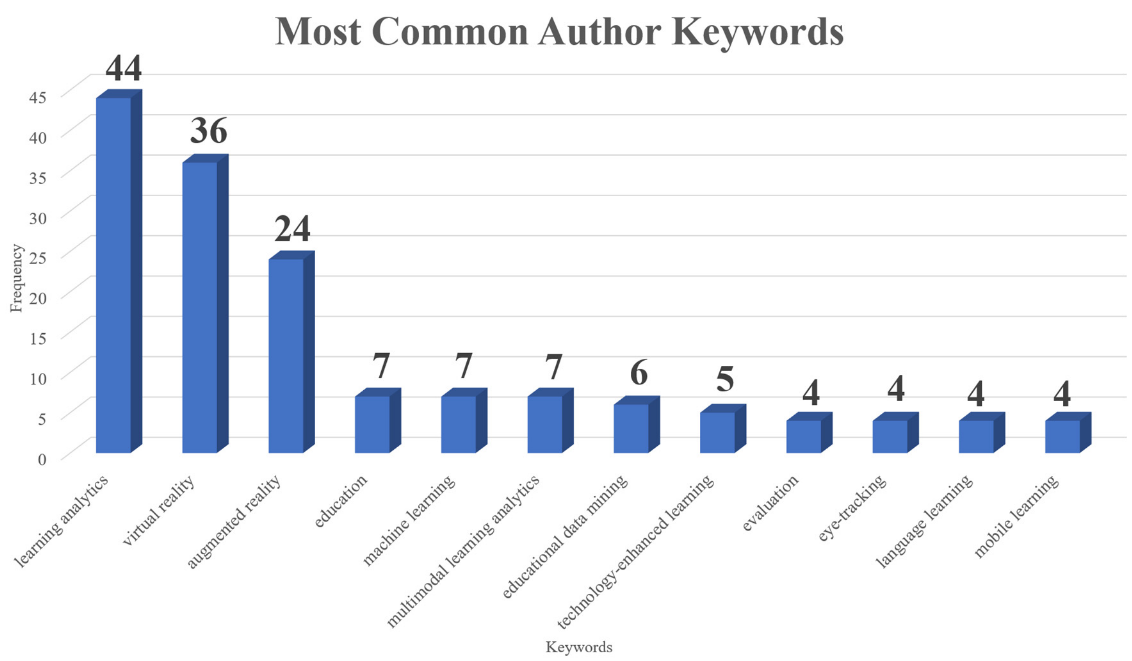

Figure 11. Author keywords.

Furthermore, the keywords were also used to examine the trend topics contained within the document collection. Based on the outcomes presented in Figure 12, the initial focus on data mining and the gradual transition to educational data mining and on learning analytics are observed. Additionally, the focus on augmented reality and virtual reality started in 2020; however, most of the emphasis was placed on virtual reality. As the field advances, more attention is drawn to the multimodal data that can be generated from extended reality experiences, which can greatly contribute to the improvement of the educational process. Their use in e-learning settings and in serious games as well as their ability to improve computer-aided instructions are also evident. These outcomes are in line with the most commonly used keywords.

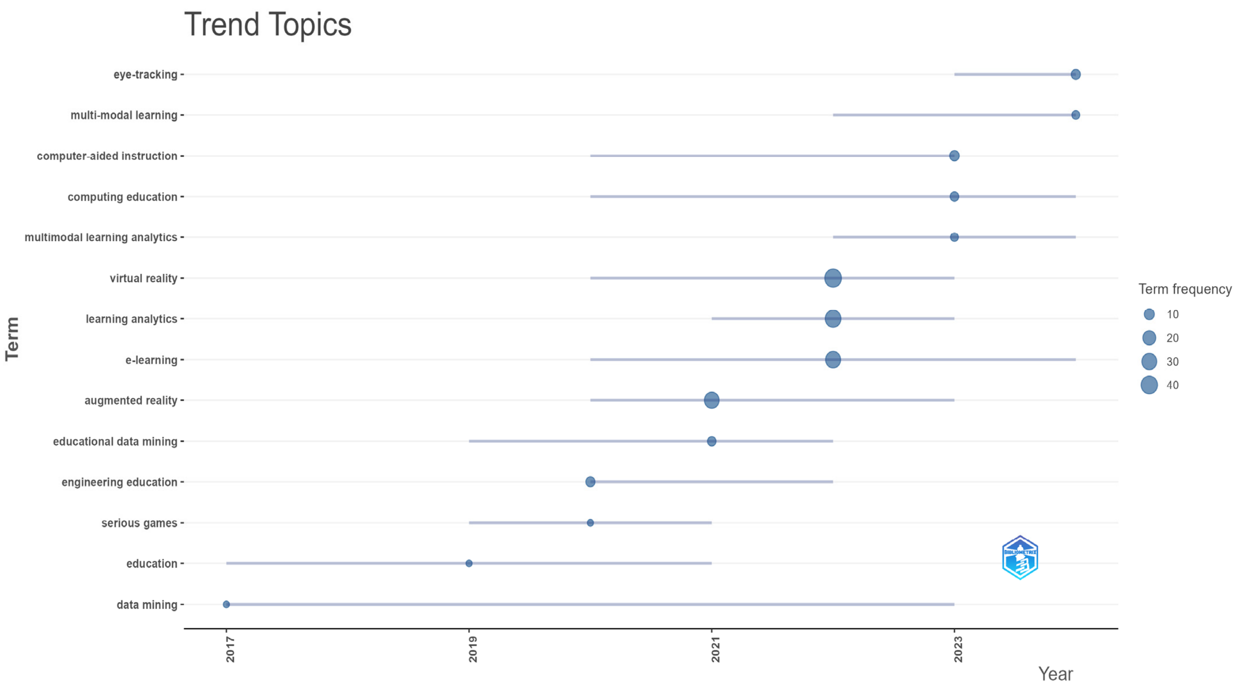

Figure 12. Trend topics.

The thematic map of the topic revealed 11 main themes that were separated into niche themes (two clusters), motor themes (four clusters), basic themes (two clusters), and emerging or declining themes (three clusters). The related outcomes are presented in Figure 13. Specifically, the themes that emerged within the niche theme category were related to (i) "Advanced analytics", "Interactive computer graphics", and "Software design" and (ii) "Public speaking", "Speaking skills", and "Language learning". The themes that emerged within the motor theme category were related to (i) "Multi-modal learning", "Multimodal learning analytics", and "Eye-tracking"; (ii) "Game-based learning", "Immersive technologies", and "Performance"; (iii) "Education", "Experiences", and "Collaborative learning"; and (iv) "Virtual reality", "Learning analytics", and "Augmented reality". The themes that emerged within the basic theme category were related to (i) "Mixed reality", "Educational Technology", and "Learning scenarios"; and (ii) "Content creation", "Active learning", and "Learning performance". The themes that emerged within the emerging or declining theme category were related to (i) "Gamification", (ii) "STEM education", and (iii) "Medical education" and "Healthcare education". Based on these results, it can be inferred that an emphasis is put on the multimodal learning analytics, game-based learning, immersive learning, students' performance, and collaborative learning. Additionally, some studies focus on the design elements and software-related considerations associated with these technologies and methods. At the core of this field lies the use of learning analytics in augmented reality and virtual reality technologies, their being used to create suitable content that increases learners' active involvement and performance, as well as the examination of their role in the context of educational technology and education in general. Their use in medical education and healthcare education is widely examined. Finally, there is increasing interest in the use of these approaches in combination with gamification elements and in their role in STEM education. Recent studies have highlighted the positive impact of gamification in education [140–144] and its close relationship with augmented reality [48] and virtual reality technologies [52].

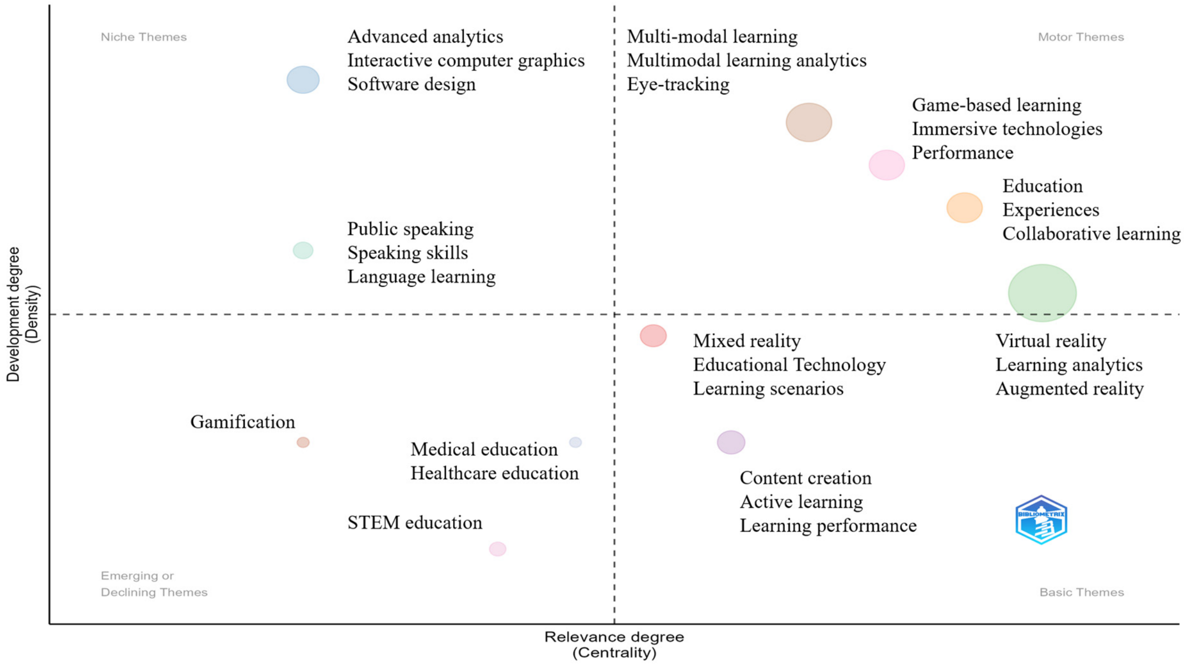

Figure 13. Thematic map.

Through a co-occurrence analysis, the relation between the keywords was further explored to identify the most prevalent clusters. Specifically, the outcomes of the co-occurrence network created through Bibliometrix using keywords plus/indexed keywords is presented in Figure 14, while the one created through VOSviewer using both keywords plus/indexed keywords and author keywords is depicted in Figure 15.

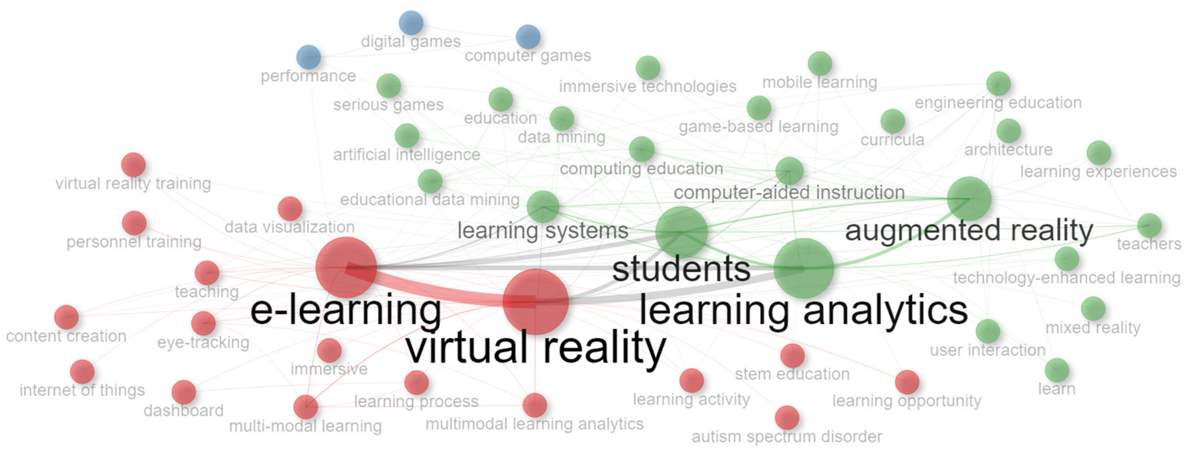

Figure 14. Co-occurrence network—Bibliometrix.

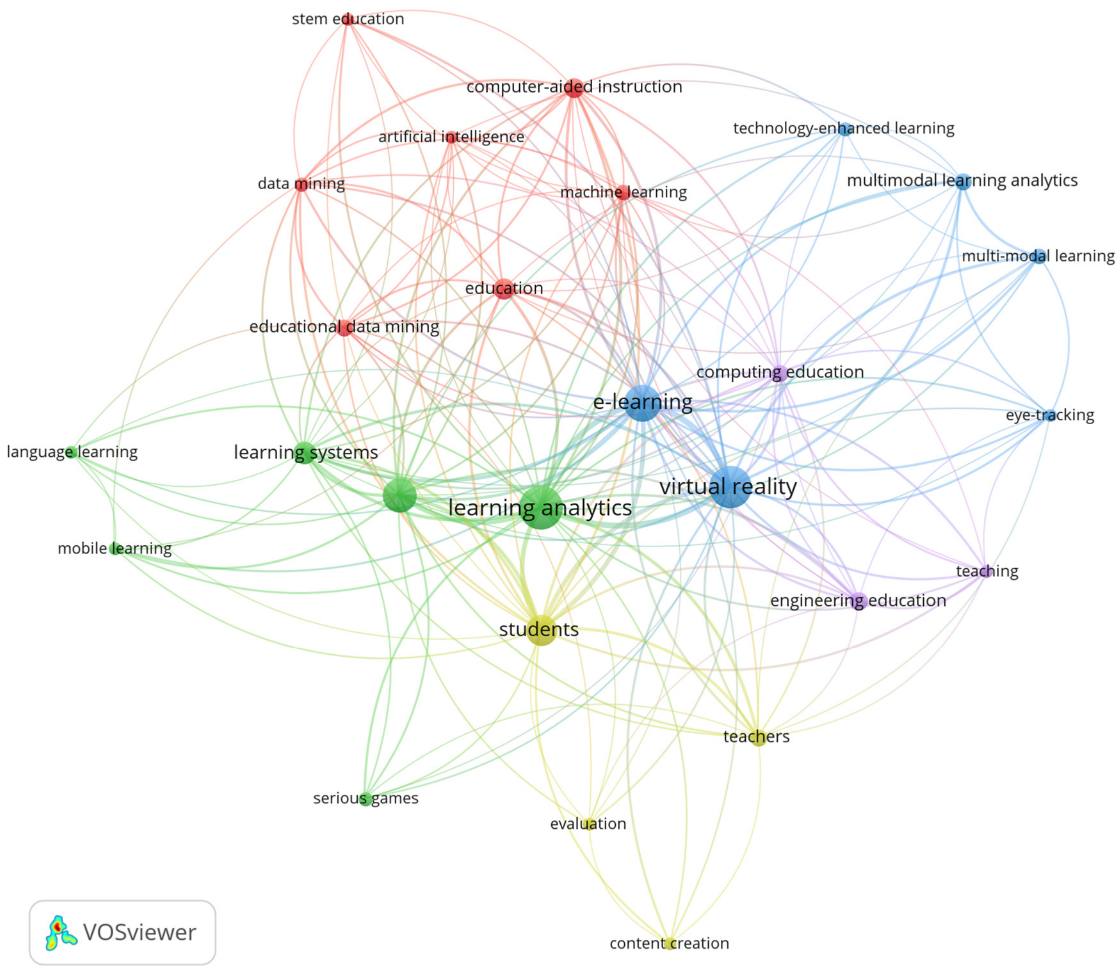

Figure 15. Co-occurrence network—VOSviewer.

In the network presented in Figure 13, three main clusters emerged. The first cluster (green color) was associated with the following keywords: "learning analytics", "augmented reality", "students", "learning systems", "computer-aided instruction", "engineering education", "computing education", "educational data mining:", "teachers", "data mining", "education", "serious games" "technology-enhanced learning", "mixed reality", "artificial intelligence", "curricula", "game-based learning", "immersive technologies", "learn", "learning experiences", "mobile learning", "user interaction", and "architecture". The second cluster (red color) was associated with the following keywords: "virtual reality", "e-learning", "eye-tracking", "multi-modal learning", "multimodal learning analytics", "content creation", "teaching", "data visualization", "immersive", "internet of things", "learning activity", "learning opportunity", "learning process", "personnel training", "stem education", "virtual reality training", "autism spectrum disorder", and "dashboard". The third cluster was related to the following keywords: "performance", "computer games", and "digital games".

In the network presented in Figure 14, a total of five clusters arose. The first cluster (red color) was related to the following keywords: "augmented reality", "learning analytics", "learning systems", "mobile learning", "serious games", and "language learning". The second cluster (green color) consisted of the keywords: "artificial intelligence", "computer-aided instruction", "data mining", "education", "educational data mining", "machine learning", and "stem education". The third cluster (blue color) comprised of the following keywords: "virtual reality", "e-learning", "eye-tracking", "multi-modal learning", "multimodal learning analytics", and "technology-enhanced learning". The fourth cluster (yellow color) had the following keywords: "content creation", "evaluation", "students", and "teachers". The fifth cluster (purple color) was associated with the following keywords: "computing education", "engineering education", and "teaching". The top-10 keywords with the highest total link strength are presented in Table 14. Of the keywords used, "learning analytics" (155), "virtual reality" (144), "e-learning" (139), "students" (112), and "augmented reality" (91) had the highest total link strength. These outcomes showcase, once again, the close relationship of learning analytics with virtual reality and augmented reality technologies. The outcomes of these networks highlight the versatile nature and wide applicability of both augmented reality and virtual reality, as well as of learning analytics and educational data mining. Additionally, they depict their ability to support both students and teachers and be integrated in various subjects and education levels. Their close relationship with machine learning and artificial intelligence is also evident. Their ability to promote technology-enhanced learning, to provide personalized and adaptive computer-aided instructions and feedback, to be used together with other educational and pedagogical approaches as well as to capitalize on the real-time identification and processing of multi-modal data is displayed.

Table 14. Co-occurrence analysis—total link strength.

Keywords	Occurrences	Total Link Strength	Keywords	Occurrences	Total Link Strength
learning analytics	45	155	machine learning	6	27
virtual reality	41	144	multi-modal learning	6	25
e-learning	31	139	multimodal learning analytics	7	25
students	23	112	teaching	4	25
augmented reality	27	91	eye-tracking	4	23
learning systems	12	62	artificial intelligence	4	19
computer-aided instruction	9	52	mobile learning	4	17
computing education	7	48	stem education	4	16
education	10	45	technology-enhanced learning	5	16
data mining	5	37	serious games	5	15
teachers	7	36	content creation	4	13
engineering education	8	32	language learning	4	12
educational data mining	7	30	evaluation	4	10

These outcomes are further validated and expanded through the topic modeling analysis. Specifically, LDA was used and the title and abstract of the documents were examined. In total, five main topics emerged. These topics were related to (1) Interactive and immersive content and activities (e.g., content creation (3.18), maker activities (3.11), learning activities (0.46), immersive technologies (0.44), etc.); (2) Data collection and processing (e.g., real time (7.52), data collected (3.6), learning process (0.56), learning data (0.16), etc.); (3) Learning process and outcomes (e.g., learning process (8.06), students' learning (0.17), learning environment (0.17), learning outcomes (0.17), immersive technologies (0.17), etc.); (4) Immersive learning and immersive learning environments (e.g., learning environments (8.25), immersive technologies (3.70), real world (3.50), students learning (0.17), learning activities (0.17), etc.); and (5) Game-based learning (e.g., based learning (4.20), learning outcomes (4.13), game based (3.56), students learning (1.50), immersive technologies (0.17), etc.). The outcomes of the topic modeling better highlight the ability of these technologies and methods to provide interactive and immersive content and activities and their ability to identify, collection, and process data in real time. Additionally, they reveal their potential to support and enrich learning processes and learning outcomes through the immersive learning environments that they offer and their ability to support other educational approaches, such as gamification and game-based learning.

Based on the aforementioned, it can be inferred that the combination of learning technologies and educational data mining within augmented reality and virtual reality environments can significantly improve teaching and learning activities and enrich the overall educational process. The studies examined report positive outcomes in terms of learning gains, learning outcomes, students' motivation and engagement, and the provision of personalized learning. Additionally, this combination not only supports students in their learning but also aids teachers to more effectively teach, supervise, and mentor students.

Due to its nature, it can be used to support different learning strategies and approaches, such as blended learning, personalized learning, and flipped classrooms while also supplementing teachers with real-time access to information relevant to students' engagement, interest, and performance [65,115,126]. These tools enable real-time identification, tracking, monitoring, and analysis of basic data and multimodal data of the learning process as well as of students' behavior, emotions, cognitive and affective states, and complex cognitive skill development [70,75,76,108,110,125,127–129], which, in turn, can lead to the development of effective student models [102,111]. Machine learning and deep learning play a vital role in the realization of learning analytics and educational data mining [145–147].

These immersive and personalized environments enable experiential, hands-on learning [123,124], offer authentic and realistic learning [65], and provide students with a sense of freedom [103]. Additionally, they promote and support social learning and collaborative learning in both co-located and distributed collaborative learning scenarios [100,106,114,131,133]. The provision of additional virtual information and feedback is viewed as interesting, understandable, and useful and supports learners, particularly those that are characterized as visual, sensor, and intuitive learners [73,103,119]. Due to these traits, students express positive attitudes toward these experiences [105]. Additionally, it can improve students understanding, performance, knowledge retention, and skills [112,118,120,122,123,132], increase their confidence [69], enhance their learning motivation and engagement [107,113], and promote students' self-efficacy [130] and self-regulated learning [117]. Hence, this combination of technologies and methods can create new learning opportunities in both formal and informal learning environments [98] and positively affect various subjects within an academic curriculum [101].

Additionally, this approach can effectively support special education [128] and enable the identification of errors in the learning design process [121]. Besides its ability to support students, this combination can also effectively support teachers [78], by automating mundane tasks [99], monitoring students' attention and focus [129], improving the evaluation and assessment processes [104], supporting learning and classroom management [109,116], and enabling teachers to provide students with personalized feedback and guidance according to their learning needs [74]. Therefore, it can be inferred that the integration of learning analytics and educational data mining within augmented reality and virtual reality environments and their adoption in classrooms can result in more efficient teaching and learning.

6. Conclusions

Individually, learning analytics, educational data mining, augmented reality, and virtual reality constitute well-established research fields. However, the integration of learning analytics and educational data mining within augmented reality and virtual reality is a novel topic that is experiencing increasing interest. Consequently, this study conducted a systematic literature review, a content analysis, and a bibliometric and scientific mapping analysis to examine the combination of these technologies and methods, their role in education, and their impact on teaching and learning.

Specifically, following the PRISMA framework, 70 relevant documents published from 2013 to 2024 were identified from ACM, ERIC, IEEE, ScienceDirect, Scopus, and WoS. The documents were separated into the following three categories: (i) Theoretical and Review studies, (ii) Proposal and Showcase studies, and (iii) Experimental and Case studies. The analysis explored different dimensions of the document collection and put an emphasis on both quantitative and qualitative analysis of the content. Additionally, the content analysis focused on identifying and examining key aspects within each category. The documents were further processed using scientometric tools, such as Bibliometrix and VOSviewer. Topic modeling through LDA was also used to further explore the merging topic. Finally, the results were discussed and the related outcomes in terms of the impact of this combination on teaching and learning were summarized. However, the use of six databases to retrieve related documents and the analysis of documents written only in English can be regarded as the main limitations of this study.

Based on the outcomes of this study, it can be inferred that the combination of learning analytics and educational data mining with augmented reality, virtual reality, and the metaverse can effectively support education and positively impact teaching and learning. The outcomes of the studies of all three categories highlighted the benefits that can be yielded through this integration for both students and teachers.

Specifically, this combination can support different educational approaches and strategies and tend to the needs of various learning styles and learners who positively view and assess its integration in education. A significant benefit yielded from this combination is the creation of immersive, intelligent, and interactive virtual learning environments that also enable the real-time identification, tracking, monitoring, and analysis of multimodal learning data of students' behavior, emotions, cognitive and affective states, as well as the overall learning and teaching processes, which is something that is not feasible through the use of other learning technologies. Hence, immersive intelligent tutoring systems that promote embodied learning, support the psychological, pedagogical, and technological aspects of the educational process, and offer evidence-based, real-time, and affective learning analytics can be created.

Additionally, students can engage in experiential and authentic learning within these safe and immersive learning environments which also promote and support collaborative learning and social learning. Through their involvement in such experiences and environments, students' engagement, motivation, and confidence can be improved. Additionally, their skills, knowledge, knowledge retention, performance, and understanding can be increased. Students' self-regulated learning and self-efficacy can also be enhanced through the personalized learning experiences offered. Teachers can also be supported via these technologies and methods through the automation of tasks, improved monitoring, management, and assessment, and the provision of personalized feedback and guidance to students based on their learning needs. As a result, the combination of learning analytics and educational data mining with augmented reality and virtual reality can constitute an effective educational means that leads to deep and meaningful learning and can create new learning opportunities in both formal and informal learning environments.

The outcomes of this study also reveal existing gaps in the literature. Specifically, there is a clear need for more experimental studies to be carried out in different educational settings to better understand their impact in education. Future studies should also focus on examining the perspectives of education stakeholders. There is also a need to develop effective standards and guidelines to examine how learning design implications affect their introduction, integration, and impact on teaching and learning. How to effectively design and develop suitable learning material is another area that needs to be further explored. Additionally, future studies should put an emphasis on evaluating the effectiveness of this approach in terms of learning gains and academic performance in prolonged interventions. Given the nature of these technologies and approaches, it is also important to explore how different socio-cultural factors affect their integration and influence. There is also a need to explore their potential to support social and collaborative learning and their use in distance education. Finally, due to the lack of information reported in the studies examined regarding the machine learning and deep learning techniques used, there is a clear need to further explore them in future studies.

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References

1. Williamson, B. *Big Data in Education: The digital Future of Learning, Policy and Practice*; SAGE Publications Ltd.: Thousand Oaks, CA, USA, 2017; ISBN 9781529714920. [CrossRef]
2. Lampropoulos, G. Educational data mining and learning analytics in the 21st century. In *Encyclopedia of Data Science and Machine Learning*; IGI Global: Hershey, PA, USA, 2023; pp. 1642–1651. [CrossRef]
3. Romero, C.; Ventura, S. Educational data mining and learning analytics: An updated survey. *WIREs Data Min. Knowl. Discov.* **2020**, *10*, e1355. [CrossRef]
4. Romero, C.; Ventura, S. Data mining in education. *WIREs Data Min. Knowl. Discov.* **2012**, *3*, 12–27. [CrossRef]
5. Romero, C.; Ventura, S. Educational Data Mining: A Review of the State of the Art. *IEEE Trans. Syst. Man Cybern. Part C (Appl. Rev.)* **2010**, *40*, 601–618. [CrossRef]
6. Baradwaj, B.K.; Pal, S. Mining Educational Data to Analyze Students' Performance. *arXiv* **2012**, arXiv:1201.3417. [CrossRef]
7. Baek, C.; Doleck, T. Educational Data Mining: A Bibliometric Analysis of an Emerging Field. *IEEE Access* **2022**, *10*, 31289–31296. [CrossRef]
8. Waheed, H.; Hassan, S.-U.; Aljohani, N.R.; Wasif, M. A bibliometric perspective of learning analytics research landscape. *Behav. Inf. Technol.* **2018**, *37*, 941–957. [CrossRef]
9. Saa, A.A. Educational data mining & students' performance prediction. *Int. J. Adv. Comput. Sci. Appl.* **2016**, *7*, 212–220.
10. Bienkowski, M.; Feng, M.; Means, B. *Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics: An Issue Brief*; Office of Educational Technology, US Department of Education: Washington, DC, USA, 2012.
11. Baker, R.S. Challenges for the future of educational data mining: The baker learning analytics prizes. *J. Educ. Data Min.* **2019**, *11*, 1–17. [CrossRef]
12. Siemens, G.; Baker, R.S.d. Learning analytics and educational data mining: Towards communication and collaboration. In Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, Vancouver, BC, Canada, 29 April–2 May 2012; pp. 252–254. [CrossRef]
13. Liñán, L.C.; Pérez, Á.A.J. Educational data mining and learning analytics: Differences, similarities, and time evolution. *Int. J. Educ. Technol. High. Educ.* **2015**, *12*, 98–112. [CrossRef]
14. Ferguson, R. Learning analytics: Drivers, developments and challenges. *Int. J. Technol. Enhanc. Learn.* **2012**, *4*, 304–317. [CrossRef]
15. Pardo, A.; Jovanovic, J.; Dawson, S.; Gašević, D.; Mirriahi, N. Using learning analytics to scale the provision of personalised feedback. *Br. J. Educ. Technol.* **2019**, *50*, 128–138. [CrossRef]
16. Bakharia, A.; Corrin, L.; De Barba, P.; Kennedy, G.; Gašević, D.; Mulder, R.; Williams, D.; Dawson, S.; Lockyer, L. A conceptual framework linking learning design with learning analytics. In Proceedings of the Sixth International Conference on Learning Analytics & Knowledge, Edinburgh, UK, 25–29 April 2016; pp. 329–338. [CrossRef]
17. Lang, C.; Siemens, G.; Wise, A.; Gasevic, D. *Handbook of Learning Analytics*; SOLAR, Society for Learning Analytics Research: New York, NY, USA, 2017.
18. Siemens, G. Learning analytics: The emergence of a discipline. *Am. Behav. Sci.* **2013**, *57*, 1380–1400. [CrossRef]

19. Clow, D. An overview of learning analytics. *Teach. High. Educ.* **2013**, *18*, 683–695. [CrossRef]
20. Slade, S.; Prinsloo, P. Learning analytics: Ethical issues and dilemmas. *Am. Behav. Sci.* **2013**, *57*, 1510–1529. [CrossRef]
21. Mangaroska, K.; Giannakos, M. Learning Analytics for Learning Design: A Systematic Literature Review of Analytics-Driven Design to Enhance Learning. *IEEE Trans. Learn. Technol.* **2019**, *12*, 516–534. [CrossRef]
22. Aldowah, H.; Al-Samarraie, H.; Fauzy, W.M. Educational data mining and learning analytics for 21st century higher education: A review and synthesis. *Telemat. Inform.* **2019**, *37*, 13–49. [CrossRef]
23. Nunn, S.; Avella, J.T.; Kanai, T.; Kebritchi, M. Learning Analytics Methods, Benefits, and Challenges in Higher Education: A Systematic Literature Review. *Online Learn.* **2016**, *20*, 13–29. [CrossRef]
24. Larrabee Sønderlund, A.; Hughes, E.; Smith, J. The efficacy of learning analytics interventions in higher education: A systematic review. *Br. J. Educ. Technol.* **2018**, *50*, 2594–2618. [CrossRef]
25. Papamitsiou, Z.; Economides, A.A. Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. *J. Educ. Technol. Soc.* **2014**, *17*, 49–64.
26. Leitner, P.; Khalil, M.; Ebner, M. Learning Analytics in Higher Education—A Literature Review. In *Learning Analytics: Fundaments, Applications, and Trends*; Springer International Publishing: Cham, Switzerland, 2017; pp. 1–23. ISBN 9783319529776. [CrossRef]
27. International Educational Data Mining Society. Educational data mining. In *International Educational Data Mining Society*; 2024; Available online: https://educationaldatamining.org/ (accessed on 5 November 2024).
28. Dutt, A.; Ismail, M.A.; Herawan, T. A Systematic Review on Educational Data Mining. *IEEE Access* **2017**, *5*, 15991–16005. [CrossRef]
29. Mohamad, S.K.; Tasir, Z. Educational Data Mining: A Review. *Procedia—Soc. Behav. Sci.* **2013**, *97*, 320–324. [CrossRef]
30. Baker, R.S.J.d.; Yacef, K. The State of Educational Data Mining in 2009: A Review and Future Visions. *J. Educ. Data Min.* **2009**, *1*, 3–17. [CrossRef]
31. Rauschnabel, P.A.; Felix, R.; Hinsch, C.; Shahab, H.; Alt, F. What is XR? Towards a framework for augmented and virtual reality. *Comput. Hum. Behav.* **2022**, *133*, 107289. [CrossRef]
32. Lee, K. Augmented reality in education and training. *TechTrends* **2012**, *56*, 13–21. [CrossRef]
33. Carmigniani, J.; Furht, B. Augmented reality: An overview. In *Handbook of Augmented Reality*; Springer: New York, NY, USA, 2011; pp. 3–46. [CrossRef]
34. Carmigniani, J.; Furht, B.; Anisetti, M.; Ceravolo, P.; Damiani, E.; Ivkovic, M. Augmented reality technologies, systems and applications. *Multimed. Tools Appl.* **2011**, *51*, 341–377. [CrossRef]
35. Burdea, G.C.; Coiffet, P. *Virtual Reality Technology*; John Wiley & Sons: Hoboken, NJ, USA, 2003.
36. Anthes, C.; Garcia-Hernandez, R.J.; Wiedemann, M.; Kranzlmuller, D. State of the art of virtual reality technology. In Proceedings of the 2016 IEEE Aerospace Conference, Big Sky, MT, USA, 5–12 March 2016; IEEE: Piscataway, NJ, USA, 2016. [CrossRef]
37. Sherman, W.R.; Craig, A.B. *Understanding Virtual Reality: Interface, Application, and Design*; Morgan Kaufmann: San Francisco, CA, USA, 2018.
38. Biocca, F.; Delaney, B. Immersive virtual reality technology. In *Communication in the Age of Virtual Reality*; Routledge: New York, NY, USA, 1995; Volume 15, pp. 127–157. [CrossRef]
39. Psotka, J. Immersive training systems: Virtual reality and education and training. *Instr. Sci.* **1995**, *23*, 405–431. [CrossRef]
40. Ryan, M.-L. *Narrative as Virtual Reality 2: Revisiting Immersion and Interactivity in Literature and Electronic Media*; JHU Press: Baltimore, MD, USA, 2015.
41. Sherman, W.R.; Craig, A.B. Understanding virtual reality—Interface, application, and design. *Presence Teleoperators Virtual Environ.* **2003**, *12*, 441–442. [CrossRef]
42. López-Belmonte, J.; Moreno-Guerrero, A.-J.; Marín-Marín, J.-A.; Lampropoulos, G. The impact of gender on the use of augmented reality and virtual reality in students with ASD. *Educ. Knowl. Soc. (EKS)* **2022**, *23*, 1–14. [CrossRef]
43. Blascovich, J.; Bailenson, J. *Infinite Reality: Avatars, Eternal Life, New Worlds, and the Dawn of the Virtual Revolution*; William Morrow & Co.: New York, NY, USA, 2011.
44. Milgram, P.; Kishino, F. A taxonomy of mixed reality visual displays. *IEICE Trans. Inf. Syst.* **1994**, *77*, 1321–1329.
45. Akçayır, M.; Akçayır, G. Advantages and challenges associated with augmented reality for education: A systematic review of the literature. *Educ. Res. Rev.* **2017**, *20*, 1–11. [CrossRef]
46. Chen, P.; Liu, X.; Cheng, W.; Huang, R. A review of using augmented reality in education from 2011 to 2016. In *Innovations in Smart Learning*; Springer: Singapore, 2017; pp. 13–18. [CrossRef]
47. Garzón, J. An overview of Twenty-Five years of augmented reality in education. *Multimodal Technol. Interact.* **2021**, *5*, 37. [CrossRef]
48. Lampropoulos, G.; Keramopoulos, E.; Diamantaras, K.; Evangelidis, G. Augmented reality and gamification in education: A systematic literature review of research, applications, and empirical studies. *Appl. Sci.* **2022**, *12*, 6809. [CrossRef]
49. Freina, L.; Ott, M. A literature review on immersive virtual reality in education: State of the art and perspectives. In Proceedings of the International Scientific Conference Elearning and Software for Education, Bucharest, Romania, 25–26 April 2015; pp. 1–8.

50. Radianti, J.; Majchrzak, T.A.; Fromm, J.; Wohlgenannt, I. A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. *Comput. Educ.* **2020**, *147*, 103778. [CrossRef]
51. Kavanagh, S.; Luxton-Reilly, A.; Wuensche, B.; Plimmer, B. A systematic review of virtual reality in education. *Themes Sci. Technol. Educ.* **2017**, *10*, 85–119.
52. Lampropoulos, G. Kinshuk Virtual reality and gamification in education: A systematic review. *Educ. Technol. Res. Dev.* **2024**, *72*, 1691–1785. [CrossRef]
53. Lampropoulos, G. Augmented reality and artificial intelligence in education: Toward immersive intelligent tutoring systems. In *Augmented Reality and Artificial Intelligence*; Springer: Cham, Switzerland, 2023; pp. 137–146. [CrossRef]
54. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Int. J. Surg.* **2021**, *88*, 105906. [CrossRef] [PubMed]
55. Blei, D.M.; Ng, A.Y.; Jordan, M.I. Latent dirichlet allocation. *J. Mach. Learn. Res.* **2003**, *3*, 993–1022. [CrossRef]
56. Aria, M.; Cuccurullo, C. Bibliometrix: An r-tool for comprehensive science mapping analysis. *J. Informetr.* **2017**, *11*, 959–975. [CrossRef]
57. van Eck, N.J.; Waltman, L. Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics* **2010**, *84*, 523–538. [CrossRef]
58. Xiao, Y.; Watson, M. Guidance on conducting a systematic literature review. *J. Plan. Educ. Res.* **2017**, *39*, 93–112. [CrossRef]
59. Higgins, J.P.; Thomas, J.; Chandler, J.; Cumpston, M.; Li, T.; Page, M.J.; Welch, V.A. *Cochrane Handbook for Systematic Reviews of Interventions*; John Wiley & Sons: New York, NY, USA, 2019. [CrossRef]
60. Liberati, A. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. *Ann. Intern. Med.* **2009**, *151*, 65–94. [CrossRef]
61. Webster, J.; Watson, R.T. Analyzing the past to prepare for the future: Writing a literature review. *MIS Q.* **2002**, *26*, xiii–xxiii.
62. Mongeon, P.; Paul-Hus, A. The journal coverage of Web of Science and Scopus: A comparative analysis. *Scientometrics* **2015**, *106*, 213–228. [CrossRef]
63. Zhu, J.; Liu, W. A tale of two databases: The use of Web of Science and Scopus in academic papers. *Scientometrics* **2020**, *123*, 321–335. [CrossRef]
64. Poitras, E.; Kee, K.; Lajoie, S.P.; Cataldo, D. Towards Evaluating and Modelling the Impacts of Mobile-Based Augmented Reality Applications on Learning and Engagement. In *Artificial Intelligence in Education*; Springer: Berlin/Heidelberg, Germany, 2013; pp. 868–871. ISBN 9783642391125. [CrossRef]
65. Son, J.; Cho, Y. A study on capturing learning data from virtual and mixed reality contents through data collection API. In Proceedings of the Workshop Proceedings of the 25th International Conference on Computers in Education, Christchurch, New Zealand, 4–8 December 2017.
66. Secretan, J.; Wild, F.; Guest, W. Learning Analytics in Augmented Reality: Blueprint for an AR/xAPI Framework. In Proceedings of the 2019 IEEE International Conference on Engineering, Technology and Education (TALE), Yogyakarta, Indonesia, 10–13 December 2019; IEEE: Piscataway, NJ, USA, 2019. [CrossRef]
67. Christopoulos, A.; Pellas, N.; Laakso, M.-J. A Learning Analytics Theoretical Framework for STEM Education Virtual Reality Applications. *Educ. Sci.* **2020**, *10*, 317. [CrossRef]
68. Christopoulos, A.; Pellas, N. Theoretical Foundations of Virtual and Augmented Reality-Supported Learning Analytics. In Proceedings of the 2020 11th International Conference on Information, Intelligence, Systems and Applications (IISA), Piraeus, Greece, 15–17 July 2020; IEEE: Piscataway, NJ, USA, 2020. [CrossRef]
69. Na, K.S.; Mohamed, F.; Isham, M.I.M.; Siang, C.V.; Tasir, Z.; Abas, M.A. Virtual Reality Application Integrated with Learning Analytics for Enhancing English Pronunciation: A Conceptual Framework. In Proceedings of the 2020 IEEE Conference on e-Learning, e-Management and e-Services (IC3e), Kota Kinabalu, Malaysia, 17–19 November 2020; IEEE: Piscataway, NJ, USA, 2020. [CrossRef]
70. Carter, M.; Egliston, B. What are the risks of Virtual Reality data? Learning Analytics, Algorithmic Bias and a Fantasy of Perfect Data. *New Media Soc.* **2021**, *25*, 485–504. [CrossRef]
71. Christopoulos, A.; Mystakidis, S.; Pellas, N.; Laakso, M.-J. ARLEAN: An Augmented Reality Learning Analytics Ethical Framework. *Computers* **2021**, *10*, 92. [CrossRef]
72. Kazanidis, I.; Pellas, N.; Christopoulos, A. A Learning Analytics Conceptual Framework for Augmented Reality-Supported Educational Case Studies. *Multimodal Technol. Interact.* **2021**, *5*, 9. [CrossRef]
73. Kurilovas, E. On Top-Down Versus Bottom-up Personalisation and Evaluation of Augmented Reality Learning Systems. In *Springer Proceedings in Complexity*; Springer International Publishing: Cham, Switzerland, 2021; pp. 327–339. ISBN 9783030620660. [CrossRef]

74. Singh, M.; Bangay, S.; Sajjanhar, A. An Architecture for Capturing and Presenting Learning Outcomes using Augmented Reality Enhanced Analytics. In Proceedings of the 2022 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct), Singapore, 17–21 October 2022; IEEE: Piscataway, NJ, USA, 2022. [CrossRef]
75. Hensen, B. A Modularity Approach in Design Science Research for Mixed Reality Learning Artifacts. In Proceedings of the 2023 IEEE International Conference on Advanced Learning Technologies (ICALT), Orem, UT, USA, 10–13 July 2023; IEEE: Piscataway, NJ, USA, 2023. [CrossRef]
76. Sulema, Y.; Pester, A.; Laforge, B.; Andres, F. Augmented Reality User's Experience: AI-Based Data Collection, Processing and Analysis. In *Springer Series on Cultural Computing*; Springer Nature: Cham, Switzerland, 2023; pp. 31–46. ISBN 9783031271663. [CrossRef]
77. Görzen, S.; Heinemann, B.; Schroeder, U. Towards using the xAPI specification for learning analytics in virtual reality. In Proceedings of the LAK Workshops, Kyoto, Japan, 18–22 March 2024; pp. 260–271.
78. Sakr, A.; Abdullah, T. Virtual, augmented reality and learning analytics impact on learners, and educators: A systematic review. *Educ. Inf. Technol.* **2024**, *29*, 19913–19962. [CrossRef]
79. Klamma, R.; Ali, R.; Koren, I. Immersive Community Analytics for Wearable Enhanced Learning. In *Lecture Notes in Computer Science*; Springer International Publishing: Cham, Switzerland, 2019; pp. 162–174. ISBN 9783030218171. [CrossRef]
80. Vidal, E.C.E.; Ty, J.F.; Caluya, N.R.; Rodrigo, M.M.T. MAGIS: Mobile augmented reality games for instructional support. *Interact. Learn. Environ.* **2018**, *27*, 895–907. [CrossRef]
81. Papagiannakis, G.; Zikas, P.; Lydatakis, N.; Kateros, S.; Kentros, M.; Geronikolakis, E.; Kamarianakis, M.; Kartsonaki, I.; Evangelou, G. MAGES 3.0: Tying the knot of medical VR. In Proceedings of the ACM SIGGRAPH 2020 Immersive Pavilion, Virtual Event, 17 August 2020; ACM: New York, NY, USA, 2020. [CrossRef]
82. Srimadhaven, T.; AV, C.J.; Harshith, N.; Priyaadharshini, M. Learning Analytics: Virtual Reality for Programming Course in Higher Education. *Procedia Comput. Sci.* **2020**, *172*, 433–437. [CrossRef]
83. Farella, M.; Arrigo, M.; Chiazzese, G.; Tosto, C.; Seta, L.; Taibi, D. Integrating xAPI in AR applications for Positive Behaviour Intervention and Support. In Proceedings of the 2021 International Conference on Advanced Learning Technologies (ICALT), Tartu, Estonia, 12–15 July 2021; IEEE: Piscataway, NJ, USA, 2021. [CrossRef]
84. Garcia Fracaro, S.; Chan, P.; Gallagher, T.; Tehreem, Y.; Toyoda, R.; Bernaerts, K.; Glassey, J.; Pfeiffer, T.; Slof, B.; Wachsmuth, S.; et al. Towards design guidelines for virtual reality training for the chemical industry. *Educ. Chem. Eng.* **2021**, *36*, 12–23. [CrossRef]
85. Shi, W.; Haga, A.; Okada, Y. Web-based 3D and 360-degree VR materials for IoT security education and test supporting learning analytics. *Internet Things* **2021**, *15*, 100424. [CrossRef]
86. Shi, W.; Haga, A.; Okada, Y. Web-Based 3D and 360 VR Materials for IoT Security Education Supporting Learning Analytics. In *Lecture Notes on Data Engineering and Communications Technologies*; Springer International Publishing: Cham, Switzerland, 2021; pp. 370–378. ISBN 9783030706395. [CrossRef]
87. Zikas, P.; Kamarianakis, M.; Kartsonaki, I.; Lydatakis, N.; Kateros, S.; Kentros, M.; Geronikolakis, E.; Evangelou, G.; Apostolou, A.; Catilo, P.A.A.; et al. COVID-19—VR Strikes Back: Innovative medical VR training. In Proceedings of the ACM SIGGRAPH 2021 Immersive Pavilion, Virtual Event, 9–13 August 2021; ACM: New York, NY, USA, 2021. [CrossRef]
88. Antzoulatos, G.; Mavropoulos, T.; Tzionis, G.; Karakostas, A.; Gonzalez Costas, A.; González Burgos, M.; Vrochidis, S.; Kompatsiaris, I. Usage of Visual Analytics to Support Immigration-Related, Personalised Language Training Scenarios. In *Lecture Notes in Networks and Systems*; Springer International Publishing: Cham, Switzerland, 2022; pp. 681–693. ISBN 9783030962968. [CrossRef]
89. Heinemann, B.; Gorzen, S.; Schroeder, U. Systematic Design for Effective Learning in Virtual Reality. In Proceedings of the 2022 International Conference on Advanced Learning Technologies (ICALT), Bucharest, Romania, 1–4 July 2022; IEEE: Piscataway, NJ, USA, 2022. [CrossRef]
90. Singh, M.; Bangay, S.; Sajjanhar, A. Augmented Reality Enhanced Analytics to Measure and Mitigate Disengagement in Teaching Young Children. In Proceedings of the 2022 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct), Singapore, 17–21 October 2022; IEEE: Piscataway, NJ, USA, 2022. [CrossRef]
91. Heinemann, B.; Schroeder, U. Learning Analytics and Classroom Management in Specialized Environments: Enhancing the VR Classroom for CS Teacher Education. In *Immersive Learning Research Network*; Springer Nature: Cham, Switzerland, 2023; pp. 37–52. ISBN 9783031473289. [CrossRef]
92. Heinemann, B.; Görzen, S.; Schroeder, U. Teaching the basics of computer graphics in virtual reality. *Comput. Graph.* **2023**, *112*, 1–12. [CrossRef]
93. Masneri, S.; Domínguez, A.; Sanz, M.; Zorrilla, M.; Larrañaga, M.; Arruarte, A. cleAR: An interoperable architecture for multi-user AR-based school curricula. *Virtual Real.* **2023**, *27*, 1813–1825. [CrossRef] [PubMed]
94. ShengKai, L.; Mouri, K.; Okamoto, M.; Matsubara, Y. Learning analytics in VR: What if we can collect learning logs in VR classroom. In Proceedings of the 2023 International Conference on Artificial Intelligence and Education (ICAIE), Kobe, Japan, 20–22 March 2023; IEEE: Piscataway, NJ, USA, 2023. [CrossRef]

95. Viol, R.S.; Fernandes, P.C.; Lacerda, I.I.; Melo, K.G.F.; Nunes, A.J.D.A.; Pimenta, A.S.G.M.; Carneiro, C.M.; Silva, M.C.; Delabrida, S. EduVR: Towards an Evaluation Platform for User Interactions in Personalized Virtual Reality Learning Environments. In Proceedings of the XXII Brazilian Symposium on Human Factors in Computing Systems, Maceió, Brazil, 16–20 October 2023; ACM: New York, NY, USA, 2023. [CrossRef]
96. Heinemann, B.; Görzen, S.; Dragoljic, A.; Meiendresch, L.; Troll, M.; Schroeder, U. A learning analytics dashboard to investigate the influence of interaction in a VR learning application. In Proceedings of the LAK Workshops, Kyoto, Japan, 18–22 March 2024; pp. 251–259.
97. Winer, A.; Geri, N. Towards learning analytics for student evaluation in the metaversity. In Proceedings of the LAK Workshops, Kyoto, Japan, 18–22 March 2024; pp. 284–291.
98. Salman, F.H.; Riley, D.R. Augmented reality crossover gamified design for sustainable engineering education. In Proceedings of the 2016 Future Technologies Conference (FTC), San Francisco, CA, USA, 6–7 December 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 1353–1356. [CrossRef]
99. Stefan, L.; Moldoveanu, F.; Gheorghiu, D. Evaluating a mixed reality 3D virtual campus with big data and learning analytics: A transversal study. *J. e-Learn. Knowl. Soc.* **2016**, *12*, 41–54.
100. Krstulovic, R.; Boticki, I.; Ogata, H. Analyzing heterogeneous learning logs using the iterative convergence method. In Proceedings of the 2017 IEEE 6th International Conference on Teaching, Assessment, and Learning for Engineering (TALE), Hong Kong, China, 12–14 December 2017; IEEE: Piscataway, NJ, USA, 2017. [CrossRef]
101. Kwong, T.; Wong, E.; Yue, K. Bringing Abstract Academic Integrity and Ethical Concepts into Real-Life Situations. *Technol. Knowl. Learn.* **2017**, *22*, 353–368. [CrossRef]
102. Hernández, Y.; Cervantes-Salgado, M.; Pérez-Ramírez, M.; Mejía-Lavalle, M. Data-Driven Construction of a Student Model Using Bayesian Networks in an Electrical Domain. In *Lecture Notes in Computer Science*; Springer International Publishing: Cham, Switzerland, 2017; pp. 481–490. ISBN 9783319624280. [CrossRef]
103. Cunningham, L.A. A virtual reality game for teaching graph theory: A study of its effectiveness in improving outcomes and encouraging autonomy. In Proceedings of the ICERI Proceedings, Proceedings of the 11th annual International Conference of Education, Research and Innovation, Seville, Spain, 12–14 November 2018. [CrossRef]
104. Gorham, T.; Jubaed, S.; Sanyal, T.; Starr, E.L. Assessing the efficacy of VR for foreign language learning using multimodal learning analytics. In *Professional Development in CALL: A Selection of Papers*; Research-publishing.net: Voillans, France, 2019; pp. 101–116. [CrossRef]
105. Schneider, J.; Romano, G.; Drachsler, H. Beyond Reality—Extending a Presentation Trainer with an Immersive VR Module. *Sensors* **2019**, *19*, 3457. [CrossRef]
106. Moon, J.; Ke, F. Exploring the treatment integrity of virtual reality-based social skills training for children with high-functioning autism. *Interact. Learn. Environ.* **2019**, *29*, 939–953. [CrossRef]
107. Chiu, H.-Y.; Kang, Y.-N.; Wang, W.-L.; Chen, C.-C.; Hsu, W.; Tseng, M.-F.; Wei, P.-L. The Role of Active Engagement of Peer Observation in the Acquisition of Surgical Skills in Virtual Reality Tasks for Novices. *J. Surg. Educ.* **2019**, *76*, 1655–1662. [CrossRef] [PubMed]
108. Antoniou, P.E.; Arfaras, G.; Pandria, N.; Athanasiou, A.; Ntakakis, G.; Babatsikos, E.; Nigdelis, V.; Bamidis, P. Biosensor Real-Time Affective Analytics in Virtual and Mixed Reality Medical Education Serious Games: Cohort Study. *JMIR Serious Games* **2020**, *8*, e17823. [CrossRef]
109. Shiba, Y.; Imai, S. Development of engineering educational support system for manufacturing using Augmented Reality. In Proceedings of the 2020 International Conference on Advanced Mechatronic Systems (ICAMechS), Hanoi, Vietnam, 10–13 December 2020; IEEE: Piscataway, NJ, USA, 2020. [CrossRef]
110. Rodríguez, A.O.R.; Riaño, M.A.; García, P.A.G.; Marín, C.E.M.; Crespo, R.G.; Wu, X. Emotional characterization of children through a learning environment using learning analytics and AR-Sandbox. *J. Ambient. Intell. Humaniz. Comput.* **2020**, *11*, 5353–5367. [CrossRef]
111. Santamaría-Bonfil, G.; Ibáñez, M.B.; Pérez-Ramírez, M.; Arroyo-Figueroa, G.; Martínez-Álvarez, F. Learning analytics for student modeling in virtual reality training systems: Lineworkers case. *Comput. Educ.* **2020**, *151*, 103871. [CrossRef]
112. Geng, X.; Yamada, M. The development and evaluation of an augmented reality learning system for Japanese compound verbs using learning analytics. In Proceedings of the 2020 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE), Takamatsu, Japan, 8–11 December 2020; IEEE: Piscataway, NJ, USA, 2020. [CrossRef]
113. Malliarakis, C.; Shabalina, O.; Mozelius, P. Can you escape from dr. Tom cat's lab? Educational escape rooms with scientists, riddles and serious games as learning tools. In Proceedings of the European Conference on Game Based Learning, ECGBL 2021, Brighton, UK, 23–24 September 2021; Dechema: Frankfurt, Germany, 2021; Volume 15, pp. 525–534.
114. Chen, L.; Liang, H.-N.; Lu, F.; Wang, J.; Chen, W.; Yue, Y. Effect of Collaboration Mode and Position Arrangement on Immersive Analytics Tasks in Virtual Reality: A Pilot Study. *Appl. Sci.* **2021**, *11*, 10473. [CrossRef]

115. Paxinou, E.; Mitropoulos, K.; Tsalapatas, H.; Kalles, D. A Distance Learning VR Technology Tool for Science Labs. In Proceedings of the 2022 13th International Conference on Information, Intelligence, Systems & Applications (IISA), Corfu, Greece, 18–20 July 2022; IEEE: Piscataway, NJ, USA, 2022. [CrossRef]
116. Wang, Z.; Tzi Dong Ng, J.; Liu, R.; Hu, X. Learning Analytics Enabled Virtual Reality Content Creation Platform: System Design and Preliminary Evaluation. In Proceedings of the 2022 International Conference on Advanced Learning Technologies (ICALT), Bucharest, Romania, 1–4 July 2022; IEEE: Piscataway, NJ, USA, 2022. [CrossRef]
117. Tzi-Dong Ng, J.; Wang, Z.; Hu, X. Needs Analysis and Prototype Evaluation of Student-facing LA Dashboard for Virtual Reality Content Creation. In Proceedings of the LAK22: 12th International Learning Analytics and Knowledge Conference, Online, 21–25 March 2022; ACM: New York, NY, USA, 2022. [CrossRef]
118. Sharma, V.; Bhagat, K.K.; Huang, H.-H.; Chen, N.-S. The design and evaluation of an AR-based serious game to teach programming. *Comput. Graph.* **2022**, *103*, 1–18. [CrossRef]
119. Tzi-Dong Ng, J.; Hu, X.; Que, Y. Towards Multi-modal Evaluation of Eye-tracked Virtual Heritage Environment. In Proceedings of the LAK22: 12th International Learning Analytics and Knowledge Conference; Online, 21–25 March 2022; ACM: New York, NY, USA, 2022. [CrossRef]
120. Cheng, C.-I. A study on learning analytics of using mobile augmented reality application to enhance cultural competence for design cultural creation in higher education. *J. Comput. Assist. Learn.* **2023**, *39*, 1939–1952. [CrossRef]
121. Khorasani, S.; Nawaz, S.; Syiem, B.V.; Wei, J.; Pardos, Z.A.; Knibbe, J.; Velloso, E. An Empirical Evaluation of Educational Data Mining Techniques in a Dynamic VR Application. In Proceedings of the 35th Australian Computer-Human Interaction Conference, Wellington, New Zealand, 2–6 December 2023; ACM: New York, NY, USA, 2023. [CrossRef]
122. Ng, J.T.D.; Liu, R.; Wang, Z.; Hu, X. Automated Analysis of Text in Student-Created Virtual Reality Content. In Proceedings of the 2023 IEEE International Conference on Advanced Learning Technologies (ICALT), Orem, UT, USA, 10–13 July 2023; IEEE: Piscataway, NJ, USA, 2023. [CrossRef]
123. Fuchs, A.; Grimm, P. Experience the Theory: New Perspectives Through VR Learning Environments for Photography Education. In Proceedings of the 2023 International Electronics Symposium (IES), Denpasar, Indonesia, 8–10 August 2023; IEEE: Piscataway, NJ, USA, 2023. [CrossRef]
124. Jiang, S.; Huang, X.; Sung, S.H.; Xie, C. Learning Analytics for Assessing Hands-on Laboratory Skills in Science Classrooms Using Bayesian Network Analysis. *Res. Sci. Educ.* **2022**, *53*, 425–444. [CrossRef]
125. Sokolikj, Z.; Ke, F.; Chakraborty, S.; Moon, J. Using Deep Learning to Track Representational Flexibility Development of Children with Autism in a Virtual World. In Proceedings of the 2023 11th International Conference on Information and Education Technology (ICIET), Fujisawa, Japan, 18–20 March 2023; IEEE: Piscataway, NJ, USA, 2023. [CrossRef]
126. Geng, X.; Yamada, M. Using learning analytics to investigate learning processes and behavioural patterns in an augmented reality language learning environment. *J. Comput. Assist. Learn.* **2022**, *39*, 532–546. [CrossRef]
127. Yano, K. A Platform for Analyzing Students' Behavior in Virtual Spaces on Mozilla Hubs. In *Immersive Learning Research Network*; Springer Nature: Cham, Switzerland, 2023; pp. 209–219. ISBN 9783031473289. [CrossRef]
128. Moon, J.; Ke, F.; Sokolikj, Z.; Chakraborty, S. Applying multimodal data fusion to track autistic adolescents' representational flexibility development during virtual reality-based training. *Comput. Educ. X Real.* **2024**, *4*, 100063. [CrossRef]
129. Moser, I.; Hlosta, M.; Bergamin, P.B.; Ramnarain, U.; Van der Westhuizen, C.; Penn, M.; Mdlalose, N.; Pila, K.; Ogegbo, A. Approximating eye gaze with head pose in a virtual reality microteaching scenario for pre-service teachers. In Proceedings of the 2024 Joint of International Conference on Learning Analytics and Knowledge Workshops, Kyoto, Japan, 18–22 March 2024. [CrossRef]
130. Arztmann, M.; Domínguez Alfaro, J.L.; Hornstra, L.; Jeuring, J.; Kester, L. In-game performance: The role of students' socio-economic status, self-efficacy and situational interest in an augmented reality game. *Br. J. Educ. Technol.* **2023**, *55*, 484–498. [CrossRef]
131. Wang, Z.; Ng, J.T.D.; Que, Y.; Hu, X. Unveiling Synchrony of Learners' Multimodal Data in Collaborative Maker Activities. In Proceedings of the 14th Learning Analytics and Knowledge Conference, Kyoto, Japan, 18–22 March 2024; ACM: New York, NY, USA, 2024. [CrossRef]
132. Yu, J.; Denham, A.R. Utilizing augmented reality for embodied mental rotation training: A learning analytics study. *British J. Educ. Technol.* **2023**, *55*, 499–518. [CrossRef]
133. Wang, Z.; Ng, J.T.D.; Hu, X. Learning analytics for collaboration quality assessment during virtual reality content creation. In Proceedings of the 2024 IEEE International Conference on Advanced Learning Technologies (ICALT), Nicosia, North Cyprus, Cyprus, 1–4 July 2024; pp. 91–93. [CrossRef]
134. Brooke, J. SUS: A quick and dirty usability scale. *Usability Eval. Ind.* **1996**, *189*, 189–194.
135. Lund, A.M. Measuring usability with the use questionnaire. *Usability Interface* **2001**, *8*, 3–6.

136. Inchley, J. *Health Behaviour in School-Aged Children (HBSC) Study Protocol: Background, Methodology and Mandatory Items for the 2017/18 Survey*; Child and Adolescent Health Research Unit (CAHRU), University of St Andrews, Scotland: St Andrews, UK, 2018.
137. Nuutila, K.; Tapola, A.; Tuominen, H.; Kupiainen, S.; Pásztor, A.; Niemivirta, M. Reciprocal predictions between interest, Self-Efficacy, and performance during a task. *Front. Educ.* **2020**, *5*, 36. [CrossRef]
138. Chao, T.-C. The development and application of an intercultural competence scale for university EFL learners. *Engl. Teach. Learn.* **2014**, *38*, 79–124.
139. Zhang, J.; Yu, Q.; Zheng, F.; Long, C.; Lu, Z.; Duan, Z. Comparing keywords plus of WOS and author keywords: A case study of patient adherence research. *J. Assoc. Inf. Sci. Technol.* **2016**, *67*, 967–972. [CrossRef]
140. Lampropoulos, G.; Sidiropoulos, A. Impact of gamification on students' learning outcomes and academic performance: A longitudinal study comparing online, traditional, and gamified learning. *Educ. Sci.* **2024**, *14*, 367. [CrossRef]
141. Parra-González, M.E.; Belmonte, J.L.; Segura-Robles, A.; Cabrera, A.F. Active and emerging methodologies for ubiquitous education: Potentials of flipped learning and gamification. *Sustainability* **2020**, *12*, 602. [CrossRef]
142. Bai, S.; Hew, K.F.; Huang, B. Does gamification improve student learning outcome? Evidence from a meta-analysis and synthesis of qualitative data in educational contexts. *Educ. Res. Rev.* **2020**, *30*, 100322. [CrossRef]
143. Lampropoulos, G.; Anastasiadis, T.; Siakas, K. Digital game-based learning in education: Significance of motivating, engaging and interactive learning environments. In Proceedings of the 25th International Conference on Software Process Improvement-Research Into Education And Training (INSPIRE), Montreal, QC, Canada, 27 May 2019; pp. 117–127.
144. Yildirim, I. The effects of gamification-based teaching practices on student achievement and students' attitudes toward lessons. *Internet High. Educ.* **2017**, *33*, 86–92. [CrossRef]
145. He, K.; Zhang, X.; Ren, S.; Sun, J. Deep Residual Learning for Image Recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 770–778.
146. Noorizadegan, A.; Young, D.L.; Hon, Y.C.; Chen, C.S. Power-Enhanced Residual Network for Function Approximation and Physics-Informed Inverse Problems. *Appl. Math. Comput.* **2024**, *480*, 128910. [CrossRef]
147. Voulodimos, A.; Doulamis, N.; Doulamis, A.; Protopapadakis, E. Deep Learning for Computer Vision: A Brief Review. *Comput. Intell. Neurosci.* **2018**, *2018*, 7068349. [CrossRef] [PubMed]

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