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TOPICAL REVIEW

The Use of Artificial Intelligence Techniques in Smart Classrooms is in Its Infancy

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ABSTRACT Smart classrooms are physical learning spaces that, using data from the environment, students and teachers, are able to provide timely and valuable information to improve teaching and learning processes and foster decision-making. In this article, we provide an overview of how artificial intelligence techniques are being used to gain insights into the teaching and learning processes by analyzing data not only from the classroom context, but also from students and teachers. We identify the latest literature addressing the use of artificial intelligence techniques with data obtained from the smart classroom, present a taxonomy for the areas of application, review the state of deployment in schools, and discuss the current limitations. From the results, we conclude that the use of artificial intelligence techniques to analyze classroom data in real settings (*i.e.,* primary and secondary schools) is still far from common. Most proposals are in the lower range of technological readiness levels and do not consider issues such as information security and privacy. Furthermore, most proposals focus on the development of technological products and do not address their impact on learning. Our paper concludes with an outlook on future work in this area with the aim of making the smart classroom a cornerstone for the future of education.

INDEX TERMS Educational technology, artificial intelligence, smart classroom.

I. INTRODUCTION

Teaching has progressed steadily thanks to new technological developments and improved teaching and learning processes [1]. Information and Communication Technologies (ICT) are now widely used in education: Tablets, interactive whiteboards, robots and programmable boards have gained popularity and complement traditional teaching tools. In addition, online learning platforms have been introduced across primary and secondary education being particularly indispensable in the light of the challenges posed by the COVID-19 pandemic. Nowadays, teachers have access to a wide range of online tools for creating educational content, and students can benefit from fully personalized learning paths within online learning environments tailored to their individual needs.

Moreover, several scenarios, such as smart cities and ambient-assisted living environments, are benefiting from the real-time collection of data and its analysis to gain timely, valuable insights. Similarly, classrooms and schools could also benefit from the integration of data collected using Internet of Things devices (IoT) and their analysis using artificial intelligence (AI) and machine learning [2].

The benefits of the smart classroom include promoting better and faster learning by leveraging digital, contextualized, and adaptive devices and software [3], [4]. Within these environments, technology helps improve the quality of teaching and learning processes by collecting and processing information from students, teachers and the environment [5], whilst aiming to facilitate decision-making [6]. The smart

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classroom can enhance effectiveness of teaching and has the potential to relieve teachers of routine tasks, thereby reducing stress and preventing burnout [7].

However, most of the literature on the technical side of smart classrooms focuses on computer-assisted learning methods and the introduction of state-of-the-art technologies in the classroom such as robots, programming languages, and generative AI. For example, in [8] authors examine the impact of smart classrooms on hard skills education by merely incorporating augmented and virtual reality technologies. Study [9] analyzes the differences in interaction and engagement between smart classroom and traditional classrooms. In this case, the authors' vision of the smart classroom is based on the addition of "advanced forms of educational technology", essentially one tablet per student, Wi-Fi, and interactive teaching platforms. The study [10] surveys the literature on smart classrooms, focusing on the smart material (virtual reality technology, distance learning tools, video recording devices, etc.), the tools for communication and participation, monitoring the environment, etc. However, they do not explore the linking of these aspects using AI techniques and their impact on learning outcomes.

The areas of application of AI are growing at an unprecedented pace and will therefore become a key enabler of the classrooms of the future. In the smart classroom scenario, data can be effortlessly mined from the computers and devices (like sensors and cameras) in the physical learning space, as well as from events and evidence collected by learning platforms. Machine learning, as a technique to learn from large amounts of data and classify information or predict future behaviors, has become a mature field with extensive research and numerous practical applications seamlessly integrated into everyday settings. For instance, data mining and machine learning have been used for learning analytics and predict student performance, specially in higher education and online learning [11], [12], [13]. Lastly, language models and generative AI are still in their infancy, but their potential is vast. In the coming years, we anticipate witnessing a plethora of applications emerging as these technologies mature and become more widely adopted.

Our article provides an up-to-date literature review on the application of AI techniques in smart classrooms: physical learning spaces that, using data from the environment, students and teachers, are able to provide timely and valuable information. This review is aimed at researchers and practitioners in the field of technology and education. We seek to encourage researchers in the fields of AI and education to understand the potential of IoT and computer science and to jointly develop strategies to improve the teaching and learning processes. Therefore, we expect that in the coming years, the literature on the topic will provide a number of results on the impact of using AI in the smart classroom in relation to learning, but also to teachers' well-being.

With the following research questions, we aim at exploring the current state in the literature of the application of AI techniques in the smart classroom.

- **RQ1.** What are the areas of application of artificial intelligence techniques in smart classrooms? The aim is to identify the main applications found in the literature analysis and provide a taxonomy of the use cases.
- **RQ2.** Which are the artificial intelligence techniques integrated in the smart classroom proposals? We aim to overview the different techniques described in the selected literature.
- **RQ3.** Which are the technological maturity and readiness of the proposals in the selected literature? To assess whether the proposals are already a reality or still in their infancy, we classify the proposals according to their technological readiness level.
- **RQ4.** To what extent are the effects on learning analyzed in the selected literature? Since smart classrooms play a key role in teaching and learning, we address if the impact on learning is addressed in the selected articles.
- **RQ5.** What are the main challenges in the current application of artificial intelligence techniques in the smart classroom? According to the knowledge extracted from the literature, the goal is to pinpoint the main challenges of the field to set the ground for further research. This question will be answered in the discussion and conclusion section.

II. MATERIAL AND METHODS

Our methodology is based on the phases described in [14] for a literature review. To provide a comprehensive overview of the field, the literature review focuses on all types of academic articles, from initial theoretical formulations and proofs of concepts to real-world implementations.

A. TOPIC CONCEPTUALIZATION

This review addresses two main topics: (i) Artificial Intelligence and (ii) Smart Classroom. John McCarthy coined the term Artificial Intelligence in 1955 as "the science and engineering of making intelligent machines" [15]. The Oxford Dictionary defines Artificial Intelligence as "the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision making, and translation between languages" [16]. Nevertheless, each concept is associated with several words. In order to find the set of search words for each topic, the following procedure was conducted:

- We searched the Web of Science and Scopus for the 1,000 most cited works published since 2021 with the topic in their title, abstract, and keywords. In this way, we obtained, for each topic, two different datasets of references.
- We then used VoSViewer [17] to create a term map from the datasets, with the aim of visualising the most important keywords. Figure 1 shows the term map from

the Scopus dataset for "Artificial Intelligence", whereas Figure 2 shows the one for "Smart Classroom".

- To obtain the final list of search keywords for each of the review topics, we selected the terms that were highlighted by both the Scopus and Web of Science term maps.

As a result, for the topic "Artificial Intelligence" we obtained 'artificial intelligence', 'deep learning', 'machine learning', 'prediction, optimisation', 'feature extraction', 'convolutional neural network', 'internet of things', 'algorithm', and 'big data'. For "smart classroom" we obtained 'smart classroom', 'smart learning', 'smart learning environment', 'smart learning space', 'smart school', 'smart education', 'smart campus' and 'learning environment'.

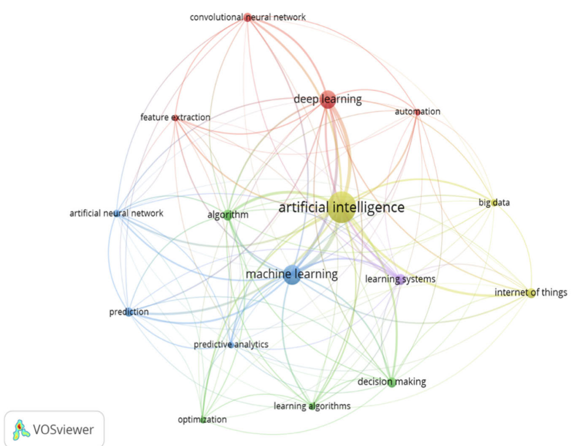

FIGURE 1. Term map for the topic "Artificial Intelligence" from the Scopus literature search.

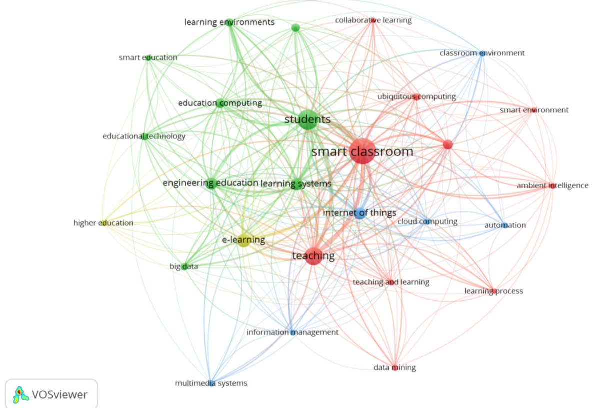

FIGURE 2. Term map for the topic "Smart Classroom" from the Scopus literature search.

B. LITERATURE SEARCH

This phase includes various steps, namely the selection of the database, the search for keywords and the backward and forward search. These steps, described below, are also summarised in Figure 3.

1) KEYWORD SEARCH

Aiming at covering a wide range of high-quality publications, we have queried four scientific databases: Web of Science, Scopus, IEEE Xplore, and ACM Digital Library. In a nutshell, queries consisted of the conjunction of two sets of keywords: one containing the list of words related to "Artificial Intelligence" and the other one with the list related to "Smart Classroom". Since we aim to provide an up-to-date review we restricted results in the last five years. According to Scopus, the number of citations before 2018 of the article by Koper is scarce. However, from 2018 onwards, the article experienced a sustained increase in interest (*e.g.,* 21 in 2018, 14 in 2019, 15 in 2020, 19 in 2021). Therefore, we limited our search to articles published between 2018 and 2023. Moreover, the search string was configured to seek within words in the title, abstract, and keywords.

For the Web of Science database, we obtained a first set of references with the following the search string:

TS=("smart classroom" OR "smart learning" OR "smart learning environment*" OR "smart learning space*" OR "smart school*" OR "smart education" OR "smart campus" OR "learning environment*") AND TS=("artificial Intelligence" OR "deep learning" OR "machine learning" OR "prediction" OR "optimi*ation" OR "feature extraction" OR "convolutional neural network*" OR "internet of things" OR "algorithm*" OR "big data")) AND (PY=("2018" OR "2019" OR "2020" OR "2021" OR "2022" OR "2023")*

where *TS* specifies that the search is to be done within title, abstract and keywords, and *PY* stands for publication year.

For Scopus and IEEE Xplore we used similar search strings (which are not included here for the sake of brevity). For the Scopus database, which includes a broad selection of topics, we restricted the search to the areas of Computer Science, Engineering, Social Sciences, Psychology and Multidisciplinary. Regarding IEEE Xplore, we selected the results in the categories of Conferences, Journals, Early Access Articles, and Magazines.

2) LITERATURE EVALUATION

After removing duplicates, a total of 5,999 literature records were retrieved. Their eligibility was evaluated based on a set of inclusion and exclusion criteria for quality assessment. In particular, we included articles written in English whose full-text was available. Moreover, the articles were required to meet our conceptualization: (i) focusing on physical classrooms rather than online teaching-learning environments, and (ii) explicitly mentioning which specific AI technique is used, *i.e.,* stating that they use "artificial intelligence" was not sufficient.

The screening of the results consisted of three phases. In the 1st and 2nd phases, the results were screened based on the title and abstract, respectively. Each article was reviewed by two of the authors of this article. Articles that were accepted were screened in a 3rd phase based on their full text.[1] Several meetings were held to discuss whether the articles met the inclusion criteria. After this initial literature search, we obtained 42 records, 4 of them reviews.

To broaden the literature selection, we explored further studies using the so-called backward search, *i.e.,* reviewing older literature cited in the selected articles, and forward search, *i.e.,* reviewing articles that cited the selected articles. Each search resulted in a new set of publications, which we again evaluated using the same procedure as for the first selection. This iterative approach enables a more thorough literature search and makes this review more robust. The backward search consisted of screening by title, then by abstract and finally by full text of a total of 2,240 articles. We finally included one article, a review, that was not in the first selection of literature. In the forward search, we analyzed 25 articles, of which one article was finally included.

Text mining over the selected articles, excluding reviews, reveals the frequency of certain keywords: 'learning' appears 1,812 times, 'emotion' 1,285, 'behavior' 753, 'attention' 350, 'engagement' 171, and 'attendance' 97.

III. RESULTS

In this section we analyze the results obtained in the literature search and relate them with our research questions. Figure 4 presents a taxonomy of the articles selected.

A. RQ1. WHAT ARE THE AREAS OF APPLICATION OF ARTIFICIAL INTELLIGENCE TECHNIQUES IN SMART CLASSROOMS?

From the selected proposals, we have identified the following areas of applications of AI, which we have divided into three categories for the sake of clarity:

- *Students' attitude analysis.* Solutions aimed at assessing the attitude of students in the classroom (*i.e.,* behavior, attention, etc.) by means, in general, of analyzing affective data. This is the category that concentrates the largest number of articles (23). This category encompasses three main areas: emotion recognition (14 articles), action detection (9 articles), and attention monitoring (2 articles). Note that [18] and [19] address both emotion recognition and action detection. A summary of the articles within this category is provided in Table 1.
- *Teacher tools.* In this category, we classify proposals focused on analyzing teachers' tasks or providing them with related tools, such as attendance tracking or teaching analysis. It includes 11 articles, covering various areas of application: attendance tracking (4 articles), teacher's action analysis (5 articles), learning analytics (2 articles). Note that [20] is also in the previous category. The articles in this category are summarized in Table 2.

[1] Please, visit https://smarttechresearch.com/opendata/SC-IA/ to access the records of the literature evaluation

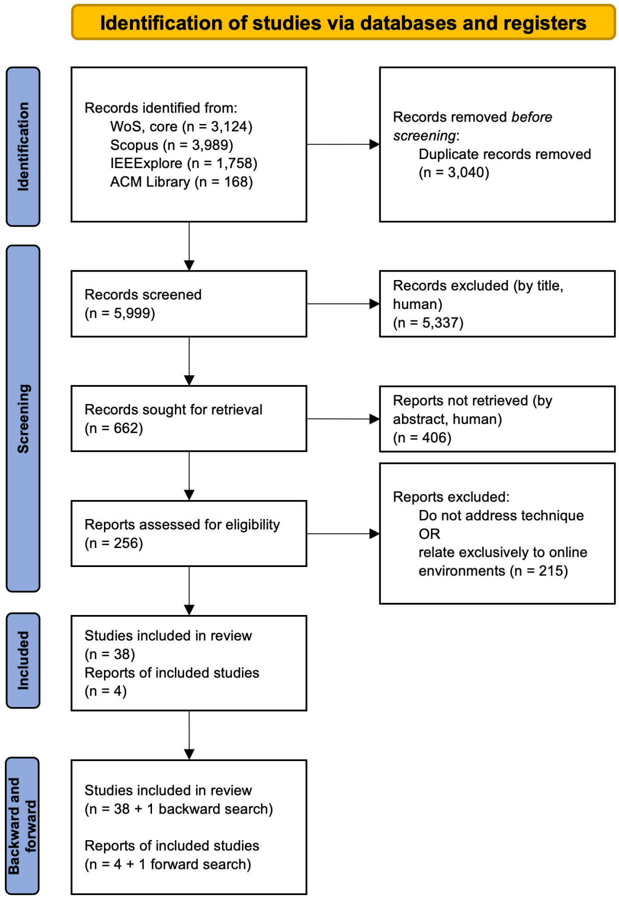

FIGURE 3. PRISMA 2020 flow diagram for systematic reviews, describing and quantifying the identification, screening and inclusion of the literature.

- *Environment and infrastructure.* This category includes solutions for the monitoring and regulating the environment (4 articles), one proposal related to the assessment of the classroom infrastructure and one article related to cybersecurity. The articles in this category are summarized in Table 3.

Figure 5 illustrates the number of selected articles per area of application, ranked by the number of articles, where it can be observed that the number with most articles is emotion recognition (14 articles) followed by action detection (13 articles). Moreover, Figure 6 depicts the number of articles per year and category. The year with a highest number of selected articles is 2021 (10 articles).

1) STUDENTS ATTITUDE

Regarding proposals for systems for emotion recognition, in [18] authors evaluate academic engagement using emotion recognition. By analyzing students' movements and emotions over time, the model provides a qualitative assessment of their cognitive state. In [19] authors provide a system that classifies students into three possible states: engaged, bored, or neutral. This system analyzes data from individual students and the class group using facial expressions. The aim of [29]

TABLE 1. List of selected articles in the category of student's attitude, sorted by area of application and ordered by year, including the analysis of learning and the AI technique used: CNN (Convolutional Neural Network), SVM (Support Vector Machine), KNN (k-Nearest Neighbors).

Reference	Title	Source	Area	Learn.	AI t.
[18]	A Deep Learning Model for Automatic Evaluation of Academic Engagement	Proc. ACM Conference on Learning at Scale	Act. + emotion	L2	CNN
[19]	Automatic Detection of Students' Affective States in Classroom Environment Using Hybrid Convolutional Neural Networks	Education and Information Technologies	Act. + emotion	L1	CNN
[20]	Teacher–Student Behavior Recognition in Classroom Teaching Based on Improved YOLO-v4 and Internet of Things Technology	Electronics	Action (st. and teacher)	L0	CNN
[21]	A Students' Action Recognition Database in Smart Classroom	IEEE Conference on Computer Science and Education	Action (st.)	L0	CNN
[22]	A Database of Students' Spontaneous Actions in the Real Classroom Environment	Computers and Electrical Engineering	Action (st.)	L1	CNN
[23]	Real-Time Analysis of Student's Behavioural Engagement in Digital Smart Classrooms Using Fog Computing and IoT Devices	Conference on Competitive Advantage in the Digital Economy	Action (st.)	L1	CNN
[24]	A Visual Intelligent System for Students' Behavior Classification Using Body Pose and Facial Features in a Smart Classroom.	Multimedia Tools and Applications	Action (st.)	L0	CNN
[25]	Research on Behavior Recognition Algorithms in Classroom Scenarios	4th International Conference on Computing Networks an Internet of Things	Action (st.)	L1	CNN
[26]	Non-Intrusive Classroom Attention Tracking System (NiCATS)	IEEE Frontiers in Education Conference	Attention	L2	CNN
[27]	Smart Classroom: A Deep Learning Approach Towards Attention Assessment Through Class Behavior Detection	IEEE Advances in Science and Engineering Technology International Conferences	Attention	L1	CNN
[28]	Unobtrusive Assessment of Students' Emotional Engagement During Lectures Using Electrodermal Activity Sensors	ACM on Interactive, Mobile, Wearable an Ubiquitous Technologies	Emotion	L1	SVM
[29]	Developing a Deep Learning-Based Affect Recognition System for Young Children	Conference: Artificial Intelligence in Education	Emotion	L1	ANN
[30]	Students' Affective Content Analysis in Smart Classroom Environment Using Deep Learning Techniques	Multimedia Tools and Applications	Emotion	L2	CNN
[31]	EduSense: Practical Classroom Sensing at Scale	Proc. ACM Conference on Interactive, Mobile, Wearable and Ubiquitous Technologies	Action (st.)	L0	ANN (n.s.)
[32]	A System for Real-Time Intervention in Negative Emotional Contagion in a Smart Classroom Deployed Under Edge Computing Service Infrastructure	Peer-to-Peer Networking and Applications	Emotion	L1	CNN
[33]	Affective Database for E-Learning and Classroom Environments Using Indian Students' Faces, Hand Gestures and Body Postures	Future Generation Computer Systems	Emotion	L1	CNN
[34]	Dual Multi-Task Network With Bridge-Temporal-Attention for Student Emotion Recognition via Classroom Video	IEEE International Joint Conference on Neural Networks	Emotion	L0	CNN
[35]	Student Engagement Recognition From Videos: A Comparison Between Deep Learning Neural Network Architectures	Bulletin of the Technical Committee on Learning Technology	Emotion	L0	CNN
[36]	Automated Reasoning of Learners' Cognitive States Using Classification Analysis	24th Pan-Hellenic Conference on Informatics	Emotion	L1	KNN
[37]	An Intelligent System for Monitoring Students' Engagement in Large Classroom Teaching Through Facial Expression Recognition	Expert Systems	Emotion	L0	CNN
[38]	Smart Classroom Monitoring Using Novel Real-Time Facial Expression Recognition System	Applied Sciences	Emotion	L2	CNN
[39]	Student Expression Recognition in Smart Education Environment Based on Convolutional Neural Network	International Conference on Dependable Systems and Their Applications	Emotion	L0	CNN
[40]	Exploring Artificial Intelligence in Smart Education: Real-Time Classroom Behavior Analysis With Embedded Devices	Sustainability	Emotion	L1	CNN

was to develop a system focused on children. Authors argue that most conventional recognition systems are unable to account for the variability of facial expressions in different populations and young children. To train the system, they use a dataset of 35,887 labeled facial images containing people of different ages and races. Some of the selected proposals are capable of analyzing students' emotions from recorded videos. For instance, the works [30], [34], [35], and [38] analyze students' moods from recorded lectures. More complex systems provide real-time measures for group

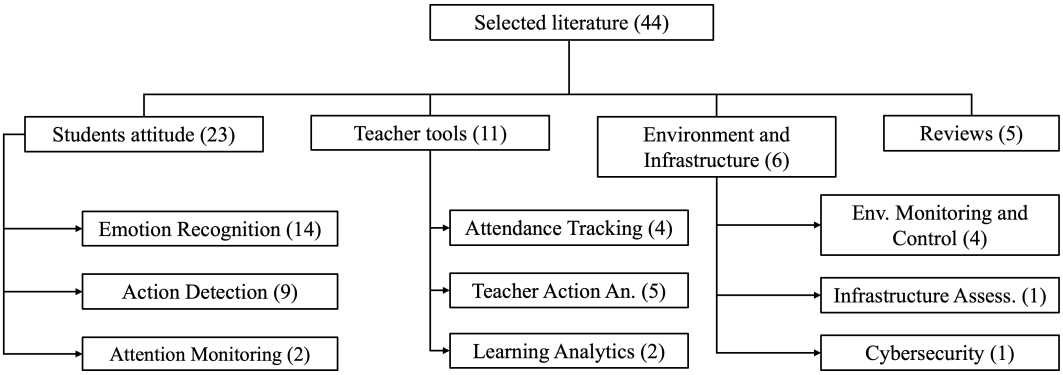

FIGURE 4. Taxonomy of the selected literature with the number of articles for each application area.

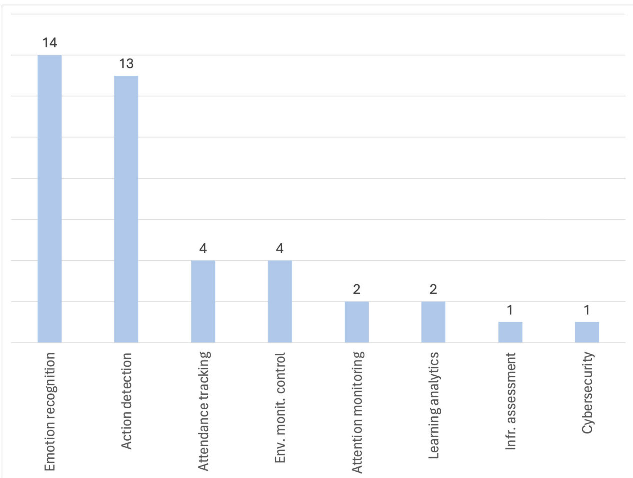

FIGURE 5. Number of articles per area.

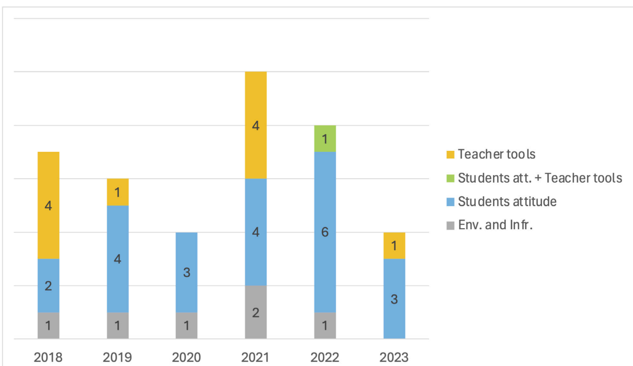

FIGURE 6. Number of articles per year and category of areas.

engagement. The aim of [32] is to detect negative emotions, whereas in [37] authors provide a measure for both individual and group emotion estimation. Similarly, in [28], [39], and [40] authors propose emotion recognition systems that analyze students' emotions in real-time.

With respect to the detection of actions, the aforementioned articles [18], [19] also analyze students' movements. Likewise, [23] presents a similar approach. The proposal [20] is able to detect a number of different actions, such as raising a hand or laying on the desk. Reference [31] present a complete system that is able to report the actions of the attendants and provide data like the number of raised hands. Finally, the system [24] provides a measure for both individual and group engagement estimation based on action recognition.

There are two articles that focus on attention monitoring. The article [26] introduces NiCATS, a method to track real-time attention levels in a Computer Science laboratory, where monitors obscure students' faces, making it difficult for teachers to accurately assess students' attentiveness. In [27], the described system offers live graphical feedback to the teacher by assigning numerical scores to students based on their concentration level. The system uses a webcam to acquire live feed from the class, providing attention and emotion data for individual students, groups, and attendance reports for each session.

All these systems require properly trained AI models to achieve accurate results. For this reason, several articles in this category focus on acquiring and labeling data for training purposes. Regarding the training of emotion recognition systems, [33] describes a database encompassing students' affective states (*e.g.,* joy, anxiety…) in both e-learning and classroom environments. This database comprises over 4,000 manually labeled images used to train a CNN based on the GoogleNet architecture [41]. The classification considered eleven affective states and included hand and body gestures. Regarding action detection systems, in [21] authors present a database for student action recognition recorded in a real smart classroom environment. Similarly, in [22] authors present another students' actions database in real classroom environments with different lighting conditions, number of students, and configurations. Data were labeled with ten actions, such as hand raising, standing up, taking notes, and holding cheeks, among others. This database, containing 4,917 images, effectively trains an action detection model. Finally, the construction of another dataset using video information from a university classroom is described in [25].

TABLE 2. **List of selected articles in the category of teacher tools, sorted by area of application and ordered by year, including the analysis of learning and the AI technique used: DL (Deep Learning, technique not specified), ANN (Artificial Neural Network, technique not specified), CNN (Convolutional Neural Network), MAS (Multi-Agent System), ML (Machine Learning, various techniques).**

Reference	Title	Source	Area	Learning	AI tech.
[20]	Teacher–Student Behavior Recognition in Classroom Teaching Based on Improved YOLO-v4 and Internet of Things Technology	Electronics	Action (st. and teacher)	L0	CNN
[42]	Using Deep Learning To Automatically Detect Talk Moves in Teachers'mathematics Lessons	IEEE International Conference on Big Data	Action (teacher)	L1	DL (n.s.)
[43]	Towards Emotionally Aware AI Smart Classroom: Current Issues and Directions for Engineering and Education	IEEE Access	Action (teacher)	L1	CNN
[44]	Automatic Instructional Pointing Gesture Recognition by Machine Learning in the Intelligent Learning Environment	ACM International Conference Proceeding Series	Action (teacher)	L0	ANN (n.s.)
[45]	A Method for Automatic Detection of Teacher's Gaze Area Based on Smart Classroom System	IEEE-Conference on Wireless Communications and Signal Processing	Action (teacher)	L0	CNN
[46]	Learning Analytics Tasks As Services in Smart Classrooms	Universal Access in the Information Society	Attendance	L1	MAS
[47]	Automated Attendance System in the Classroom Using Artificial Intelligence and Internet of Things Technology	Conference on Information and Computer Science	Attendance	L0	CNN
[48]	DeepClassRooms: A Deep Learning Based Digital Twin Framework for On-Campus Class Rooms	Neural Computing and Applications	Attendance	L0	CNN
[49]	Implementation of Recognition System of People and Computers in a Classroom Through Artificial Vision	Advances in Intelligent Systems and Computing	Attendance	L0	CNN
[50]	Student Learning Context Analysis by Emotional Intelligence With Data Mining Tools	International Journal of Intelligent Engineering and Systems	Learning analytics	L2	DM
[51]	Will the Student Get an A Grade? Machine Learning-Based Student Performance Prediction in Smart Campus	Conference on Advances in Sciences and Engineering Technology	Learning analytics	L1	ML (v.t.)

2) TEACHER TOOLS

Regarding the area of attendance tracking, articles [46], [47], [48], and [49] describe systems providing teachers with a list of the students currently in the classroom.

In the area of teachers' action analysis, article [42] introduces TalkBack, a system designed to provide teachers with a detailed record of the discursive strategies used in their classes, facilitating improved teaching actions. Article [43] proposes a real-time feedback system that offers suggestions to teachers to enhance the quality of their speech by recommending adjustments to non-verbal behaviors such as hand gestures, facial expressions, and body language. Reference [44] aims to automatically recognize the so-called instructional pointing gestures. Similarly, in [45], authors propose a method for evaluating the position and gaze of the teachers, among other factors. Additionally, in [20] authors address the detection of teachers' actions, including pointing to projection, walking around, and writing on the board.

Finally, regarding learning analytics, authors of [50] seek to recognize emotions and combine these data with academic information to predict outcomes. Article [51] investigates the use of various machine learning techniques to predict students' grades using a variety of data such as grades, attendance, demographics, and gender.

3) ENVIRONMENT AND INFRASTRUCTURE

Four articles address environment monitoring and control. In [52], the authors aim to mitigate the adverse effects of environmental factors through the Smart Classroom Incubator algorithm, which runs on a specific IoT-based hardware infrastructure. Similarly, works [53] and [54], present an IoT-based system focused on air quality regulation, capable of adjusting heating, ventilation, and air conditioning systems to enhance indoor air quality in real-time. Finally, the authors of [55] propose a framework for automating devices in smart classrooms to reduce user intervention.

Leveraging the analysis of an AI-driven survey, in [56] a system for evaluating and scoring smart classrooms in terms of comfortableness for learning is described, which is able to offer suggestions whenever necessary.

Lastly, the cybersecurity concerns by outlining a network infrastructure for smart classrooms designed to bolster security through intrusion detection are addressed in [57].

B. RQ2. WHICH ARE THE ARTIFICIAL INTELLIGENCE TECHNIQUES INTEGRATED IN THE SMART CLASSROOM PROPOSALS?

AI is generally employed for data processing and analysis, encompassing objectives ranging from high-level information retrieval to machine learning and task automation across various scenarios, such as virtual assistants, image analysis, search engines, and speech and facial recognition systems, among others. Machine learning techniques are used to automate tasks such as classification, identification, and recognition, enabling applications like assessing students' attitudes, analysing teachers' actions, detecting deteriorating

TABLE 3. List of the selected articles in the category of environment and infrastructure, sorted by area of application, including the analysis of learning and the AI technique used: CNN (Convolutional Neural Network), ANN (Artificial Neural Network, technique not specified).

Reference	Title	Source	Area	Learning	AI tech.
[53]	IoT Network-Based ANN for Ventilation Pattern Prediction and Actuation To Optimize IAQ in Educational Spaces	Conference Materials Science and Engineering	Environment monitoring and control	L0	CNN
[55]	Learning the Classroom Automation Preferences With Low User Intervention	IEEE 2nd Global Conference on Life Sciences and Technologies	Environment monitoring and control	L0	ANN
[54]	Data Driven Indoor Air Quality Prediction in Educational Facilities Based on IoT Network	Energy and Buildings	Environment monitoring and control	L0	ANN
[52]	Design and Implementation of an IoT-Based Smart Classroom Incubator	Applied Sciences	Environment monitoring and control	L0	CNN
[56]	Assessment of Smart Learning Environments in Higher Educational Institutions: A Study Using AHP-FCE and GA-BP Methods	IEEE Access	Infrastructure	L1	ANN
[57]	Accelerating a Secure Programmable Edge Network System for Smart Classroom	IEEE SmartWorld	Cybersecurity	L0	CNN

air quality, etc. Tables 1, 2 and 3 specify the specific AI techniques used in each article, while the distribution of the usage of such techniques per year is provided in Table 4.

TABLE 4. Artificial intelligence technique, per year, in the selected articles.

AI technique	2018	2019	2020	2021	2022	2023	Total
ANN (n.s.)		2	1	2			5
CNN	3	4	3	7	8	3	28
DL (n.s.)	1						1
DM	1						1
KNN				1			1
MAS	1						1
ML (v.t.)						1	1
SVM	1						1
Total	7	6	4	10	8	4	39

Data mining consists of discovering patterns and trends from data using various statistical and machine learning techniques. Article [50] reports using data mining, with no further details.

One of the most common AI techniques is classification, which involves the process of categorizing data into predefined classes based on their features or attributes. These techniques aim to learn relationships and patterns from labeled data to make predictions or decisions about new data. Several studies employ different AI-driven classification techniques: k-Nearest Neighbors (KNN) [36], Support Vector Machines (SVMs) [28], and SVMs, KNN, and decision trees [51].

Notwithstanding, given their ability to learn complex patterns from data, Artificial Neural Networks (ANNs) are widely used techniques. ANNs are computational structures consisting of interconnected components, known as neurons, organized into layers including an input layer, one or more hidden layers, and an output layer. Neurons within layers are connected, assigning specific weights to inputs and integrating activation functions. Essentially, neurons process input data to generate outputs. For ANNs to perform tasks with precision, they require extensive training with large datasets, during which weights are iteratively adjusted to optimize output accuracy. There are four articles that use ANNs, but they do not state which specific kind of network architecture they use. Advancements in computational power enable training ANNs with numerous neurons and layers, facilitating processing of large datasets. Consequently, deep learning techniques have emerged to address numerous problems requiring extensive data processing. One of the most prominent techniques in deep learning is convolutional neural networks (CNNs), widely used in tasks like image classification and object detection. Hence, unsurprisingly, CNNs are the most prevalent AI techniques in the selected literature, featured in 28 articles. In addition, article [42] merely mentions the use of deep learning.

Alternatively, in [46], authors use a Multi-Agent Systems model, a popular strategy suitable for dynamic and complex environments, composed of multiple autonomous agents capable of making decisions and interacting with each others to accomplish common goals or solve complex problems.

It might be of interest to conduct a detailed analysis to determine the extent to which the selected works describe the AI techniques used. Specifically, when analyzing these techniques, it is important to gather as many details as possible regarding implementation, limitations, real-time responses, etc. This will enable experts in the computer science field to identify potential areas for future work in this area. Accordingly, we have categorized the selected literature based on the level of detail provided regarding the proposed method or technique. The works are classified into the following categories:

- *AI-L1*. The article mentions the use of an AI technique but no further details are given (*e.g.,* it states "deep learning" but does not specify what kind of method).
- *AI-L2*. The article describes details (*e.g.,* layers, input data, training and tests), but puts more emphasis on sensors, network, etc.
- *AI-L3*. The AI technique is the focus of the article.

Based on the data in Table 5, we can see that only 11 articles have the AI method as the central axis and the

TABLE 5. Level of detail about the use of the AI technique in the selected literature.

AI details	n	References
Level 1	13	[42], [31], [30], [36], [18], [53], [21], [29], [44], [55], [34], [45], [51]
Level 2	15	[32], [56], [26], [35], [48], [49], [52], [22], [23], [27], [37], [38], [39], [25], [40]
Level 3	11	[57], [46], [50], [43], [28], [33], [19], [47], [54], [20] [24]

TABLE 6. Classification of the selected articles by technological readiness level.

TRL	n	References
TRL 1-2	6	[43], [42], [21], [29], [52], [25]
TRL 3-4	27	[57], [18], [46], [50], [28], [53], [44], [33], [55], [56], [26], [35], [48], [49], [36], [47], [34], [45], [22], [23], [27], [37], [38], [20], [40], [24], [51]
TRL 5-6-7	6	[31] [30], [32], [19], [54], [39]
TRL 8-9	-	-

results obtained are analyzed, compared and described in detail. Specifically, [19], [20], [24], [28], [33], [43], [46], [47], [50], [54], and [57] are focused on the AI technique. However, there is a great heterogeneity in the testing of the AI methods and presentation of the results.

We also analyzed the types of data processed by AI in the selected literature. A total of 28 articles use images or videos, while 6 articles rely on sensor data (from environmental sensors to wearable devices designed to detect electrodermal activity). In article [26] both video and sensor data are combined into their analysis.

C. RQ3. WHICH ARE THE TECHNOLOGICAL MATURITY AND READINESS OF THE PROPOSALS IN THE SELECTED LITERATURE?

Evaluating the feasibility and readiness of existing technologies in practical applications is of particular interest. In this line, the selected works have different levels of maturity, ranging from proofs of concepts to frameworks that have been tested in actual classroom settings. To assess whether the proposals are already a reality or still in their infancy, we have classified them based on their Technological Readiness Level (TRL), defined by the ISO 16290:2013 scale. Given the limited information available in the selected articles, we have simplified the classification process by assigning each proposal to one of the following groups of levels:

- *TRL 1-2.* Basic principles and formulation of the technology, without demonstrators or testing.
- *TRL 3-4.* Proofs of concept and technologies validated in a laboratory.
- *TRL 5-6-7.* Validation and demonstration in a relevant or operational environment (in our case the classroom).
- *TRL 8-9.* Complete and real system working in the classroom.

Table 6 shows that the majority of articles fall into the TRL 3-4 category, indicating proofs of concepts validated in laboratory settings. It is noteworthy that while these articles may use real classroom data for testing and demonstration, they remain at the laboratory stage. Few articles achieve higher TRL levels of 5-6-7, representing validation and demonstration within classroom environments. Unfortunately, none of the reported works have reached full functionality in a real-world environment (TRL 8-9). Notably, EduSense [31] has been extensively tested in real settings.

In terms of the readiness and usefulness of the proposal, it is interesting to note that the proposals provide teachers with real-time information so that they can intervene during the lecture if necessary. There are 34 articles proposing systems that extract information from images, videos or sensor data, with the exception of those describing video databases for training purposes. Of these articles, 17 report that they work in real time.

D. RQ4. TO WHAT EXTENT ARE THE EFFECTS ON LEARNING ANALYZED IN THE SELECTED LITERATURE?

Regarding this question, we have categorized the selected articles into three categories, depending on whether they address learning:

- *Learning-L0.* The article does not address learning.
- *Learning-L1.* The article mentions learning.
- *Learning-L2.* The includes some analysis concerning learning.

From Table 7 we can observe that 17 articles do not discuss the relevance of their proposals for learning or teaching, while 18 articles mention the relevance of using AI within the smart classroom on learning, but do not provide any discussion on its effects or related experience. Notably, only 3 articles from the selected literature discuss learning to some extent.

Article [26] examines key indicators of student attention. Using eye metrics data and facial images, teachers can determine where students are looking on a given slide and evaluate whether the information is being presented in a way that is beneficial to learning. The article correlates the results of using the tool with knowledge acquisition.

In [50] authors address emotion-based learning to increase student learning in the smart classroom. The study evaluates learning outcomes in the classroom and iteratively adjusts the learning environment based on the results. Moreover, the

TABLE 7. Classification of the selected articles on whether they address learning.

TRL	n	References
Learning-L0	18	[57], [31], [53], [21], [44], [55], [34], [45], [35], [48], [52], [49], [37], [47], [54], [39], [20], [24]
Learning-L1	18	[28], [42], [46], [43], [29], [30], [32], [33], [19], [56], [36], [22], [23], [27], [25], [40], [38], [51]
Learning-L2	3	[18], [26], [50]

TABLE 8. List of review articles selected in the literature review, ordered by year.

Reference	Title	Source
[60]	How Smart Are Smart Classrooms? A Review of Smart Classroom Technologies	ACM Computing Surveys
[59]	A Review on Sentiment Discovery and Analysis of Educational Big-Data	WIREs Data Mining and Knowledge Discovery
[61]	Automatic Engagement Estimation in Smart Education/Learning Settings: A Systematic Review of Engagement Definitions, Datasets, and Methods	Smart Learning Environments
[63]	Survey for Smart and Adaptative Education	International Conference on Education Technology Management
[62]	A Critical Evaluation, Challenges, and Future Perspectives of Using Artificial Intelligence and Emerging Technologies in Smart Classrooms	Smart Learning Environments

authors propose a model to evaluate student performance by correlating emotions and grades.

In [18] authors propose a deep learning model designed for automatic evaluation of academic engagement, based on BROMP [58], which is a quantitative coding standard for the observational learning process. Authors aim at assessing whether the student is learning.

Last but not least, it is worth being mentioned that only two out of 39 articles explicitly address primary education, the rest of the articles report using data collected from adults.

E. REVIEW ARTICLES

We have identified 5 reviews that explore the use of AI in classrooms (see Table 8). In [59], the importance of Sentiment Discovery and Analysis (SDA) applications in learning environments is described. It discusses how SDA can be applied in education and identifies some future trends and research directions in the field. Survey [60] identifies the different techniques and technologies employed in smart classrooms to create an efficient and effective learning environment. This study addresses technological challenges related to content delivery, students participation, and assessment. Additionally, it outlines the hardware devices used and their purpose in supporting instruction. While these reviews mention AI, they mainly identify and analyze different aspects related to the technology and its application in educational settings, rather than specifically elaborating on the AI techniques themselves.

One of the reviews that briefly enumerates AI techniques is [61], which explores recent advancements in automatic engagement estimation. However, despite listing the AI methods used, the focus remains on defining engagement and discussing the datasets employed in the reviewed papers. Similarly, critical assessment of the use of AI and new technologies in smart classrooms is presented in [62]. However, neither of these works addresses the maturity of the proposals nor their impact on learning. Also, they do not elaborate on the methodology for selecting the articles. Finally, in [63] authors present a classification of proposals according to the a number of topics related to intelligence (*e.g.,* intelligent adaptive learning, intelligent classroom, artificial intelligence and machine learning, neural networks…). There is a description of these proposals and some discussion, but the review does not deeply elaborate on the AI itself. However, we have observed that studying the effects of AI within the smart classroom is not the central topic of the selected reviews.

IV. DISCUSSION

In this section, we address several aspects that are worth being discussed, namely the readiness of proposals, the complexity of engagement assessment, and the pivotal issue of security and privacy.

A. FEASIBILITY AND READINESS

The majority of research in this area primarily focuses on young adult students, overlooking the unique needs and challenges of students in primary and secondary education settings. This hinders the development of AI solutions tailored to different educational levels. Moreover, proposals focusing on students often neglect modern, innovative learning methodologies. While the selected papers commonly assume that students sit passively and engage solely with traditional learning materials or direct their attention towards the teacher during class, contemporary educational practices increasingly emphasize dynamic approaches. Innovations such as group work, collaborative activities, and active movement within the learning space are now commonplace in primary and secondary schools.

Many studies, as indicated by the results, primarily focus on prototypes and demonstrators, lacking extensive deployments in real educational settings. The majority of the analyzed proposals are proofs of concepts and technologies validated in laboratory settings, lacking descriptions of working systems deployed in real classrooms. Consequently, there is a notable absence of long-term deployments in real settings, such as primary and secondary schools, which would allow for more comprehensive testing. Testing AI systems in real-world environments is crucial for identifying prototype shortcomings and making necessary improvements. The significance of AI in smart classrooms will become evident with the availability of working examples that demonstrate its benefits to stakeholders, including educators and policy-makers. However, the lack of real smart classroom settings, where students and teachers can interact with technology, learning materials, and AI-monitored environments, makes it challenging to conduct studies on the impact of smart classrooms on modern education. As a result, there is a scarcity of studies assessing the impact of AI techniques on teaching and learning outcomes. While these techniques show promise, their effectiveness in improving educational outcomes remains largely unexplored.

B. ENGAGEMENT ASSESSMENT

The analysis highlights a predominant focus in the literature on pursuing the assessment of students assessment, by means of monitoring one or a combination of aspects. Articles predominantly explore systems designed for emotion monitoring, ranging from identifying emotional states such as boredom, neutrality, confusion, and frustration, to detecting specific actions like raising hands, distraction, or engaging in conversation. While six articles prioritize engagement as a pivotal theme, its definition proves multifaceted, encompassing various dimensions like active participation and enthusiasm demonstration. Indeed, the definition and evaluation of engagement vary significantly across studies [61]. Monitoring engagement requires analysis, spanning from observable actions like eye gaze, head pose, and body posture, to emotional indicators such as surprise and happiness, as well as physiological indicators like heart rate and electrodermal activity. Additionally, diverse data related to students' participation, including access to online resources, questionnaire response times, and involvement in classroom discussions, require consideration. While selected articles address each engagement element individually, effective engagement monitoring demands simultaneous consideration of multiple factors. In this sense, studies such as those like [18] and [19] integrate both action and emotion detection to achieve comprehensive engagement assessment.

Managing the cognitive state of students poses a significant challenge, especially in classrooms with a high student-to-teacher ratio, where some students may require individualized attention. Various articles address this challenge by automating emotion or action recognition through video analysis using CNNs. Notwithstanding, despite the ongoing educational revolution, particularly in primary schools characterized by active methodologies and collaborative work groups, the majority of proposals in the selected literature mainly focus on young adults and demonstrate the effectiveness of their detection algorithms with seated students.

The selected literature does not conceptualize teachers' engagement but provides an assessment of their tasks through analyzing the actions while teaching. In this line, several articles categorized under teacher tools prioritize the evaluation of speech quality and various aspects of non-verbal communication, employing both video and audio recordings for analysis. Additionally, automatic attendance tracking emerges as another prevalent teacher tool identified in the selected literature. It is noteworthy that proposals related to students' attitudes can also serve as tools for teachers, aiming to provide teachers with timely insights into individual or collective aspects of student behavior, presence, or emotions. A key concept in the smart classroom is that both students and teachers must be provided with a comfortable environment to learn and teach. Consequently, there are solutions aiming at controlling the environmental conditions of the physical space.

Cutting-edge computer systems have attained the capability to process video and sensor data through real-time machine learning techniques. Accordingly, the examined proposals generally demonstrate the capacity to operate in real-time scenarios, thereby enabling prompt delivery of information to teachers when needed. This facilitates immediate adjustments, such as interrupting the explanation to facilitate group activities or opening windows for air circulation, among other potential actions.

C. INFORMATION SECURITY AND PRIVACY

The use of AI-based systems, particularly those employing facial recognition and other biometric data, raises significant concerns from both information security and privacy perspectives. Safeguarding sensitive student information and ensuring compliance with data protection regulations are critical challenges that must be addressed.

Given that classrooms involve humans, including infants, it is essential to highlight that crucial aspects such as information security and privacy are generally overlooked in the selected literature, albeit with a few exceptions. Computer systems are susceptible to various attacks aimed at stealing information or disrupting the services they offer, either temporarily or permanently. Moreover, the data stored in these systems are vulnerable to theft and manipulation. As most proposals utilize images of students and teachers, guaranteeing security and privacy is paramount. This concern is particularly relevant for systems intended to assess classroom attendance or student behavior, which rely on cameras to capture facial images. Regarding privacy, in [40] authors explicitly refer the removal of biometric information from the data collected by the devices that feed the emotion recognition algorithm. Moreover, [31], state that no footage is stored, and incoming audio and images are immediately featured.

In terms of cybersecurity, [57] is dedicated to the application of security and the detection of intruders in the network, while [56] addresses security as only one of the aspects contributing to the evaluation of the learning environment. Moreover, none of the selected articles addresses the ethical issues regarding the use of student data in the context of the smart classroom.

Solving these problems demands an interdisciplinary approach. First, a thorough analysis of the security of computers, networks, and other devices is necessary, just like with any other information system. To preserve system integrity, regular security audits and vulnerability assessments should be carried out. It is crucial to guarantee the CIA triad for data: confidentiality, integrity, and availability. Effective management of identities and security components, such as digital certificates, as well as the integration of secure communication and data storage technologies can accomplish this. Systems should be built with privacy-by-design and data minimization in mind, keeping and sharing only the most necessary information, in accordance with data privacy laws. Beyond just pseudonymizing data, it is recommended to use privacy-enhancing technologies for specific domains such as microdata storage in order to attain k-anonymity or l-diversity. Regarding the processing of videos, systems must ensure that no video is leaked or stored improperly. This can be managed by performing real-time video analysis within devices using tamper-proof elements. If video data need to be stored, privacy technologies designed for video surveillance must be applied prior storage [64] Finally, raising awareness among teachers, students, and families about security and privacy issues, and how they are being correctly addressed within the smart classroom environment, is essential.

V. CONCLUSION AND FUTURE WORKS

The integration of information and communication technologies (ICT) into educational institutions is continuously evolving. Transforming traditional classrooms into smart classrooms holds the promise of enhancing the teaching and learning processes, but it also poses challenges that must be addressed. In this article, we have explored cutting-edge applications of AI techniques, including machine learning and deep learning within smart classrooms. These applications include the analysis of student attitudes, assessment of teaching methodologies, and the management of physical infrastructures within smart classrooms.

Numerous researchers are primarily concentrating on leveraging AI techniques, particularly convolutional neural networks, for diverse applications, such as emotion recognition, student and teacher action detection, and attendance monitoring. Although existing literature suggests the feasibility of performing these tasks in real-time, potentially providing benefits to teachers during classroom sessions, there is a lack of extensive experiments conducted in real-world settings. As a result, the impact of smart classrooms on teaching and learning is still awaiting comprehensive study.

To ensure comprehensiveness while focusing on recent research, we rigorously selected literature explicitly addressing AI techniques. However, it is important to acknowledge the limitations of our study. Since we queried scientific literature databases, we may have overlooked commercial products and tools available in the market, as well as experiments not indexed in these databases.

In conclusion, the use of AI techniques in smart classrooms is still in its early stages. Despite the widespread adoption of technology-enriched classroom models and the integration of ICT into education, the reality is that real-time data collection from these tools and the application of machine learning to enhance the teaching and learning processes are still distant goals. Hence, significant advancements and further research are needed to fully realize this potential. Notably, during the period of 2020-2022, numerous schools faced closures due to the COVID-19 pandemic. As a result, many classrooms incorporated online platforms into their teaching methods. The increased acceptance and utilization of technology in classrooms may pave the way for the integration of AI to better understand classroom dynamics and enhance the teaching and learning processes.

We believe that fostering the development of a smart classroom, capable of addressing one or more of these challenges, can serve as a valuable tool to enhance the quality of teaching in the current context. Future research endeavors should consider:

- To conceptualize the technical side of smart classrooms as an ecosystem comprising interconnected, interoperable, and cognitive components, each dedicated to analyzing a particular dimension. Commercially available ICTs can be used to collect data from a variety of sources in a non-invasive way, respecting individual privacy and addressing ethical issues. Despite the heterogeneity of data and interoperability challenges among different systems, the smart classroom must be designed as a whole. In addition, solutions must take into account that students in primary and secondary schools are to learn through innovative methods and, hence, they are not assumed to be seating during the entire lecture time.
- This conception as an ecosystem of components paves the way for research into the application of federated learning (which involves training machine learning models across multiple decentralized devices or servers), can be particularly beneficial in this environment. One potential system within this ecosystem is the online learning environment itself, which can collaborate with physical classroom sensors and devices to improve the overall educational experience.
- Moreover, since evaluating engagement is not straightforward, the literature should be expanded with new research on artificial intelligence and machine learning models capable of accurately monitoring how teachers and students feel during lectures. These models should incorporate data acquired from a variety of sources, such as biomedical signals from non-invasive wearables and real-time video footage, while also considering environmental parameters like noise and air quality.

- Assessing the impact of the smart classroom is crucial. To enhance the effectiveness of smart classrooms, with the aim of making smart classrooms better, it is essential to develop practical settings where teachers and ICT engineers collaborate to create reliable scenarios for testing the utility and impact of smart classrooms on learning and teaching. Several initiatives are deploying technology-enriched classrooms that facilitate learning by doing, enable the development of soft skills, promote team building, and provide access to a variety of state-of-the-art learning technologies. These physical learning spaces, which naturally align with the concept of the smart classroom addressed in this article, could be perfect scenarios for testing.
- Finally, considering that learning in today's schools does not take place in a single room, it is not far-fetched that smart classrooms will evolve and open the door to more complex scenarios, such as cognitive schools. In these settings, a multitude of intelligent agents distributed across physical spaces, information systems, and mobile devices would help in better understanding how children learn, interact, and build relationships both within and outside our schools.

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