Unmasking Cognitive Engagement: A Systematized Literature Review of the Relationships Between Students' Facial Expressions and Learning Outcomes

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Abstract

Cognitive engagement, a complex concept in the field of education, has a great impact on student learning that can be assessed using facial expression analysis. Facial expression analysis uses visual information to detect and recognize human emotions as a measure of student's cognitive engagement, particularly during problem–solving activities. This systematized literature review explores the empirical literature to understand the relationships between students' cognitive engagement levels and human emotions to highlight the different phases of engagement levels concerning problem–solving tasks and corresponding emotions (that act as potential indicators of deeper cognitive engagement). It is essential to quantify the cognitive engagement level to assess the efficacy of the educational strategies, cognitive skills, and motor skills in terms of learning outcomes. However, while the available literature reviews offer summaries of various cognitive engagement techniques and their impacts, they neglect to synthesize the technical aspects of emerging technologies and trends that may provide useful associations between cognitive engagement in educational settings and emotions–based facial expressions. In this literature review, we have identified significant associations between students' cognitive engagement during problem–solving tasks and facial expressions. The nuanced analysis of facial cues reveals key indicators of heightened cognitive engagement, such as expressions of curiosity, excitement, concentration, determination, and satisfaction. These emotions are proposed as valuable markers for deeper cognitive engagement in educational contexts. By synthesizing the existing research, this review sheds light on how students' cognitive engagement is associated with visible facial expressions, and how facial expressions can help educators comprehend students' engagement levels in real–time. This review also reveals the emotions associated with underlying cognitive processes to improve instruction teaching and learning and personalized learning. Last, this review further seeks to highlight gaps that can guide future research. This systematic literature review explores one potential cause of the lack of student engagement in education settings, and visible expressions associated with engagement through systematic analysis of literature. Findings from this review will be used to advance pedagogy and educational strategies to advance the student–centered educational environment.

Keywords: Facial Expressions, Cognitive Engagement, Cognitive Skills, Emotions, Problem–Solving

Introduction

Cognitive engagement involves actively employing mental processes in tasks or problem–solving, utilizing attention, memory, reasoning, and decision–making. Simultaneously, facial expression entails the orchestrated use of facial muscles for emotional communication, classified by the Facial Action Coding System (FACS) into specific action units, e.g., raising eyebrows (AU1) or smiling (AU12) [1]. This systematic framework enables standardized analysis of facial expressions. The integration of cognitive engagement and facial expressions underlines their interconnected role in human communication and interaction, providing insights into the intricate relationship between mental involvement and emotional signaling in various contexts. This study aims to explore the intricate relationship between students' cognitive engagement and facial expressions, these two facets of the learning experience, and delve deeper into the realm of non–verbal communication to unearth potential indicators of heightened cognitive engagement. Within the domain of problem–solving, the research spotlight has increasingly illuminated the significance of facial expressions. This heightened attention is underscored by its direct relevance to student learning outcomes, a fundamental facet of

the ABET Engineering Criteria, as well as various other accreditation models [2]. When reshaping contemporary engineering education, several elements deserve attention. These decisions are influenced by evolving industry needs and societal context. Interdisciplinary learning, integrating fields like data science and entrepreneurship, is crucial for holistic problem–solving. Soft skills such as communication, teamwork, and leadership are essential for effective collaboration [3].

Notably, the emphasis on the evaluation of students' engagement and performance through modern technological means, including the analysis of facial expressions, signifies a substantial evolution in engineering education. This transformation constitutes the fifth major paradigm shift within the engineering education discipline that emphasizes formative and summative assessment, student engagement, active learning, mastery model research outcomes, and objectives [4]. The importance of incorporating facial expressions into the problem–solving process is highlighted in many research papers. The development of a facial expression recognition system with applications across various fields includes psychology and education [5]. Therefore, the significance of analyzing facial expressions is in gaining insights into emotional states during interactions between humans and computer systems [6]. Also, the teaching model leverages facial expressions to enhance the teaching–learning experience [7] by using an automated analysis of facial movements in computer–mediated tutoring, demonstrating the predictive value of facial expressions concerning engagement, frustration, and learning outcomes [8]. Problem–solving events can trigger unique patterns of facial expressions and physiological activity [9], and human interactions with computer systems result in facial expressions that can vary based on the type of task being performed [10]. Moreover, when a problem–solving task is tackled collaboratively within a team, certain facial expressions, such as widened eyes and raised brows, were commonly observed during programming sessions. An in–depth examination of participants' facial expressions in collaborative coding activities revealed that high–performing teams displayed a range of emotions, including confusion and frustration, which later transitioned to expressions of delight and neutrality [11].

In contrast, low–performing teams displayed a greater prevalence of boredom [12]. These studies collectively propose that students' facial expressions hold the potential for detecting and predicting their levels of cognitive engagement during problem–solving tasks. Facial behaviors emerged as robust predictors of cognitive engagement states by using a Support Vector Machine (SVM) model showcased exceptional performance in distinguishing between engaged and less engaged states [13]. However, by using only one classification model and without using legitimate benchmarks to verify the performance of the model, there were no appreciable differences found between high and low performers in terms of cognitive engagement overall [14]. By analyzing behavioral cues from head movements, facial expressions, and gaze behavior provide an answer to the question of how student engagement could be automatically measured and monitored [15]. However, a framework based on facial finding points and the Facial Action Coding System (FACS) can decode action units to assess the student’s inclination to participate in the learning process, denoting behavioral engagement, and their emotional disposition toward learning, reflecting emotional engagement [16]. When reshaping contemporary engineering education, several elements deserve attention. These decisions are influenced by evolving industry needs and societal context. Interdisciplinary learning, integrating fields like data science and entrepreneurship, is crucial for holistic problem–solving. Soft skills such as communication, teamwork, and leadership are essential for effective collaboration [17]. This literature review seeks to unravel the intriguing connection between students' cognitive engagement levels and the subtle yet telling language of their facial expressions during the process of problem–solving. The inspiration behind this investigation is rooted in the understanding that cognitive engagement, encompassing elements like focus, curiosity, and the exertion of mental effort, etc.; plays a pivotal role in the efficacy of learning and problem–solving. This study explores new areas in

educational research by closely looking at how facial expressions and cognitive engagement work together.

Scope and Research Questions

Students engage in problem–solving tasks differently within different learning environments, such as traditional in–person settings and the increasingly prevalent online contexts. By considering these distinct scenarios, we intend to discern whether the dynamics of cognitive engagement and corresponding facial expressions vary in response to the learning environment. Through advanced data analysis techniques, we aim to identify recurring facial cues that reliably indicate a deep state of cognitive engagement, potentially offering educators valuable insights into gauging and fostering students' active involvement in learning. Numerous scientific explanations have been cited to justify the relationship between students' cognitive engagement levels and their facial expressions and the impact of various emotions (happy, sad, neutral, frustration, etc.) on cognitive engagement during problem–solving tasks. Emotions play a crucial role; they can have both positive and negative impacts on a learner's motivation. Positive emotions, such as joy or enthusiasm, are associated with increased cognitive engagement, self–regulation, and the use of more advanced learning strategies. In contrast, negative emotions like anger can lead to feelings of anxiety and boredom, resulting in reduced effort, poor performance, increased reliance on external motivation, and a decline in self–regulatory strategies [17]. Emotional state can reveal student’s preferences for teaching content, educational media, and the learning environment. This understanding is valuable for identifying individual cognitive styles and learning interests. Additionally, a learner's emotions can also mirror the influence of their knowledge level, cognitive structure, and level on their subjective learning experiences [18]. This insight can be instrumental in analyzing the mechanisms involved in the learning process. Consequently, there is a pressing need to explore emotion recognition in educational settings. By undertaking this meticulous examination of prior scholarly work, we gain valuable insights and discern the contributions made by earlier researchers in this field of inquiry to answer the following research questions:

(1) What associations have been established between students' cognitive engagement levels during problem–solving tasks and their facial expressions?
(2) What specific emotions have researchers proposed as potential indicators of deeper cognitive engagement in educational contexts?

Methods

Analysis Method

This systematized literature review is conducted by using a well–defined searching method and investigation method on available research literature related to students’ cognitive engagement and associated visible facial expressions (emotions). In crafting the literature review, adherence to the methodological guidelines outlined by Borrego [19] has been conscientiously observed, ensuring a meticulous and scholarly approach. The structured framework has guided the comprehensive examination of relevant literature in a manner reflective of best practices in scholarly writing. The review used research databases, search strings, and inclusion criteria for an unbiased search to provide a narrative description that elaborates meaning full story about the existing research in this field.

Search Procedure

Multiple search databases were queried to select papers to write a literature survey. EBSCO host, Wiley Library, and IEEE Xplore databases were selected because they provide the advanced search

option to apply practically identical search strings to select papers to ensure that the chosen papers align with the objectives and focus of your research. EBSCO host was selected to access the diverse array of research material (i.e., peer–reviewed scholarly journals and conference papers) that makes it ideal for interdisciplinary research. Wiley Library has a long history of publishing high–quality peer–reviewed research articles related to education and many other disciplines. Moreover, it provided access to full–text articles published in the various Journals related to education and engineering education including the Journal of Engineering Education (JEE). IEEE–Xplore primarily publishes research papers related to engineering and technology, but it becomes highly relevant when the research topic involves technology and digital tools. So, it is an appropriate database to search articles focused on engineering or technology techniques to solve problems in the education field. The research string consisted of three components to form five distinct research strings. Each string is designed to encompass a specific set of synonyms combinations gleaned from prior research articles.

Table 1: Complete Search String and Database Query Results

Sr#	Search Strings	Database	Results
1	("Cognitive Engagement" OR "Cognitive Involvement" OR "Mental Engagement" OR "Academic Engagement" OR "Active Learning") AND ("Facial Expressions" OR "Facial Reactions" OR "Emotional Detection" OR "Emotion" OR "Facial Emotion") AND ("Problem–Solving" OR "Task Resolution" OR "Critical Thinking" OR "Analytical Problem Solving" OR "Task Performance")	IEEE Xplorer	56
2	("Emotion Detection" OR "Emotion" OR "Facial Emotion") AND ("Cognitive Engagement" OR "Cognitive Involvement" OR "Mental Engagement" OR "Academic Engagement" OR "Active Learning") AND ("Problem–Solving" OR "Task Resolution" OR "Critical Thinking" OR "Analytical Problem Solving" OR "Task Performance")	Wiley Library (15)	36
3	("Active Learning" OR "Cognitive Engagement" OR "Academic Engagement") AND ("Facial Reactions" OR "Emotional Detection" OR "Emotion" OR "Facial Emotion") AND ("Problem–Solving" OR "Task Resolution" OR "Critical Thinking" OR "Analytical Problem Solving" OR "Task Performance")		
4	("Academic Engagement" OR "Cognitive Engagement") AND ("Facial Expressions" OR "Facial Reactions" OR "Emotional Detection" OR "Emotion" OR "Facial Emotion") AND ("Problem–Solving" OR "Task Resolution" OR "Critical Thinking" OR "Analytical Problem Solving" OR "Task Performance")	EBSCO host (21)	
5	("Facial Emotion" OR "Emotion" OR "Emotional Detection") AND ("Active Learning" OR "Cognitive Engagement" OR "Academic Engagement") AND ("Critical Thinking" OR "Problem–Solving" OR "Task Resolution" OR "Analytical Problem Solving" OR "Task Performance")		

The first component for the research sting is “cognitive engagement” to find the article relevant to this concept and the other research stings marked as “cognitive involvement”, “mental engagement”, “academic engagement”, and “active learning”. The second component “facial expressions” is used

to find articles in specific educational settings. Other words used in the same context are “facial reactions”, “emotional detection”, “emotion” and “facial emotion.” The third and last component is “problem–solving task” which targets the paper where the researcher used a problem–solving task to collect the data. We have incorporated synonym terms to explore a broader spectrum of literature which enables us to capture a more in–depth and multifaceted understanding of the topic, considering various facets and dimensions. The search strings were used to search relevant paper titles, abstracts, and keywords by using the selected search databases followed by applying the filter to find the peer–reviewed articles written in the English language in the last 10 years (2013–2023). We found 15 and 21 articles by using the EBSCO host and Wiley Library respectively. IEEE Xplore yielded 56 peer–reviewed articles.

Inclusion Criteria

It is necessary to establish well–defined inclusion criteria to select papers to make sure the selected papers address the research questions and objectives. The following criteria were used to shortlist further the selected articles by title, abstract, and full text.

Table 2: Inclusion Criteria

Criteria	Explanation	Justification
Relevance to Research Question	Include papers that directly address the relationship between students' cognitive engagement during problem–solving tasks and their facial expressions.	This ensures that the selected papers are closely aligned with your research focus.
Publication Date	Include papers published within the last 10 years (2013–2023).	Recent research is more likely to reflect current methodologies and findings in the field
Empirical Research	Include papers reporting on empirical studies	Empirical studies provide direct evidence and insights into the research question.
Educational Context	Include papers conducted in educational settings (e.g., face–to–face, online learning environments).	The educational context is central to the research question
Research Methodology	Quantitative, qualitative, or mixed methods approaches if they address the research question.	Different methodologies provide complementary perspectives
Peer–Reviewed Journals and Conferences	Publications should be peer–reviewed	Peer–reviewed sources are typically more reliable and credible
Language	Include papers published in English languages	Language can impact access to data and research findings

Data and Method Analysis

In the data analysis phase, we used the following coding process, we read the 25 scholarly articles to compile the database consisting of four major categories “citation” “sample characteristics”, “research design characteristics”, and “research outcomes”. In each selected article, we extracted the information for the coding table to write an exclusive reflection for each article to find the common patterns in this research. The sub–categories of each major category with their descriptions are given

in table 3. During the method analysis phase, we used a thematic analysis approach to identify the frequent and central themes used by various research articles. A comprehensive review was performed on selected articles by carefully analyzing the objectives, research questions/hypothesis, method of collecting and analyzing data, the research outcomes, implications, and limitations of each study to form a reflective synthesis to establish preliminary connections. This approach enables us to extract the common themes for further analysis.

Table 3: Overview of the Coding Framework

Major Category	Sub–Category	Description
Paper Type	Title	Title of article
	Citation	Publisher, year, and publication type
Sample Characteristics	Issue Targeted	What is the core idea of the paper
	Sample Size	What is the sample size used for the research?
	Educational Setting	Is the experiment conducted online or face–to–face?
	Education Level	What is the education level of participants (high school, undergrad, or graduate)
	Task Type	Description of the problem–solving task
	Location	Where was the study conducted (Uni name with country)
	Type of Intervention	Which type of intervention was used?
	Level of Intervention	What is the level of intervention?
Research Characteristics	Stated Hypothesis	Does the author state any hypothesis?
	Research Question	What is the research question?
	Data Collection Method	Survey, Video recorded interview etc.
	Research Method	Experimental, observational, survey, qualitative, etc.
	Emotion	Emotion involved or measured during the analysis
	Independent/ Dependent Variables	Variable name with type involved in the experiment
	Internal/ External Validity	Validity name with type involved in the experiment
	Association Level	Associations between facial expressions/ emotions and engagement
Research Outcomes	Conclusion	Author’s key finding with closing remarks
	Future Directions	Autor’s future direct of research
	Limitations	What are the limitations of this study?
	Recommendations	How to overcome the limitation.
	My reflections	Highlight key findings and results along with impact.

Analysis

The thematic analysis was conducted by carefully examining and comparing the data across the included studies. The purpose of this approach is to highlight the core idea and results presented in the latest research rather than generating new knowledge. The first phase of this approach was to overview the 25 selected articles and build an understanding of the objectives, research questions, and results of each article. The lead researcher engaged in reflective analysis, taking note of substantive findings, and making initial connections. In the second phase, a more in–depth analysis was conducted, aiming to analyze the specific methodology used to generate the results, discussions with relevant arguments to justify their argument followed by any implications and limitations stated

in the articles. After a thorough analysis, potential themes were identified and extracted for further analysis.

Results

After the data collection and analysis phases, two themes were identified explaining the *association between emotion and cognitive engagement* and *emotional indicators of cognitive engagement* with their impact on cognitive engagement during problem–solving tasks. These themes explain the phenomena of how emotions influence cognitive engagement and their levels by explaining the role of positive and negative emotions during problem–solving activities. Most of the articles shed light only on positive emotions but a smaller subset discussed the impact of negative emotions. The emotions were supported by various factors. These factors were correlated to multiple indicators that can amplify or diminish cognitive engagement during problem–solving tasks.

Theme 1: Emotional Indicators Shaping Cognitive Engagement.

Multiple studies have explored the direct or indirect association between facial expressions (emotions) and cognitive engagement during problem–solving tasks. Researchers used self–report questionnaires, semi–structured interviews, and online surveys to collect data and record facial expressions by using a variety of tools to monitor participants' facial expressions. Recorded data is coded then different types of research methods are applied to find the association between facial expressions and cognitive engagement. However, some other factors can influence the emotions during the observation period. Mancini and colleagues [20] observed that there is a different type of association between students' facial expressions and their cognitive engagement during the different phases of problem–solving tasks. It is evaluated that less cognitive engagement during the creative blocking phase but higher during the evaluation and refinement phases during the problem–solving activity. The impact of emotional expressions on cognitive engagement seems to be phase–specific and tied to the nature of the emotions experienced during those phases of problem–solving. Because emotions serve as the connection between the body and the mind, facial expressions or emotions and cognitive skills are terms often associated with students with Attention–deficit Hyperactivity Disorder (ADHD) and Specific Learning Disorder (SLD). This mind–body connection is stated [21] as *"Emotions are the meeting point between the body and the mind, which conveys the mental representation of reality"*. This implies that emotions play a significant role in shaping one's perception and understanding of their surroundings, which could impact cognitive engagement during problem–solving tasks.

The positive association between the students' cognitive engagement level and emotions depends on task performance along with valence. Whitehill and colleagues [22] found that if students show positive emotions with high valence, their engagement is very high. But, even if students have positive facial expressions if the positive feeling decreases, their engagement is either engaged or less engaged. Contrarily, a different study indicates that valence does not play a role in measuring cognitive engagement, suggesting that positive emotions are directly proportional to cognitive engagement because when individuals experience positive emotions, their performance and engagement tend to be higher[23]; conversely, negative emotions show an inverse relationship with cognitive engagement, potentially leading to decreased performance and lower levels of engagement [24]. While Saas [25] and Wytykowska [26] found a direct and strong association between positive emotion (surprise) and cognitive engagement, they found it changes over time in educational settings. There can be multiple factors that can change the engagement levels like the teacher's communication method and teaching style, subject interest, and duration of the engagement. It is observed that the engagement level is inversely proportional to the time. Facial expressions such as

happiness, surprise, fear, disgust, anger, and sadness can be significant indicators to measure the cognitive engagement level and can increase the engagement level by up to 56% in the learning environment. However, each emotion's arousal and valence level play a vital role when the outcome or performance is associated with facial expressions [27].

Student cognitive engagement can also be classified as active, semi–active, and passive during problem–solving tasks and can be measured by using different techniques like machine learning, baseline models, and statistical techniques [28]. Active cognitive engagement is associated with smiles, excitement, or focused looks, and boredom, disinterest, or blank look faces represent passive engagement. It is found that there is a positive association between emotions and cognitive engagement but there are other factors, such as the student must be physically interacting with the learning material for higher or active engagement otherwise it is observed that when students are not involved in activities their engagement level decreases [28]. It is believed that positive emotions are always associated with positive outcomes which is not true in all cases as it is observed that sometimes negative emotions have a positive impact too. Emotions such as confusion contribute to frustration which ultimately becomes the reason for higher cognitive engagement, however, positive emotions are always directly proportional to outcomes that represent higher cognitive engagement. Facial expressions are aligned with higher cognitive engagement but factors like affective attitude, social cues, and the learning process can alter the nature of emotions toward the focus [29].

Theme 2: Exploring Emotional Cues in Cognitive Engagement Dynamics

Pirmoradi [30] revealed that positive and negative emotions are the indicators of deep cognitive engagement among students during problem–solving tasks that can be used to gauge their level of cognitive engagement. Emotional responses of the undergraduate students from the Computer Science (CS) department were recorded by using Web Real–Time Communication (WebRTC) software during the problem–solving task in a controlled environment. The results show that positive and negative emotions are closely linked to cognitive engagement and quality of research outcomes. "*The participants spent a statistically significant larger portion of their time experiencing positive emotions in the high–relevance condition ($F(1,62)=5.546$, $p<0.05$), and negative emotions in the low–relevance condition ($F(1,62)=5.32$, $p<0.05$). Participants expressed positive emotions more often when provided with high relevance search results, and negative emotions when provided with low relevance search results*".

Boredom, anxiety, and frustration are associated with self–learning behaviors. That is why they have a deep impact on self–related learning strategies (elaboration) and cognitive engagement in online educational settings [31]. On the one hand, boredom is considered a negative emotion, and it significantly hinders deep cognitive engagement which is clear from the statement "*boredom was negatively related to elaboration and metacognition"*. On the other hand, anxiety is also considered a negative emotion that is stated as, "*anxiety positively predicted the metacognition significantly"* but the study shows frustration shows a mixed effect because it shows negative behavior for the elaboration but positive for the metacognition *"frustration negatively related to both elaboration and metacognition"* [31]. These statements clearly show emotions such as boredom, anxiety, and frustration have a distinct impact on various self–regulated learning behaviors and affect the deep cognitive engagement among students in academic settings. Arousal is mostly associated with emotions that represent the intensity of the emotion, it ranges from low to high where high arousal means high engagement and low arousal often draws less impact or less intense focus resulting in low engagement [32],[33]. Based on this concept, a supervised machine learning model and regression technique were used to label the 16 human emotions in two categories to predict the engagement level. The high–arousal emotions (pride, joy, elation, anger, disgust, envy, sadness,

surprise, and fear) group predict positive engagement while the low–arousal emotions (interest, happiness, hope, satisfaction, relief, shame, and guilt) group negatively predicts the engagement level. These results revealed that arousal plays a vital role in measuring engagement levels because people get more engaged when they experience positive or high–arousal emotions and less engaged when feel low–arousal emotions [34].

Kumar and colleagues [35] revealed that positive emotions (happiness, pride) and negative emotions (anger, fear, sadness, and disgust) can influence cognitive engagement during different stages of creative problem–solving (essay writing) processes and reported positive emotions as *"so at first glance I thought that it was something like Picasso's work and I was like very happy that I have direction now however, I felt really happy that I came up with this idea of one nation one flag while I was thinking of making something similar to the Eiffel tower."*, and negative emotions during the task are reported as, *"I was not able to come up with an idea right away which pissed me off and at this point, I was confused and irritated about converting this circle or not"*. It is evident that during the evaluation and refinement phase of the creative problem–solving activity, positive emotions are dominant while negative emotions are noticed during the creative blocks or finding the strategy to solve the problem.

Discussion

The analysis of this research literature's major findings addresses the associations between students' cognitive engagement levels during problem–solving tasks and their facial expressions and specific emotions proposed as potential indicators of deeper cognitive engagement in educational contexts. These studies explore the relationship between students' engagement and emotional responses during engineering design activities that primarily focus on electrodermal activity, eye–tracking along with the relevance of facial expressions by using automatic emotion recognition software and screen recordings to capture students' emotional states during mathematical problem–solving; it suggests a strong connection between students' emotions and their engagement during learning tasks. Also, the literature identifies emotions (i.e., happiness, sadness, frustration, anger) linked to various phases of problem–solving tasks and highlights the emotions associated with cognitive engagement.

The first research question focuses on the established associations between students' cognitive engagement levels during problem–solving tasks and their facial expressions. A comprehensive examination of the major findings within the research literature collectively reveals the pivotal role of emotions in shaping students' experiences, particularly in the context of learning and engagement during problem–solving. Emotions, whether positive, such as happiness, surprise, enjoyment, and hope, or negative, like anger and anxiety, emerge as crucial determinants of students' engagement and academic achievements. The association level between facial expression and student engagement can be strong [25] or depends on arousal and valence [27] and moderate [28]. Arousal measures the nature of the emotion whether it is positive or negative and valence measures the intensity. These two components define the level of cognitive engagement during problem–solving tasks. The nature of arousal is confusing in educational settings specifically when evaluating the level of engagement because sometimes negative emotions help students to focus and gain the required goals and engagement level [36]. The research underlines the importance of recognizing issues and variations in emotional responses, particularly in students facing math difficulties. They highlight the dynamic nature of these emotional states, which can significantly shift across diverse learning activities and influence the engagement level [37]. For example, negative emotions raise frustration levels which can be helpful during focused learning and problem–solving s but when the time constraint is involved, the same emotion can be the reason for a lower engagement level [1].

The second research question focused on the specific emotions have researchers proposed as potential indicators of deeper cognitive engagement in educational settings. When we are talking about specific emotional indicators, education settings play a vital role whether it is online or face–to–face along with the education level of the students. Multiple articles reported that the level and type of intervention can impact the students' emotions related to cognitive engagement. For example, emotions like neutral, happy, sad, and angry can affect a student's intellectual functioning, achievement, and effectiveness of high school students in problem–solving, specifically when observational and technology–based intervention was used in the individual level intervention used in face–to–face educational settings [38]. Also, Holm and colleagues [39] observed that enjoyment, pride, anger, anxiety, hopelessness, shame, and boredom can be the deep indicators in the same settings, emotions have a positive association with performance, but different types are associated with males and females while engaging with solving the problem activity. However, just by changing the intervention level from group to classroom or group level, single emotion stress was observed that can change cognitive engagement level [40].

Another research [41] exhibited a noteworthy association between students' engagement and their mathematical problem–solving proficiency. However, there was no significant association identified between mathematical problem–solving ability and the emotions of anxiety, hopelessness, boredom, pride, and anger. The connections between mathematical problem–solving skills and feelings of anxiety, hopelessness, and boredom were characterized by weak associations [42]. Similarly, the relationship between mathematical problem–solving ability and the emotions of pride and anger was deemed negligible. These outcomes aligned closely with a study conducted by Tornare [43] indicating that, except for feelings of hopelessness, emotions like anxiety, boredom, pride, and anger did not significantly correlate with mathematical problem–solving proficiency. This occurs because how students experience their achievements in math problems is tied to their thoughts about their skills and hard work, rather than just external factors. For example, if a student feels joyful after successfully solving a challenging math problem, it's because they believe they did well and they take pride in their achievement, not solely because the problem was hard [44]. In online educational settings, researchers revealed the significant impact of positive emotions (such as happiness, surprise, smile, humor, interest, and enjoyment) and negative emotions (like anger, sad, fear, confusion, frustration, and bored) emotions on cognitive engagement, while the intervention level was personalized for individual (undergrad or graduate) students and revolved around technology and instructional approaches [27],[28], however, it is observed that there was a strong association between the (positive and negative) facial expressions and cognitive engagement.

These distinctions are not simply informative but are essential for providing effective support and tailored interventions. From an educational strategy perspective, these studies advocate for the inclusion of emotional considerations within teaching methods and curriculum design. Creating a learning environment that not only acknowledges but actively addresses students' emotions is pivotal. Emotions such as hopelessness, often viewed as negative, should be recognized as cues for tailored support mechanisms. However, engagement level or particular emotions are not the only factor when we study the impact of facial expressions on students' cognitive engagement levels during problem–solving tasks.

Conclusion and Future Research

Through an array of studies, it becomes obvious that facial expressions serve as indicators of cognitive involvement, offering insight into the depth of engagement. Positive emotions like happiness, surprise, and interest align with higher cognitive engagement levels, while negative emotions such as frustration and anxiety also exhibit distinct roles, sometimes enhancing focus and

determination during complex tasks. The phases of problem–solving display a varied emotional landscape, with positive emotions dominating during evaluation and refinement, and negative emotions surfacing during creative blocks or strategy formulation. This pattern highlights the dynamic nature of emotional responses throughout different stages of learning. Moreover, the analysis underscores the pivotal role of emotions in shaping students' experiences in academic environments, where individual emotions act as signals, impacting the level and depth of engagement. The associations between facial expressions and engagement are evident, showcasing the potential for automatic emotion recognition software to capture and understand students' emotional states during learning. This helps us to understand how emotions influence learning and academic achievements. Education strategies should encompass emotional considerations within their framework, allowing for tailored interventions and curriculum designs that acknowledge and address diverse emotional responses. Recognizing emotions, whether positive or negative, becomes vital in fostering a learning environment that supports students' diverse emotional experiences. Nevertheless, it's crucial to note that while emotional expressions significantly impact cognitive engagement, they are not the sole determinants, and multiple factors contribute to the complexity of student engagement during problem–solving tasks.

These studies offer exciting prospects. The research should delve deeper into developing automated facial recognition algorithms tailored explicitly for educational contexts, thereby enhancing the understanding of emotions in educational settings. Efforts to address the scalability and efficiency of real–time facial expression analysis in educational settings should take center stage. The technical challenges related to analyzing multiple students' facial expressions simultaneously need careful consideration. The findings of this literature review offer valuable insights into teaching practices. Understanding the nuanced relationship between students' facial expressions and cognitive engagement can guide educators in creating more effective and tailored learning environments. Teachers can implement targeted interventions and adjustments in their teaching methods and by integrating emotional considerations into curriculum design and teaching strategies can foster a supportive learning atmosphere that addresses the diverse emotional experiences of students, ultimately enhancing their overall academic outcomes.

Further in future studies research should evolve towards a more nuanced approach to understanding students' emotional states. Instead of simply categorizing emotions as positive or negative, investigations should delve into the complexity of emotions such as confusion, which explore their potential benefits for learning. This could enable the development of emotionally adaptive learning environments that enhance student engagement and performance, thereby shaping online and interactive education. Longitudinal studies can illuminate how emotions evolve over–time and their long–term impact on academic trajectories, thereby shaping more effective and emotionally aware educational strategies. Additionally, the development of comprehensive dashboards for educators to effectively use this technology is a promising endeavor that could enhance non–face–to–face education monitoring. Balancing imbalanced data issues and improving the accuracy of training models should be a priority.

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