Application of Facial Emotion Recognition in Teaching-Learning Process for Quality Assessment and Enhancement

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ABSTRACT
The existing literatures based on AI- facial emotion recognition (FER) presents a challenge for non-specialists, necessitating a collaborative inter-disciplinary effort to establish a comprehensive framework that enhances comprehension of this new technology and its implications for the end-users. Prevailing categorizations principally revolve around methodological, implementation, and analytical aspects, along with limited attention to its educational applications as well as user-centric perspectives. This current study primarily focuses on potential educators who prefer to work upon FER tools. It introduces a threefold classification of these educators, based upon their orientation, context, and preferences, drawing from established taxonomies of affective educational objectives and relevant theoretical foundations. Also, this research systematically gathers and categorizes the various FER solutions documented in the literature. This work holds significance for advancing the comprehension of the interplay between educators and FER technology among proponents, critics, and end-users.

Keywords
Facial emotion recognition, FER in education, FER teacher users

1. INTRODUCTION
Facial emotion recognition (FER), identical with terms like facial expression recognition and facial affect detection, represents a technology or methodology which is designed to identify emotional cues conveyed through facial expressions. In other words, FER functions dually: it magnifies visual facial details alike to a magnifying glass or binoculars while also serving as a translator, converting facial descriptors from mathematical language into a more accessible format. By augmenting human innate abilities to perceive and analyze facial features, FER technology unlocks a broad spectrum of applications. The academic discourse on the utilization of automatic facial emotion recognition in the realm of education henceforth referred to as "FER" traces its origins, perhaps, to the work of [1]. Just as some educators, observe their students' facial expressions to formulate preliminary hypotheses regarding the teaching-learning process, a FER system can similarly "observe" students or their recorded interactions, collecting and processing data related to facial expressions. The requisite technology is presently available, but the standards governing its application remain in development.

The proclamation is that a section of the students should undergo FER experimentation without a clear declaration of whose effectiveness it enhances, to what extent, and through what means, is viewed as insensitive by critics of this approach, as indicated in references [2, 3, 4]. Conversely, criticizing FER without specifying the precise areas of concern appears unsuccessful. Existing studies on FER in educational contexts are often characterized in terms of technology types and/or applications. This study introduces a novel dimension by introducing the category of "users" to draw attention to the diversity of teacher-user profiles, their distinct needs, and preferences. These profiles are determined based on established educational theories and related disciplines.

3. Literature Survey
Many promoters of Facial Emotion Recognition (FER) propose that FER-generated feedback pertaining to student affect could serve as the foundation for educators to implement personalized and/or general interventions, as evident seen in references [6, 7, 8, 9, 10, 11]. In a related vein, reference [12] theorized that "academic emotions," defined in accordance with the framework by [5], could be discerned through machine analysis of a student's facial expressions. Subsequently, a FER system was developed in this context, supposedly capable of identifying these academic emotions by employing a model designed for the continuous tracking of emotional facial patterns.

The assumption that academic emotions can be automatically detected has even led to calls for the creation of facial expression databases specifically focused on academic emotions. An illustrative instance of this is the DAiSEE database, which has apparently been employed in seven different studies [14]. Researchers following to this assumption appear to draw parallels between [13]'s psychological methodologies for evaluating academic emotions and distinguishing them from more general emotions, and the mathematical methods of observation and analysis typically employed in FER.

Bloom's work [16] has elucidated the distinction between the cognitive and affective domains of educational objectives, emphasizing a hierarchical range wherein the latter occupies a lower position compared to the former. Krathwohl's affective taxonomy [17] delves into objectives characterized by qualities such as interest, attitudes, values, appreciation, and adjustment, with their assessment often relying on questionnaire-based strategies.

The initial affective taxonomy established by Krathwohl et al. has not only served as a source of inspiration but has also stimulated numerous researchers to develop additional taxonomies [18, 19, 20], along with related classification systems [21, 22]. Among these various affective taxonomies, Krathwohl's framework remains the most comprehensive, despite its acknowledged limitations. One notable limitation relates to the challenges in operationalizing objectives expressed in terms of values, attitudes, and similar constructs, making the taxonomy more suitable for curriculum development rather than instructional planning. Another limitation arises from the complexities inherent in distinguishing and differentiating between the various categories, a point raised by the authors themselves. Some researchers have observed that Krathwohl's affective taxonomy heavily draws upon behaviorist principles, such as the division of affective activities into categories like "receiving" and "responding" [23]. Additionally, it has been noted that this taxonomy concentrates on internal constructs, which contrasts with behaviorism's emphasis on observable behaviors [24]. Despite being admittedly broad, abstract, and limited in scope, Krathwohl's taxonomy continues to serve as a pivotal reference in the domain of educational objectives related to affect.

John Dewey insight-fully commented that interest possesses emotional, active, and objective facets, with its core concept revolving around active engagement, absorption, or complete involvement in an activity due to its perceived value [25]. In essence, when describe a student as "interested," it signifies that the student is actively engaged by something of personal interest.

[26] Further, underscores that interest serves as an indicator of emotional engagement. While Dewey acknowledges that interest does not necessarily equate to engagement, Renninger suggests that emotional engagement tends to accompany any genuine interest. Complicating matters further, [27] competes that engagement becomes possible only when interest is present. This study acknowledges the possibility that a student can genuinely be interested in something without necessarily being actively engaged in it, discounting the notion of "emotional engagement" as passive behavior, potentially imperceptible and, therefore, insignificant for the intended purpose. Furthermore, it recognizes that a student's engagement does not invariably indicate interest, as it may result from extrinsic rather than intrinsic motivation, where the student's actions may be driven by desires unrelated to learning, which is an aspect that a machine cannot discern. Finally, this study aligns with [17]'s perspective that genuine interest, marked in Krathwohl's affective continuum by the transition from passive to active responses, might be obvious through a combination of FER techniques and teacher observation, whereas genuine engagement, situated beyond subcategory "3.3 Commitment," may prove to be elusive.

2. METHODOLOGY

Describing the relationship between FER (Facial Emotion Recognition technology) and potential teacher-users is a complex effort, necessitating an interdisciplinary understanding bridging the realms of exact science and art. Compounding this complexity is the scarcity of established methodological models for such research. To conclude this investigation and provide direction for those embarking on similar pursuits, it has chosen a categorization approach, recognizing that the task is not insurmountably sophisticated.

The identification of distinct categories is fundamental in the realm of knowledge. The chosen method involves an extensive review of existing literature, aligning with the approach of integrating underlying principles and combining themes while structuring and categorizing in a meaningful manner. This methodology serves the dual purpose of systematic deduction of essential concepts and the creation of a structured, cohesive categorization framework in intellectual discourse.

The extensive literature review has simplified the identification of pertinent criteria, factors, and gaps in prior categorizations related to FER technology and applications. In this study, extend this categorization to encompass FER users, particularly focusing on FER teacher-users. Previous categorizations in this study were centered on classifying FER based on specific technological or application-related criteria. For instance, established a "methodology" category to group FER solutions characterized by their technological attributes, and organized tools with comparable technological frameworks or mechanisms within this category. Similarly, formed an "applications" category to represent FER solutions tailored for specific educational purposes, which were further structured into subcategories such as student engagement assessment, student interest detection, and student attention surveillance, among others. However, these categorizations primarily served as compilations of classes readily available in the literature and thus were more appropriately positioned. As previously mentioned, categorization approach surpasses two main criteria, introducing a novel category dedicated to the users of FER technology, with a specific emphasis on teacher-users. By sorting tools into this user-centric "users" category and acknowledging various user subcategories, including teachers, education administrators, parents, students, and researchers, it can be differentiating tools that cater to diverse user needs and preferences.

Ultimately, this study refines its focus on a significant subset within the user subcategories, explicitly teachers, further classifies them based on theoretical traditions in education and related fields.

3. MODEL ANALYSIS

Understanding user needs is dominant for the success of any automation system, and yet both supporters and critics of Facial Emotion Recognition in Education have overlooked two fundamental inquiries:

a) What categories of FER users exist within educational backgrounds?

b) What are the necessities and demands of FER end users?

This section endeavors to address these inquiries through a categorization effort aimed at assisting those engaged with FER. It serves to define the distinction between teacher-users and non-teacher users while providing clarity on the assorted approaches educators adopt in detecting student emotions through facial expressions.

The objective of presenting a schedule of potential FER users extends beyond contextualizing the focus on teacher-users. It also lays the foundation for user-centered FER design thinking processes and standardization endeavors. This citation provides a broad overview of the primary potential categories of FER users, without examining into their specific particulars, needs, or preferences. The order of presentation is not indicative of priority, and it does not aspire to encompass all conceivable categories of FER users. Moreover, this paper does not aim to delve into specific subcategories or furnish exhaustive explanations of user needs for each group within this straightforward list.

A. Teachers

B. Parents

C. Students
D. Researchers
E. Evaluators
F. Psychologists
G. Education board representatives
H. Policy makers
I. School administrators
J. Special education professionals
K. Teacher trainers
L. Educational technologists
M. Counselors
N. Curriculum designers
O. Talent scouts

Neglecting the foundational step of identifying and considering users, as emphasized in innovation creation [27], in pursuit of reporting favorable outcomes and advancing the state-of- the-art, might be a common practice within computer science research. However, it may not always align with best practices. Particularly in the realm of educational technology designed for teachers, there are two predominant schools of thought, albeit with nuanced distinctions. These can be categorized as follows, as the human-vs-user-centered framework proposed by [28] does not appear to be a suitable fit.

Creating New (Non-Human) Teachers: This category encompasses endeavors to develop technologies such as intelligent tutoring systems, adaptive learning platforms, virtual or augmented reality solutions. These innovations are aimed at potentially replacing human teachers or reducing their role to on-site support [8, 29]. This raises questions regarding whether individuals overseeing these systems can still be considered "teachers." Often, technologies falling under this category do not necessitate a user-centered design, leading to rapid development that may outpace research on user needs.

Enhancing (Human) Teachers: This category focuses on technologies designed to improve the capabilities and performance of human teachers. For example, Facial Emotion Recognition in Education, speech recognition tools, eye-tracking systems, data analytics platforms, and AI-based assessment tools. FER, often referred to as "for teachers" [14, 15, 31], should not be perceived as a universally applicable tool "for teachers" in a general sense. Instead, it should be closely linked to specific descriptions of particular teachers or groups of teachers. This distinction carries significant implications, as it affects the overall understanding and discourse on the subject.

To address the challenge of terminology, some have resorted to estimating teacher quality, referring to "good" teachers, as if there were a universally agreed-upon definition of what constitutes a "good" teacher. In earlier scholarly works, education researchers [32, 33] employed specialized terms:

a) "Intellectual instructors" to describe teachers focused on cognitive teaching objectives.
b) "Sentimental instructors" to denote teachers concerned with students' emotional and affective development.

However, there have been limited efforts to introduce new terminology for these teacher types in recent literature. This could be attributed, at least in part, to the diminishing emphasis on affective objectives, as noted by Krathwohl, and the enhanced shift towards cognitive objectives over the years.

4. CONCLUSION

This paper has demonstrated that specialized knowledge within the domain of computer science can be effectively communicated to those outside the field by delineating its practical applications and technological foundations. Additionally, it has highlighted several misconceptions that have diverted the focus of Facial Emotion Recognition in Education research away from educators. In an effort to rectify this, the paper has proposed a comprehensive categorization of teacher-users based on their teaching orientation, circumstances, and preferences. This categorization further refines teacher-users into 96 distinct categories and subcategories, each characterized by unique attributes. Teachers and other potential users can reference these classification frameworks to gain a deeper comprehension of FER technology and its applicability in education, as well as to ascertain their specific user requirements. The introduction of the "teacher-users" category also enables developers and proponents to develop a more comprehensive perspective of teachers as potential users of FER technology.

This work may also prove valuable for reviewers and critics of FER. However, it is important to acknowledge certain limitations. The categories presented herein are primarily aligned with a single taxonomy of affective educational objectives. Furthermore, there are examples where speculation and argument have taken precedence over solid theoretical foundations and empirical evidence in studies related to affective educational objectives, including those that have informed this study.

Assumed the relative scarcity of FER technology in educational settings and the limited availability of empirical data for analysis, this paper serves as an initial exploration into the relationship between FER and potential teacher-users. The proposed categorization system will require validation through comprehensive coverage of teacher characteristics, case studies, and data on teacher experiences with FER technology as such information becomes accessible. As analytical models of affective educational objectives become more intricate and FER technology advances, the classification schemes will necessitate revision and expansion.

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