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Affective e-learning approaches, technology and implementation model: a systematic review

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ABSTRACT

A systematic literature study including articles from 2016 to 2022 was done to evaluate the various approaches, technologies, and implementation models involved in measuring student engagement during learning. The review's objective was to compile and analyze all studies that investigated how instructors can gauge students' mental states while teaching and assess the most effective teaching methods. Additionally, it aims to extract and assess expanded methodologies from chosen research publications to offer suggestions and answers to researchers and practitioners. Planning, carrying out the analysis, and publishing the results have all received significant attention in the research approach. The study's findings indicate that more needs to be done to evaluate student participation objectively and follow their development for improved academic performance. Physiological approaches should be given more support among the alternatives. While deep learning implementation models and contactless technology should interest more researchers. And, the recommender system should be integrated into e-learning system. Other approaches, technologies, and methodology articles, on the other hand, lacked authenticity in conveying student feeling.

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1. INTRODUCTION

Technological advancements have significantly altered the practice of teaching and learning. Educators all around the world have faced unprecedented pressure to incorporate technology into their instructional methods, particularly during the innovative epidemic coronavirus disease 2019 (COVID-19). The pandemic interference resulted in the absolute lockdown of all educational levels' learning centers. All students at all levels were held in one location, resulting in schools utilizing remote technologies to continue the learning process. In several countries, radio and television transmissions were utilized to extend the learning process, particularly for students at the lowest level of school [1]. As a result, the e-learning system which had been creeping into most countries was thoroughly accepted at all levels. E-learning is the use of web innovations to effectively deliver education to students irrespective of where they are [2]. To address the issue, many technologies were used, including remote tools such as Zoom, Google meets, Google Classroom, and Microsoft Teams for online courses [3]. They were put to use by educational institutions to stay connected to students and facilitate consistent learning. Furthermore, intelligent online tools that automatically collect their students' feelings, and provide feedback, and level of participation emerged [4].

However, there are difficulties in effectively assessing student engagement levels due to inaccurate detection of student emotions.

E-learning was popularized in the late 1980s as the computer-based-test. It consists of a computer system linked to a multi-media device, such as compact disk-read only memory (CD-ROM). This invention resulted in the development of the Internet and web technologies. A web-based training program was launched two decades later. It employed web technology as a resource to communicate information to users via the internet [5]. With the incorporation of a pedagogical approach in 2002, e-learning developed rapidly, leading to the acceptance of blended learning in a variety of organizations and educational institutes. Intelligent tutoring systems, a built-in expert system that can be used to track a learner's progress and tailor their training according to their learning style, modern knowledge level, and effective teaching methods in e-learning systems were presented [6]. Following that, the learning method was formed as a new wave for e-learning development, with a concentration on tertiary course material and learning processes. In 2007, a new technology known as the flipped classroom was introduced. It is a mixed learning strategy that allows traditional classes to be entirely flipped by distributing course content via the internet via videos, podcasts, and so on. It enables students to practice their coursework offline before presenting it online, or vice versa [7]. This technology resulted in the adaptive system, a more advanced system than the intelligent tutoring domain which is one of the artificial intelligence (AI) techniques. In e-learning, intelligence helps with human psychology, learning, natural language, non-monotonic reasoning, strategy and diagnosis, thinking under uncertainty, and chronological reasoning [8]. To summarize, educational learning skills have evolved from effective thinking capacity to emotional factors such as how the learner feels, what he believes, and what attitudes he has. Affective computing can be used to detect student participation or engagement levels during the learning process using computer vision techniques [9]. It aids in using an adaptable pedagogical platform that detects the level of student participation and in addition, participation in additional activities is required for online classes. In Figure 1, the classification of the aforementioned e-learning domains is shown.

The purpose of this study is to conduct a systematic evaluation of the current literature on student engagement, emotion detection, and virtual e-learning systems. And we were able to gather, review, evaluate, and discover several options using the proposed systematic review. Most widely used approaches were highlighted and pertinent areas for further research were presented.

This article gives a systematic review of literature studies on various technologies, implementation plans, and methodologies for measuring student engagement in the classroom from 2016-2022. 1,135 papers that were taken from various databases and subjected to the study's selection criteria and quality assessment questions. After the search across the seven repositories produced 1,135 items, 30 studies that satisfied the study's inclusion criteria were analyzed.

The remaining part of this paper is organized as follows; section 2 elucidates on the e-learning approaches. The related research to the study is then summarized. Section 3 presents the approach used to conduct the systematic literature review, which includes the definition of the research questions, inclusion/exclusion criteria, the search strategy and the conduct of the systematic review proper. The results of the study are discussed in section 4 by way of addressing all of the research questions using the collected data from each of the primary studies identified for the study. Section 5 summarizes the study's findings and concludes the study.

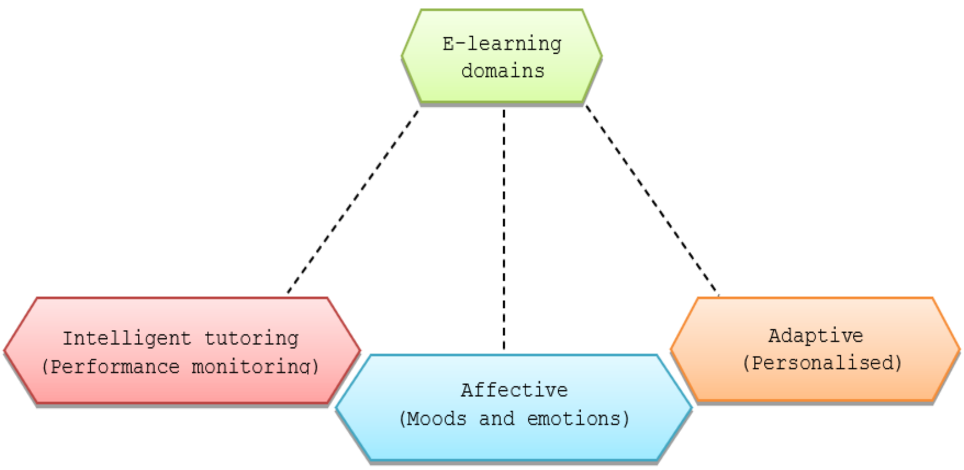

Figure 1. Classification of e-learning domains

2. DESIGN APPROACHES' RELATED WORK

The gap between human intuitive knowledge and emotion recognition is being filled by a wide range of technologies. Affective computing provides the capability to communicate, interpret, and recognize emotions, which are expressed through psychological, physiological, and behavioral emotions [10]. There is a substantial body of work that investigates and reviews student assessment in an e-learning environment [11], [12]. However, the studies lack extensive information about the primary techniques, methodology, and technological advancements employed in the development of e-learning platforms that identify and analyze learners' levels of involvement throughout learning. For example, Wong *et al.* [12] carried out research that includes a comprehensive overview of studies on self-regulated learning support systems in various types of online learning settings, as well as how they address human factors. Its goal was to inform academics, administrators, and instructors in terms of how self-regulated learning aid is currently implemented in Blended learning and virtual education environments, as well as making suggestions for a personalized tutoring support system.

In [13], the study provided an analysis of the methodologies and trends in educational research in e-learning. An issue with the review is that it solely looked at e-learning modalities. In [14], the study looks into the underlying causes of the discrepancy between the acceptance of online learning and its success rate. This paper's review scope covers identifying suggested retention rate-boosting tactics and observing potential causes of the less-than-ideal completion rates in online learning settings. Publication trends and patterns, research themes, research techniques, and research venues were assessed in [15] and then compared to previous decades' research themes. The focus was on online learner characteristics and online participation without regard for the e-learning approach. As a result, various scholarly perspectives on e-learning methodology, tactics, and technological participation were thoroughly explored.

2.1. Hybrid approach

Research based on the depiction of human emotions via physiological signals was conducted in [16]. This study proposes a hybrid approach for classifying human emotions that combines electroencephalogram (EEG) and facial expression. The study looked into using non-contact technology to collect student emotions. In [17], the study presented a convolutional neural network (CNN) and long short-term memory (LSTM) classifier used to categorize the emotional expressions of physically disabled people (deaf, dumb, and bedridden) and autistic children based on facial landmarks and EEG signals. An algorithm for real-time emotion recognition using virtual markers through an optical flow algorithm has also been developed. The study examined the application of contact devices for the observation of student emotions.

Apart from the aforementioned reports, Gao *et al.* [18], presented the n-Gage, a student engagement sensing system that automatically detects student in-class multidimensional learning involvement utilizing a combination of sensors from wearables and surroundings. The research investigated the use of a contact device to capture student feelings. In [19], it was proposed that facial micro-expressions are more reliable than facial macro-expressions for revealing emotions. They are uncontrollable, subtle, involuntary movements in response to external stimuli. This study proposes using facial micro-expressions in conjunction with brain and physiological signals to detect underlying emotions more reliably. We describe our models for estimating arousal and valence levels based on a combination of facial micro-expressions, EEG signals, galvanic skin responses (GSR), and photoplethysmography (PPG) signals. The research looked into using a contact device to capture student emotions.

2.2. Psychological approach

According to the study in [20], dynamic student behavior analysis is a significant step in improving internet of things based (IoT) e-learning for automated feedback and measuring student engagement. This study contributes to identifying e-learners' emotional states and dynamically changing the learning content. To understand the student's emotions regarding the individual courses offered by the tutor, a mix of face-based emotion and learner-pupil detection is used. The research investigated the use of non-contact technology to assess student emotions. The study in [21] offers a compact frame-based facial expression recognition framework for facial expression recognition that outperforms advanced algorithms even as requiring many fewer criterion. By combining temporal information with gated recurrent units, the proposed framework is extended to a frame-to-sequence technique. The study investigated the use of non-contact technology to collect student emotions. A practical application of a real-time engagement evaluation via facial expression using an optimized CNN presented is presented in [22]. It created a facial recognition and engagement model that is used in a web-based learning app. The study investigated the use of non-contact technology to collect student emotions.

A unique learning engagement detection method based on data acquired (student behavior) from cameras and mice in an online learning environment was proposed in [23]. The cameras were used to capture photographs of the students' faces while also recording mouse movement data. The study looked at the use of non-contact technology to record student emotions. According to Nezami *et al.* [24], engagement is a key indicator of the quality of the learning experience and plays a significant role in the development of intelligent educational interfaces. In order to respond appropriately, any such interface must be able to recognize the level of engagement; however, there is very little existing data to learn from, and new data is expensive and difficult to acquire. This paper presents a deep learning model that overcomes the data sparsity challenge by pre-training on readily available basic facial expression data before training on specialized engagement data. The study looked into using non-contact technology to track student emotions.

Meanwhile, Horvat and Jagušt [25] claimed that the ability to objectively and continuously assess student engagement and the learning curve is a critical area for improving e-learning pedagogies. In this regard, the researchers propose a novel procedure for personalized and adaptive assessment of learning performance based on automated affective state estimation methods. This study envisions an intelligent agent in this preliminary report that constantly monitors students' behavior parameters during online learning classes. The agent evaluates key psychophysiological features related to emotion and attention using unobtrusive video surveillance and machine learning. The research examined using a contact device to obtain student emotions.

The study in [26], examined how challenging it is for teachers to gauge students' engagement when there is no direct interaction between teachers and students. In order to measure student participation with no reliance on data generated by an e-learning platform, the paper will analyses online lecture videos. In order to comprehend students' emotions and gauge their level of engagement during a lecture, an intelligent application for teachers was created. The use of non-contact technology to gather student emotions was examined in the study.

Nevertheless, Kuruvayil and Palaniswamy [27], stated that the machine learning community finds it difficult to automatically recognize facial emotions in scenarios like partial occlusions, varying head poses, and lighting conditions. The primary cause of the difficulty in training an effective machine learning or deep learning model is the scarcity of sufficient samples with the aforementioned conditions in the baseline datasets. We have used the idea of meta-learning to overcome this obstacle. It has been established that metric-based meta-learning, which employs prototypical networks, fits few-shot problems well without experiencing significant over-fitting. The use of non-contact technology to gather student emotions was examined in the study. The suggested method uses a meta-learning approach for still images to perform emotion recognition from facial expressions, and it is resistant to partial occlusions, different head poses, and different lighting conditions.

The study in [28], introduced a brand-new model for predicting engagement called the deep facial spatiotemporal network (DFSTN). The long short-term memory (LSTM) network with global attention (GALN), which is used to create an attentional hidden state, and the pre-trained SE-ResNet-50 (SENet), which is used to extract facial spatial features, are the two modules that make up the model. The model's training methodology changes as the performance metric changes. The DFSTN's ability to record facial spatial and temporal data is useful for detecting the fine-grained engaged state and enhancing the performance of engagement prediction. The use of non-contact technology to gather student emotions was examined in the study.

In an online learning environment, engagement is a crucial indicator of users' learning experiences. Enhancing the accuracy of engagement recognition can benefit users' learning experiences, online learning platform recommendation strategies, and timely feedback for instructors on their courses. Using the features that OpenFace has recorded in order to estimate the level of participation, the study proposes the deep engagement recognition network (DERN), which combines temporal convolution, bidirectional LSTM, and attention mechanism [29].

Research results published in [30] suggest images of facial expressions are analyzed to determine a person's mental state. Human emotions, on the other hand, are much more complicated, and these psychological states may not only be reflected through a learner's basic emotion (i.e., analyzing a single image), but rather through a combination of two or more emotions that may be reflected on the face over time. The use of four complex emotions, which combine fundamental human emotions frequently felt by a learner during a learning session, was made. Instead of discrete images, a fixed set of continuous image frames was taken into consideration in order to accurately capture these mixed emotions. To categorize the fundamental emotions and then determine the learners' mental states, we developed a CNN model.

The study in [31], advocates that measuring how engaged students are during lectures has gotten difficult and difficult due to the change from physicalto synchronous virtual environments. Since the virtual world has certain intrinsic features, typical signs like students' faces, gestural expressions, or even hearing their voices can be easily concealed (e.g., cameras and microphones can be turned off). The goal of this paper is to suggest a methodology and its corresponding model for measuring student engagement in virtual learning environments. The methodology and model are based on a systematic analysis of more than 30 different types of digital interactions and events that occur during a synchronous lesson.

2.3. Physiological approach

In [32], the study provided an remote photoplethysmography (rPPG) measurement approach that is the first to use deep spatiotemporal networks to reconstruct exact rPPG signals from raw facial movies. Our approach can recover rPPG signals with correct pulse peaks despite the limitation of trend consistency with ground truth pulse curves. The research looked into the use of non-contact technology to collect student emotions. In Carroll *et al.* [33] the creation and testing of a measuring and classification technique that uses non-invasive physiological and behavioral monitoring technology to directly assess involvement in the classroom, simulation, and live training contexts are described. A training program for unmanned aircraft systems (UAS) to examine the capacity to reliably assess learner involvement and differentiate between levels of learner engagement in the classroom, simulation, and live situations using physiological and behavioral inputs.

While in [34], the study suggests using ensemble learning to build a machine learning model that can identify four main human emotions-anger, sadness, joy, and pleasure-while incorporating electrocardiogram (ECG) signals. This analysis combines four ECG signal-based feature extraction techniques: empirical mode decomposition, with-in-beat analysis, and frequency spectrum analysis. These four techniques are used as feature extraction methods. Liu [35], suggests a machine learning-based strategy that enables teachers to effectively deliver remote instruction by providing real-time monitoring of students' mental state and classifications. This study investigated four different classification methods using publicly accessible (EEG data collections: the traditional deep neural network, the conventionally well-liked support vector machine, the most recent convolutional neural network, and the recently popular extreme gradient boosting (XGBoost) model.

The study in [36], investigated the potential for emotion identification using heart sound data. First, we created a tiny library of heart sounds representing different emotions, while simultaneously recording the individuals' ECGs for comparison. Second, two markers for evaluating emotions were developed based on the properties of heart sound signals: dynamic spectral variability (DSV) and heart rate variability (HRV) of heart sounds are the difference between succeeding heartbeats in the heartbeat (the ratio of diastolic to systolic duration variability). Afterward, we derived both nonlinear and linear characteristics across twain emotion performance measures in order to distinguish between four different types of emotions. In contemplation of providing a trustworthy methodology for emotion recognition utilizing wearable technology, Domínguez-Jiménez *et al.* [37], present a model for recognizing three emotions-humor, melancholy, and neutral-from physiological signals. While in Sepúlveda *et al.* [38] used wavelet signal analysis to enhance the performance of emotion recognition from ECG signals. Using a wavelet scattering approach, the academic, military, industrial, government, and other sources (AMIGOS) database is utilized to extract the ECG signal's properties. These features can then be obtained at various time scales and used as inputs for various classifiers, allowing for performance evaluation. Nocua *et al.* [39], suggest that finding intellectual student involvement in online learning has proven difficult for higher education institutions as a result of the COVID-19 epidemic. In this study, a non-self-report method was used to measure students' heart rate data to determine how engaged their minds were throughout active learning tasks.

2.4. Cognitive approach

In [40], the study attempt to elicit emotional responses from a typical e-learning system. Without a doubt, the topic of this study is the use of EEG signals to detect emotions, and learning will occur based on the emotions found. In this research, an EEG headset will be used to capture the brain waves of a person after assessing their mental state and identifying their emotions using algorithms and a database. The computer is able to observe the user's emotional state through EEG-based emotion recognition. The user's learning experience will therefore be enhanced as a result of this. Shaw and Patra [41], suggest creating a prototype (model) to track student progress in flipped learning by passively recording each student's brain waves as they watch a lecture video. The pupils are divided into two categories (weak and strong) based on their attention levels and three categories (weak, good, outstanding) based on the Siamese neural network's analysis of recorded brain waves (EEG data).

Apart from that, Ma [42], through the use of emotional recognition technology, which incorporates facial expression, eye movement, body motions, emotional text, and emotional images, created an emotional interaction model for e-learning. The key advancements concern providing learners with the proper emotional adjustment or compensation, improving model recognition, and maintaining learners' interest in a learning topic or task in order to maximize learning outcomes. When assessing the learners' learning cognitive state, this model can increase the learners' capacity for emotional recognition in the context of online learning. Hiremath and Patil [43], proposed to identify sarcasm in spoken language. The method makes use of the fundamental cognitive aspects of human speech by recording three types of data: voice, text, and temporal face features. The recorded data is unstructured because it is made up of parameters for moods and emotions that lead to sarcasm, which influences facial and glottal expressions. The study in [44] investigated the relationship between cognitive emotions and academic e-self-efficacy and academic adjustment to test the accuracy of an ad hoc software developed to recognize and categorize cognitive emotions from facial expressions in two distinct environments, namely a video lecture and a chat with a teacher. Li *et al.* [45], developed a supervised machine-learning algorithm model to predict students' levels of cognitive involvement while they worked through a clinical reasoning problem in an intelligent tutoring system.

3. METHOD

This study adopts the systematic review process as described in [46]. The procedure entails obtaining, assessing, and evaluating several ways to emotion detection in online learning student involvement. The research technique section is mostly concerned with planning, conducting research, and presenting the findings. Basically, the researcher creates then defines study objectives on emotion detection in determining student participation level. Secondly, the author examines several databases for pertinent information and extracts key certainty. Eventually, the researcher provides a summary of the results of a comprehensive study.

3.1. Research questions

The primary stage of doing a comprehensive study is to identify research topics. This maneuver should be swift and direct. The following are the study questions in this study's condition: i) RQ What are the actual degrees of student engagement for categorizing emotion detection systems for e-learning?; ii) RQ What is the ideal model for implementing an e-learning system in terms of emotion detection?; and iii) RQ What is the most effective technology for collecting emotional student engagement?. The research topics for this study, however, are listed in Table 1.

Table 1. Research questions

Research questions	Motivation
RQ1: What exactly are the student engagement levels for categorizing emotion detection systems for e-learning?	This question allows us to explore the student engagement category for the emotion detection system. It will help to identify challenges in the existing system and proffer solutions to improve them.
RQ2: What is the best model for e-learning system implementation when it comes to detecting emotions?	This question gives a more in-depth understanding of the model's evolution. Furthermore, it will reveal its inadequacies to determine what extra work is needed on the field or the best and least challenging way to be utilized with commons.
RQ3: What is the best technology used in capturing emotional student engagement?	This question enables a more in-depth comprehension of non-contact means of detecting the state of mind of the student during the learning process.

3.2. Defining search strategy

This review's specific search method involved defining the demographic, choosing resources, creating search queries, and establishing eligibility and exclusion criteria. The research questions were used to determine the query phase. The search phrase shown in Table 2 was used to conduct a survey on the seven preferred online repository in order to locate the major literatures. Google Scholar, arXiv, ResearchGate, Semantic Scholar, Microsoft Academic, ScienceDirect, and virtual-lyrics representation code (LRC) are among the seven databases. The search terms used and the number of primary studies returned from each of the repositories are displayed in Table 2.

Table 2. Search strings and results

Database	Query phrase	Number of papers
Google Scholar	Remote-photoplethysmography (rPPG) emotion detection	347
arXiv	Student engagement in an online class	7
ResearchGate	Types of e-learning systems	102
Semantic Scholar	Emotion detection using the physiological signal for e-learning	371
Microsoft Academic	CNN emotion detection using the psychological method for student engagement	168
ScienceDirect	Types of physiological emotion detection method for student engagement	121
Virtual LRC	Emotion detection for e-learning	19

3.3. Performing review process

In this paragraph, the details of how the review was implemented is presented. In the first phase of the search, 1,135 papers were found, and the titles of these papers were then analyzed, as well as a cursory glance at their abstracts. Only articles that explored a sub-area of Student participation in an online class and emotion detection were kept during this approach, as 590 papers were removed, leaving 545 papers examined in the second phase of the search strategy. These 545 papers were subjected to the inclusion and exclusion criteria defined in Table 3, and a pre-selection criterion of selection papers not older than six (6) years. 515 papers were removed and the preferred reporting item for systematic review and meta-analyses (PRISMA) Statement (preferential reporting items for systematic reviews and meta-analyses) utilized in [47] was adopted and depicted in Figure 2, 30 papers were finally arrived at as the primary studies for this systematic review.

Table 3. The inclusion/exclusion criteria

S/N	Inclusion criteria	Exclusion criteria
1	The research centered on emotion detection or learners' (level of) involvement/engagement.	The study lies outside cognitive emotion detection for learner engagement.
2	Articles that discuss issues on physiological or psychological emotion detection and learning are included.	Articles that do not focus on emotion detection for learner engagement are excluded.

Because of its technicality, which is made up of a reliable and predetermined exploration technique along with quality assessment requirements, the systematic literature review (SLR), as opposed to the traditional literature review, was used in this study project. In order to choose the studies that best answered our study goals, we first evaluated the primary studies that had been found. The systematic review (SR) included all studies that met the aforementioned inclusion criteria.

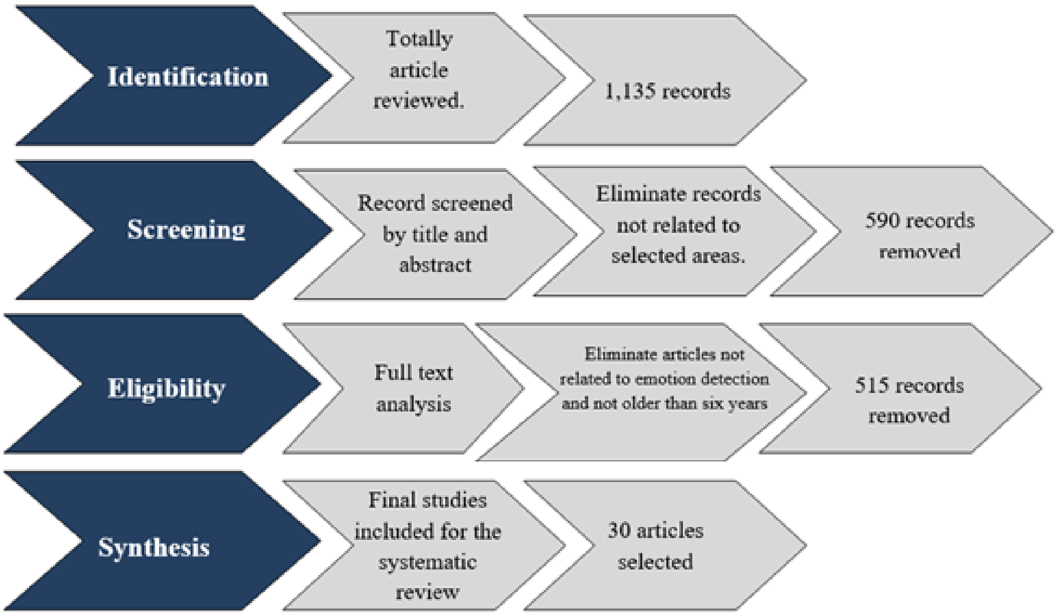

Figure 2. PRISMA flow chart of the systematic review on emotion detection for student engagement

3.4. Quality assessment

One of the most significant aspects of every systematic review is the evaluation of the quality of the studies used as primary studies for the review in [5]. Table 4 presents the five (5) quality evaluation questions used in this study. The 5 questions are answered for each of the 30 studies identified from the searching strategy. A "yes" attracts 1 point and a "no" to the question attracts 0 points [46], [48]. According to the results in Table 5, all the selected papers passed the benchmark of 50% for quality assessment. Table 6 (see in appendix) presents the primary studies' sources and focus while Figure 3 shows the distribution of the studies in terms of their focus.

Table 4. Quality assessment question

Question	Quality assurance questions
1	Is the purpose of this study mentioned explicitly in the review?
2	Is the study's methodology sufficiently explained?
3	Did the authors of the review adequately describe the studies that were included?
4	Have the authors of the reviews disclosed any potential conflicts of interest?
5	Is there a convincing explanation and discussion from the review authors of any apparent inconsistency in the results?

Table 5. Quality assessment result

Authors and Year	Reference	Q1	Q2	Q3	Q4	Q5	Total	Percentage
Guo *et al.* (2019)	[16]	Yes	Yes	Yes	Yes	Yes	5	100%
Hassouneh *et al.* (2020)	[17]	Yes	No	Yes	Yes	Yes	4	80%
Gao *et al.* (2020)	[18]	Yes	Yes	Yes	Yes	Yes	5	100%
Saffaryazdi *et al.* (2022)	[19]	Yes	No	Yes	Yes	Yes	4	80%
Parthiban and Samy (2021)	[20]	Yes	Yes	Yes	Yes	Yes	5	100%
Kuo *et al.* (2018)	[21]	Yes	Yes	Yes	Yes	No	4	80%
Karimah and Hasegawa (2021)	[22]	Yes	Yes	Yes	No	Yes	4	80%
Zhang *et al.* (2020)	[23]	Yes	Yes	No	Yes	Yes	4	80%
Nezami *et al.* (2020)	[24]	Yes	Yes	Yes	Yes	Yes	5	100%
Horvat and Jagušt (2020	[25]	Yes	Yes	No	Yes	Yes	4	80%
Hasnine *et al.* (2021)	[26]	Yes	Yes	No	Yes	Yes	4	80%
Kuruvayil and Palaniswamy (2022)	[27]	Yes	Yes	Yes	No	Yes	4	80%
Liao *et al.* (2021)	[28]	Yes	Yes	Yes	Yes	Yes	5	100%
Huang *et al.* (2019)	[29]	Yes	Yes	Yes	Yes	Yes	5	100%
Mukhopadhyay *et. al.* (2020)	[30]	Yes	Yes	Yes	Yes	Yes	5	100%
Solé-Beteta *et al.* (2022)	[31]	Yes	Yes	Yes	Yes	Yes	5	100%
Yu *et al.* (2019)	[32]	Yes	Yes	Yes	Yes	Yes	5	100%
Carroll *et al.* (2020)	[33]	Yes	Yes	Yes	Yes	Yes	5	100%
Dissanayake *et al.* (2019)	[34]	Yes	No	No	Yes	Yes	3	60%
Liu (2021)	[35]	Yes	Yes	Yes	No	No	3	60%
Xiefeng *et al.* (2019)	[36]	Yes	Yes	Yes	Yes	Yes	5	100%
Domínguez-Jiménez *et al.* (2020)	[37]	Yes	No	Yes	Yes	No	3	60%
Sepúlveda *et al.* (2021)	[38]	Yes	Yes	Yes	Yes	Yes	5	100%
Nocua *et al.* (2021)	[39]	Yes	Yes	Yes	Yes	No	4	80%
Prabhu *et al.* (2016)	[40]	Yes	Yes	Yes	No	Yes	4	80%
Shaw and Patra (2022)	[41]	Yes	Yes	Yes	Yes	Yes	5	100%
Ma (2016)	[42]	Yes	Yes	Yes	Yes	Yes	5	100%
Hiremath and Patil (2021)	[43]	Yes	No	Yes	Yes	Yes	4	80%
D'errico *et al.* (2018)	[44]	Yes	Yes	No	Yes	Yes	4	80%
Li *et al.* (2021)	[45]	Yes	Yes	Yes	Yes	No	4	80%

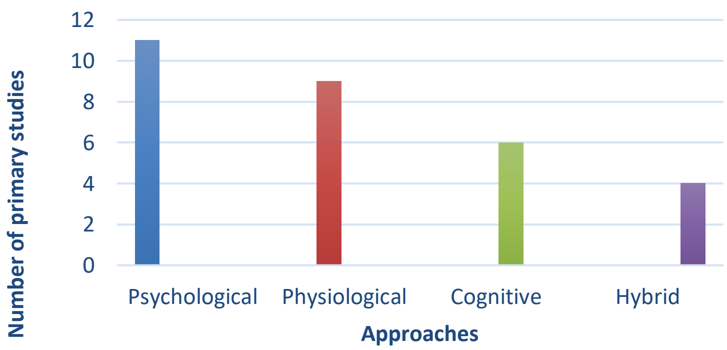

Figure 3. Primary studies distribution in terms of their focus

4. RESULT AND DISCUSSION
4.1. Answering the research questions

The responses to the research questions posed for this study are presented and addressed in this part. Each RQ was answered using relevant articles taken from the data collected. As previously stated, the systematic literature review (SLR) was carried out in this research paper in accordance with the direction proffered by Yousuf *et al.* [46], Farooq *et al.* [47], in which literature from various repository sources were investigated using predefined keywords to assemble pertinent study materials, as well as exceptional evaluation criteria to counter the summarized research questions. Furthermore, as demonstrated in [48], [49], it summarized the empirical evidence of both the merits and limits of a certain strategy and identified gaps in order to identify topics for further exploration.

RQ1: What exactly are the student engagement levels for categorizing emotion detection systems for e-learning?

Emotion detection is categorized into three that is, psychological/behavioral, physiological and cognitive student engagement levels [4]. A few numbers of literature combined two methods which are called the hybridized as detailed in [16]–[19]. The rest of the literature is based on the three main methods. The different categories and their engagement level are depicted in Table 7.

Table 7. Engagement level

S/N	Approaches	Engagement levels
1	Psychological (behavior)	It reflects on attending and participating in class.
2	Physiological (mind)	It considers student interest, enjoyment, frustration or willingness to learn.
3	Cognitive (mental)	It reflects on mental efforts, meeting or exceeding the task requirements in class.

RQ2: *What is the best model for e-learning system implementation when it comes to detecting emotions?*

Most of the approaches used in the literature are notable in machine learning. However, the deep learning models are remarkable in emotion detection implementation and are recently used [19]–[24]. It serves as a valuable practical reference for studies on learners' emotion identification and pictorial depiction of expressions in a virtual environment. When it comes to complicated issues like picture classification, natural language processing, and speech recognition, deep learning shines [50]. As seen in [51], a chart of the most recent e-learning model is constructed in Figure 4 and the summary is presented in Table 8.

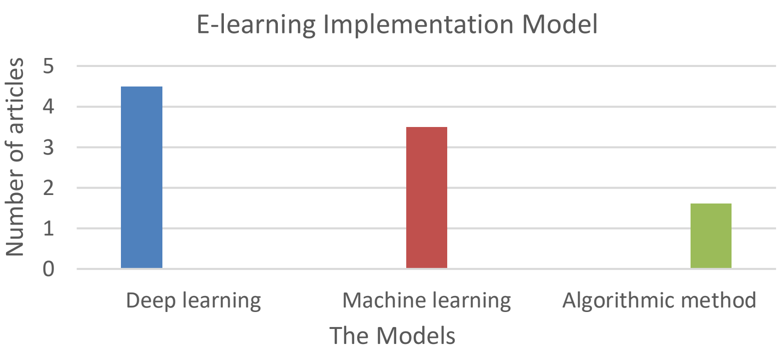

Figure 4. E-learning implementation model recently used

Table 8. Summary of RQ2 findings

Model	Article number
Deep learning	[17], [19]–[24], [26], [28], [29], [30], [32], [35], [41]
Machine learning	[16], [18], [25], [27], [33], [34], [37], [38], [44], [45]
Algorithmic method	[31], [36], [39], [40], [42], [43]

RQ3: *What is the best technology used in capturing emotion in student engagement?*

Researchers' current state was the subject of technology involved in emotion capture. Many of the technologies employed are contact devices for recording emotions. Non-contact devices, on the other hand, can be more accurate because emotions are caught without individuals' awareness, and contact devices are expensive, as shown in [10], [23], [32]. All the research questions focus on contemporary inadequacies and gaps. However, the summary in Figure 5 depicts the outcome of three research questions posed for this study and it is also presented in Table 9.

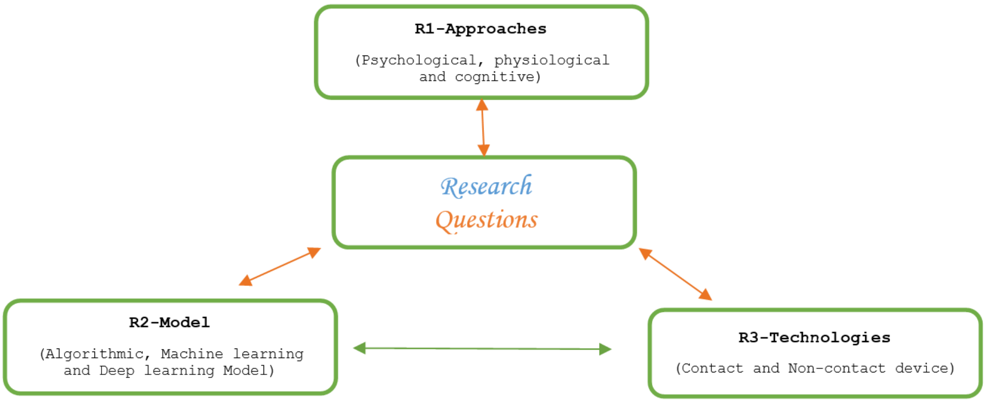

Figure 5. Diagram representing the result of the research questions

Table 9. Summary of RQ3 findings

Technology	Article number
Contact device	[17]–[19], [30], [33]–[36], [37], [38], [40], [41]
Non-contact device	[16], [20]–[29], [31], [32], [39], [42]–[45]

4.2. Result discussion

Nevertheless, neither of the previously mentioned publications discussed any of the required characteristics, namely: i) collaboration of multiple learning technologies, ii) automated evaluation, iii) tracking of students' progress, iv) recommender system, nor did they give an optimal answer for present e-learning challenges. Consequently, a large bulk of accessible published papers on e-learning assessment were analyzed in this publication. Among the various e-learning methodologies, the physiological approach has received the most attention. Because physiological stress can have an impact on students' motivation, focus, awareness, and social relationships, all of which are regarded as key aspects in attaining academic achievement. As a result, the methods used to capture student emotions were examined in this study. Considering the fact that emotions can be faked, a non-contact gadget helps in capturing genuine feelings during learning. Furthermore, the deep learning model was used in the majority of the implementation models. It has risen to prominence in emotion detection due to its ability to generate complicated statistical models directly from its iterative output, as well as to generate accurate predictive models from enormous amounts of unlabeled, unstructured data. Nonetheless, in the face of multiple online resources, an e-learning recommender system [52]–[55] is proposed to give learners individualized services by automatically recognizing their preferences.

4.3. Research limitations and recommendations for future research

This paragraph describes the study's limits and stipulations that can have an influence on the final findings and motivate many scholars to carry out additional study because research is an ongoing process. The purpose of the study was to ascertain the approaches, technologies, and methods of implementation currently employed for gauging student involvement in class. This was done by conducting a thorough search of the databases of solely English-language papers in Google Scholar, arXiv, ResearchGate, Semantic Scholar, Microsoft Academic, ScienceDirect, and Virtual LRC. Due to their publication in a language other than English, other pertinent research publications may have been overlooked. It is clear from SLR that there has to be more research done on how to gauge student engagement throughout learning. The study's findings indicate that no research has been done on creating an e-learning system that can gauge student engagement with smart features for tracking student progress and making recommendations. The report also reveals a lack of research in the area of developing new systems that are appropriate for the significant demand fora self-intelligent e-learning system. Researchers are encouraged to take part in this current investigation. Today, deep learning is being used more and more frequently to address a variety of problems in the real world. Due to this, current e-learning emotion detection systems require cutting-edge, creative design approaches that incorporate the following features: i) a hybridized approach of capturing student emotion using deep learning; ii) a progress tracking system to better improve student academic success; and iii) a recommender system that provides learners with personalized services by automatically recognizing their preferences. The recommender system for e-learning is currently being studied by authors of different disciplines. Hence, the writer encourages potential scholars to carry out more studies.

5. CONCLUSION

Over the years, there has been a lot of research into e-learning systems that can measure student engagement in the classroom. The ideas, technology, and implementation methodology lack sophisticated capabilities such as a deep learning hybridization system, integrated recommender system, and tracking student progress. However, more study is needed on a crucial strategy for improving the user experience that might greatly raise student engagement, learning outcomes, and pedagogical innovation.

APPENDIX

Table 6. List of selected primary studies (*continue*)

Primary study	Reference	Title	Database	Approaches
Guo *et al.* (2019)	[16]	A hybrid physiological approach of emotional reaction detection using combined FCM and SVM classifier	ResearchGate	Hybrid
Hassouneh *et al.* (2020)	[17]	Development of a real-time emotion recognition system using facial expressions and EEG based on machine learning and deep neural network methods	ScienceDirect	Hybrid
Gao *et al.* (2020)	[18]	n-Gage: Predicting in-class emotional, behavioral and cognitive engagement in the Wild.	Google Scholar	Hybrid
Saffaryazdi *et al.* (2022)	[19]	Using facial micro-expressions in combination with EEG and physiological signals for emotion recognition	Google Scholar	Hybrid
Parthiban and Samy (2021)	[20]	Emotion detection in IoT-Based e-learning using convolution neural network	Semantic	Psychological
Kuo *et al.* (2018)	[21]	A compact deep learning model for robust facial expression recognition	Semantic	Psychological
Karimah and Hasegawa (2021)	[22]	A real-time engagement assessment in online learning process using convolutional neural network	Semantic	Psychological
Zhang *et al.* (2020)	[23]	Data-driven online learning engagement detection via facial expression and mouse behavior recognition technology	Microsoft	Psychological
Nezami *et al.* (2020)	[24]	Automatic recognition of student engagement using deep learning and facial expression	Google Scholar	Psychological
Horvat and Jagušt (2020	[25]	Emerging opportunities for education in the time of COVID-19 adaptive e-learning intelligent agent based on assessment of emotion and attention.	Microsoft	Psychological
Hasnine *et al.* (2021)	[26]	Students' emotion extraction and visualization for engagement detection in online learning.	ScienceDirect	Psychological
Kuruvayil and Palaniswamy (2022)	[27]	Emotion recognition from facial images with simultaneous occlusion, pose and illumination variations using meta-learning	ScienceDirect	Psychological
Liao *et al*. (2021)	[28]	Deep facial spatiotemporal network for engagement prediction in online learning	ResearchGate	Psychological
Huang *et al.* (2019)	[29]	Fine-grained engagement recognition in online learning environment.	ScienceDirect	Psychological
Mukhopadhyay *et. al.* (2020)	[30]	Facial emotion detection to assess learner's state of mind in an online learning system	Semantic	Physiological
Solé-Beteta *et al.* (2022)	[31]	A data-driven approach to quantify and measure students' engagement in synchronous virtual learning environments	Virtual LRC	Psychological
Yu *et al*. (2019)	[32]	Remote photoplethysmography signal measurement from facial videos using spatio-temporal networks	Microsoft	Physiological
Carroll *et al.* (2020)	[33]	Automatic detection of learner engagement using machine learning and wearable sensors	Virtual LRC	Physiological
Dissanayake *et al.* (2019)	[34]	An ensemble learning approach for electrocardiogram sensor based human emotion recognition	Semantic	Physiological
Liu (2021)	[35]	Predicting stress in remote learning via advanced deep learning technologies	arxiv	Physiological
Xiefeng *et al.* (2019)	[36]	Heart sound signals can be used for emotion recognition	Google Scholar	Physiological
Domínguez-Jiménez *et al.* (2020)	[37]	A machine learning model for emotion recognition from physiological signals	Google Scholar	Physiological
Sepúlveda *et al*. (2021)	[38]	Emotion recognition from ECG signals using wavelet scattering and machine learning	ResearchGate	Physiological
Nocua *et al.* (2021)	[39]	Assessment of cognitive student engagement using heart rate band in distance learning during COVID-19	Microsoft	Physiological
Prabhu *et al.* (2016)	[40]	Affective e-learning using emotion detection	Google Scholar	Cognitive
Shaw and Patra (2022)	[41]	Classifying students based on cognitive state in flipped learning pedagogy	ScienceDirect	Cognitive

Table 6. List of selected primary studies

Primary study	Reference	Title	Database	Approaches
Ma (2016)	[42]	Design of an emotional interaction mode in e-learning world	Google Scholar	Cognitive
Hiremath and Patil (2021)	[43]	Sarcasm detection using cognitive features of visual data by learning model	ScienceDirect	Cognitive
D'errico *et al*. (2018)	[44]	Cognitive emotions in e-learning processes and their potential relationship with students' academic adjustment	Google Scholar	Cognitive
Li *et al*. (2021)	[45]	Automated detection of cognitive engagement to inform the art of staying engaged in problem-solving	Google Scholar	Cognitive

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