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AI-Based Facial Emotion Recognition Solutions for Education: A Study of Teacher-User and Other Categories

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Abstract

Existing information on artificial intelligence (AI)-based facial emotion recognition (FER) is not easily comprehensible by those outside the field of computer science, requiring cross-disciplinary effort to determine a categorisation framework that facilitates exploration of the impact this technology has on users. Most proponents classify FER in terms of methodology, implementation and analysis; relatively few by its application in education; and none by its users. This paper is concerned primarily with users of FER for education, particularly teachers. It proposes a three-part classification of these teachers, by orientation, condition, and preference, based on theoretical traditions in educational psychology and philosophy, as well as on teacher surveys. It also compiles and organises the types of FER found in or inferred from the literature into *technology* and *applications* categories, as a prerequisite for structuring the proposed *teacher-user* category. This work has implications for the understanding of the relationship between teachers and FER among its proponents and critics, as well as for education practitioners.

Keywords: Facial emotion recognition, AI in education, AI teacher-users, Computer vision in education.

1. INTRODUCTION

The overwhelming bulk of literature about artificial intelligence (AI) in schools is about the impact of AI on students. The very idea that there is a question about AI effect on teachers is largely unexplored. For instance, since the beginning of the Artificial Intelligence in Education series from Springer's Lecture Notes in Artificial Intelligence, on average, the word ”teacher/s” counts over nine times less than the word ”student/s”, as if teaching and learning have lost touch with each other. This study focuses on teachers as AI users, distinguishing from the outset between the teaching *art* and the teaching *technique*. The former, unlike the latter, is not supported by mechanistic constancy and ratiocination, but rather by improvisation and sub-rational expedients, which is why formal education depends upon teachers, not machines. Because the art of teaching, like that of parenting,

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involves far more emotions than we realize [1], it remains uncertain whether humans or machines can truly be trained for it.

Although numerous machines can and do perform teachers' roles in terms of teaching techniques and evaluating student cognition [2], existing "emotional" machines designed to replicate elements of the teaching art act like sensory and analytic "prostheses" [3], for teachers, rather than as functional replacements. This paper is concerned with one subset of these tools for teaching art, Facial Emotion Recognition AI (FER).

Facial emotion recognition, facial expression recognition, facial affect detection etc. are terms often used interchangeably to refer to a technology or methodology designed to detect sentiment cues from the face. In plain terms, on the one hand, FER amplifies visual details just like a magnifying glass or binocular, and on the other, it acts as a translator, converting facial descriptions from mathematical language into words. By enhancing human natural ability to recognise and analyse facial characteristics it opens up a wide range of applications such as emotion-aware technology, personalized user experiences, mental health monitoring, and, in the context of education, automatic attendance [4], and adaptive learning/teaching [5]. The fact that human bodies have greater appearance variations and occlusions than faces, may be one reason why there seems to be a greater interest in facial recognition rather than that of the whole body [6]. Research on FER in education begun perhaps with [7], and advanced rapidly. As when some teachers, though not all, observe their students' facial expressions to formulate a provisional hypothesis of the teaching-learning outcome, so a FER system can now "watch" students, or recordings of them, collecting and processing facial expression-related data. The technology needed is already in place, but standards are not, hence the need to understand its impact on users.

Studies on FER in education, as far as examined by this study, are characterised in terms of technology *types* and/or *applications*. This study introduces the category of *users* to call due attention to variations in teacher-user orientation, i.e. teacher types based on teaching; condition, i.e. teacher needs as per the requirements or restrictions of the job; and preference, i.e. teacher wants. These variations are determined based on established theories in educational psychology and philosophy of education, as well as on teacher surveys. The main contribution of this paper is a categorization of FER teacher-users (whether present or prospective).

The structure of this paper is organized into seven sections. The Literature Review section focuses on the relations between: a) student face and learning; b) emotions and learning; and c) FER and student emotions. The Theoretical Framework section presents the education-related theories guiding this study, followed by a section on Methodology, which includes the organizing of existing *technology* and *application* categories of FER, as well as the teacher survey results which served as materials for the proposed classification. The section containing the new *teacher-user* category unfolds after that, followed by Discussion and Conclusion.

2. LITERATURE REVIEW

This section reviews related work that shed light on several fundamental questions prudently avoided in the literature about FER in education.

2.1 The Student Face and Learning

Question #1. What is a "learning" face?

Some of the most erudite teachers in history, such as Pythagoras and Socrates, are known to have taken student physiognomy very seriously in distinguishing those who *can* learn from those who cannot [8]. However, no equivalent records exist about teachers' efforts to identify students who *are* learning from those who are not. In recognizing, for instance, that someone is in pain, health professionals consider the facial expression a more reliable source of information than a patient's verbal account of the pain [9]. While the recognition of a "suffering" face and that of the "learning" face may be related, no studies were found to either define a "learning" face, or to ascertain its distinctive features.

On grounds of logic, because everyone has facial habits and characteristics, one can make better sense of emotions on a learner's face *after* becoming familiar with the framework of that face and with the ways in which that framework is used when learning. A contraction and furrowing of the brow may be:

a) a sign that the learner is experiencing an emotion (concentration, confusion, anger etc.), or
b) simply a personal habit one needs not explain.

2.2 Emotions and Learning

Question #2. What emotions are compatible/incompatible with learning?

First, despite the many theoretical propositions suggesting that positive emotions increase the propensity for learning [10–16], there is no criterion whereby some emotions are considered conducive to learning and others not. A grieved student's desire to learn may be at its apex, and a visibly happy student may fail to focus on learning. Pekrun, one of the most cited scholars in education-related FER literature, remarked that "simplistic conceptions of negative emotions as bad and positive emotions as being good should be avoided because positive emotions are sometimes detrimental and negative emotions such as anxiety and shame beneficial." [11]. Secondly, there are criteria by which some emotions are deemed desirable or undesirable in schools. For instance, there is obviously something emotionally wrong with a student crying in school, just as it is inappropriate to burst into laughter during a class, if nothing is amusing. However, unless behavioural correction, psychological therapy etc. are included the education service, educators are not strictly and directly concerned with student conduct, depression, maladjustment etc.

2.3 FER and Student Emotions

Question #3. How can machines distinguish general emotions from "academic" emotions on student face?

Student affect can be related either to a general emotional state, or to an emotional response towards the educational content. Teachers whom [17], might call "good" practitioners of the teaching art, may intuitively perceive or infer the difference between the two emotional profiles through subconscious processing of accumulated experiences. However, the present study has found no established ways of making the distinction between general and particular emotions accessible from a mathematical standpoint so that automated recognition can be facilitated by machines.

Many FER proponents suggest that FER-generated feedback on student emotions can serve as basis for teachers to implement personalised and/or generalised interventions [18–23]. Lin S-Y et al,'s [24], presupposed that ”academic emotions”, as defined by Pekrun R, et al. [11], can be recognized on a student's face by a machine, and went on to develop a FER system that reportedly identifies such emotions of students using a model for continuous facial emotional patterns.

The assumption that academic emotions can automatically be detected led to the creation of databases focusing on ”academic emotions”. One example is DAiSEE, reported to have been used in seven studies [25]. Researchers who work with this assumption seem to equate Perkun's psychological methods of measuring academic emotions [26], and differentiating them from general emotions using mathematical methods of observation and analysis used in FER.

3. THEORETICAL FRAMEWORK

While student cognitive behaviour is considered public matter, the affective one is deemed private. This is one reason why, despite undeniable affective implications of all teaching and learning, typical schools are only preoccupied with the evaluation of cognitive educational objectives (testing knowledge), relegating the evaluation of affective educational objectives (testing emotions) to the status of a teacher's hobby, which there is no responsibility to expend public resources on. Another reason is that, unlike cognition, which is adapted to quantitative analysis, measuring student affective achievement is difficult, whether the method is scientific or not.

3.1 Affective Educational Objectives

Bloom et al. [27], brought out the distinction between cognitive and affective domains of educational objectives, pointing to a scale of consciousness on which the latter is positioned lower than the former. Krathwohl et al.'s affective taxonomy [28], deals with objectives expressed as interest, attitudes, values, appreciation and adjustment, which are evaluated using questionnaire strategies. Given the wide meaning of these terms, they were encompassed into ranges of behaviour and ordered into five categories.

1.0 Receiving
2.0 Responding
3.0 Valuing
4.0 Organization
5.0 Characterization by a value complex

The lowest level in the affective continuum is characterized by a covert emotional state in which the student is attentive and passively ”receives” the teaching. *Acceptance* is an overt and active state marked in the ”responding” level. At the third level, the student already pursues the subject or activity. At the fourth and fifth levels, the behaviour is described as attitudes which form a structure within a network of values. In the range of meaning (Fig, 1), *interest* can be located between the starting phase of ”1.0 Receiving” and the middle of ”3.0 Valuing”. *Appreciation* overlaps with *interest* to a greater extent than *attitudes*, *values* and *adjustment*, which are marked at higher levels in the taxonomy. Krathwohl et al. do not categorise emotions as more or less conducive to learning, but do remark that the emotional component is inconspicuous at the lowest levels of the taxonomy, but prominent at the middle levels, and decreased towards the top [28]. In essence, *interest* and *appreciation* are considered more detectable than the other emotional states, making them particularly relevant for the study of FER in education. Krathwohl et al.'s, FIGURE 1 [28], depicts where student interest, appreciation and the other goals are located.[1]

The original affective taxonomy elaborated by Krathwohl et al. inspired and provoked numerous researchers to produce other such taxonomies [29–31], and related classifications [32, 33]. Of all the affective taxonomies noted, Krathwohl's remains the most prescriptive and its limitations are thoroughly recognized by the authors. One such limitation is that the objectives expressed in terms of values, attitudes etc. are not well operationalised and thus the taxonomy is recommended for curriculum construction rather than instruction planning. Another limitation stems from the difficulties that authors admit facing when making the distinctions between and among categories. Some critics of Krathwohl's taxonomy pointed out that the concepts used, such as the division of affective activities into ”receiving” and ”responding” categories, is strongly based on behaviourism [34]. Others remarked that Krathwohl's affective taxonomy focuses on internal constructs, which goes against the behaviourist focus on observable behaviours [35]. Although admittedly too general, abstract and limited in scope, Krathwohl's taxonomy remains the preeminent framework in the affective domain of educational objectives.

3.2 *Student Engagement* as an Affective Learning Objective

In recent years the word ”engagement” gained popularity in FER-related research and, generally, in works related to the affective domain of educational objectives. Fredricks JA [36], drawing on Bloom et al. [27], and Krathwohl et al. [28], identified three dimensions to student engagement:

a) ”behavioural engagement”, which implies that the student is present, attentive, participatory — similar with the first phase of Krathwohl's ”1.0 Receiving” category, where interest may be covert, extrinsic, or passive (such as when a student is: either not necessarily interested in what is being taught, but wishes to make a good impression, obtain praise, high grades, degrees etc.; or ready to become interested in the subject or activity, though not interested yet);

b) ”emotional engagement”, characterised by affective reactions like interest, enjoyment, sense of belonging — corresponding with Krathwohl's ”2.0 Responding” and ”3.0 Valuing” categories, where interest is overt, active and intrinsic (as when a student is more interested in the educational content than in getting good grades); and

[1] A replication of this figure was omitted to avoid truncation.

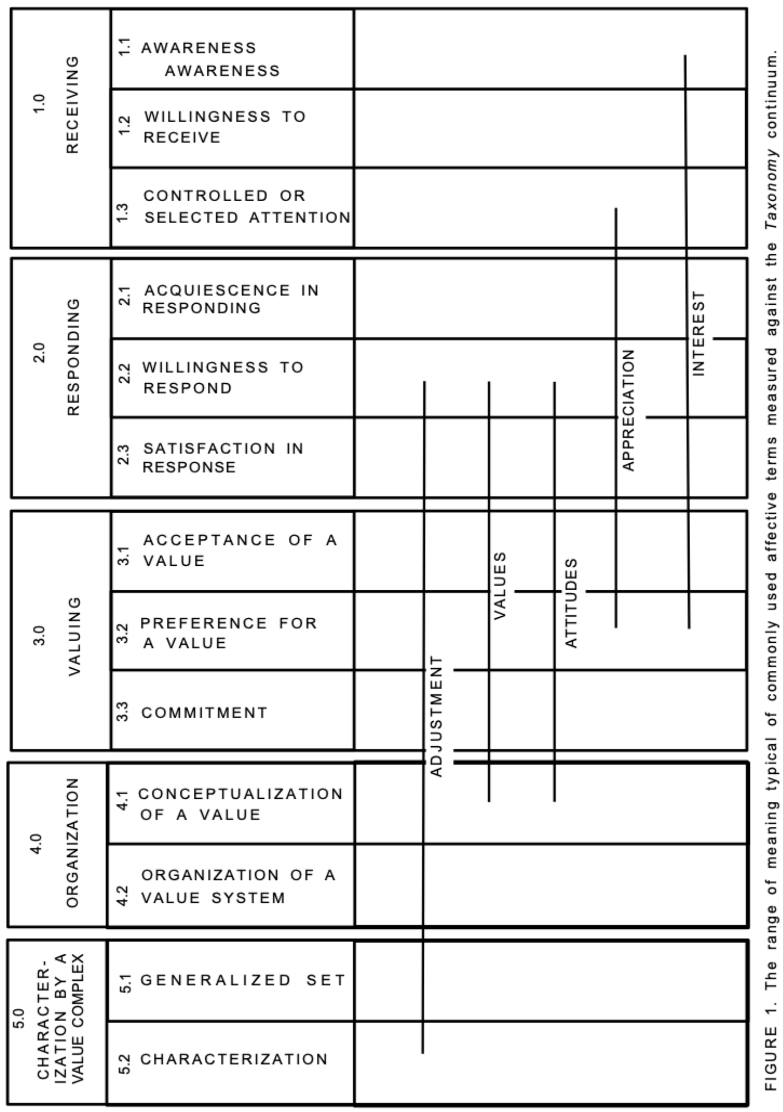

Figure 1: The range of meaning typical of commonly used affective terms measured against the Taxonomy continuum. [28, p.37] © Pearson.

c) ”cognitive engagement”, describing students invested in learning and willing to go beyond requirements — Krathwohl et. al recognize that the last two categories ”4.0 Organization” and ”5.0 Characterization by a value complex” in his affective taxonomy are, at least in part, cognitive (student conceptualizes the value to which he previously responded, and this value is integrated and organized into a value-system which may come to characterize the student as an individual).

3.3 *Student Interest* and *Student Engagement*

John Dewey remarked that *interest* ”has its emotional as well as its active and objective sides” and that ”the root idea of the term seems to be that of being engaged, engrossed, or entirely taken up with some activity because of its recognized worth” [37]. In other words, to say that a student is ”interested” means that the student is either engaged, absorbed, or consumed by whatever is that interesting to that student. Ann Renninger wrote: ”Interest is one indication of emotional engagement” [38]. While Dewey acknowledges that interest may not necessarily imply engagement, Renninger seems to suggest that whenever someone is interested in something, emotional engagement is always present. Freeman’s assertion that ”engagement is only possible when interest is present” [39], further complicates matters.

This study admits that a student can be genuinely interested in something without being actively engaged in it, and does not take into account ”emotional engagement”, which it regards as passive behaviour, likely undetectable and, thus, irrelevant. It also considers that engagement on the part of a student does not necessarily indicate interest, as it may occur when the student’s motivation may be extrinsic, rather than intrinsic (i.e. student behaviour may be influenced more or entirely by desires other than learning), a distinction that a machine cannot make. Finally, this study takes Krathwoh et al.’s, view that *interest* is a primary educational objective, and argues that while genuine interest, marked in their affective continuum by transition from passive to active responses, might be detected using a combination of FER techniques, including methods such as reasoning about transition between facial expressions proposed by [40], coupled with teacher vigilance, genuine dedication (located past subcategory ”3.3 Commitment”) may not.

3.4 *Verbal Inquiry* and *Visual Detection* as Student Affect Assessment Methods

Theories on student affect such as those of [28], [38], [11], etc. typically rely on *asking* students questions related to their feelings. In fields like psychiatry and criminology, this method is called ”verbal inquiry” to contrast it with ”visual detection”. The method of asking is practical when the subjects *are not* well known. If the subjects *are* well known, observation is natural. A distinction can thus be made between:

a) ”Detective” teachers — Teachers who know their students very well would not need to ask them questions about their feelings as much as those who just met their students, and are likely to try and detect their students’ emotions (which students are free to attempt hiding).

b) ”Inquisitive” teachers — Teachers who are not (yet) well acquainted with their students may rely less on visual detection and more on asking students for information (which students are under no obligation to supply).

3.5 Student *Attention*, *Interest*, *Satisfaction* and *Emotional Intelligence* in the Context of Detection

Four aspects extracted from Krathwoh et al.’s work [28], are especially relevant in the context of FER for education:

a) *Student attention* is *not* an indication of genuine interest in the educational content.

The ”1.0 Receiving” category is characterised by an ”extremely passive position or role on the part of the learner” whereas subcategory ”2.1 Acquiescence in responding” is considered ”the first level of active responding after the learner has given his attention”. Many approaches [41–44], to testing student affect, both traditional or AI-based, focus on seeing that each student is attentive or ”receiving” the teaching, to which the present study adds that *receipt* does not constitute *acceptance*. The student may examine the received content at a later time and decide then whether to accept or reject it. Thus, *acceptance* goes beyond *receipt*, and it is the prerequisite for any advancement from the ”1.0 Receiving” level to the level in Krathwohl's taxonomy, which a student reaches after transitioning from a passive to an active stance. Acceptance or refusal is conditioned by manner and time, variables with which student's affective state can be more objectively tracked and measured.

b) *Student interest* is considered overt emotion, thus detectable only before *values* become internalised.

The range of overt emotions coincides with that of interest, both being commonly observed at the middle levels of the affective continuum, which denotes the probability for detection of a student's interest, or readiness to become interested. While a student's interest may occur in the ”1.0 Receiving” level (i.e. the student giving passive attention to the subject), emotion is considered covert and undetectable at that level. Emotion decreases as interest becomes internalized, and may not be detected beyond the ”3.0 Valuing” level. If the idea that interest stops occurring when a student becomes committed to a particular subject seems baffling, it is because ”interest” is understood as a process rather than as an outcome.

c) *Student satisfaction* may or may not be detectable.

In Krathwohl et al.'s words ”Emotional responses, even those that signify satisfaction and enjoyment, may not necessarily be overtly displayed.”

d) *Emotional intelligence* is considered covert emotion, thus undetectable

According to Goleman, emotional intelligence includes one's ability to control and motivate oneself, zeal and persistence [45], seems to be located along categories ”4.0 Organization” and ”5.0 Characterization by a value complex”, which evaluate affective objectives that ”appear to require, at the very least, the ability to (...) comprehend” [28].

4. METHODOLOGY

Describing the relationship between FER and teacher-users is complex because it requires a kind of interdisciplinary understanding that spans the boundaries between an exact science and an art. The fact that there are few methodological models for this kind of research only adds to the challenge. For the purpose of concluding this investigation and offering further direction for those engaging in a similar undertaking, the approach chosen is *categorisation*, recognising that the task is not so complex as to defy it.

The discerning of types is one of the most fundamental branches of knowledge. The method employed here involves on the one hand, engaging with literature and organizing existing FER categories, and on the other, collecting essential data from teachers. Being merely a compilation of classes, the majority of which can be found in literature, and a synthesis of primary data, their presentation seemed more fitting in this section on ”Methodology” because they serve as materials for the development of the newly proposed *teacher-user* category. This approach aligns with that of incorporating underlying principles and unifying themes while organising and categorising in meaningful ways. It is designed to satisfy the need for systematic and rigorous deduction of pure notions, as well as structured and cohesive categorisation method.

4.1 Organizing Existing FER Categories

The student’s face has been a repository of emotions pertaining to educational achievement since the beginning of teaching, but until the advent of FER it has hardly been considered analytically decipherable. Recent studies in affective computing and AI propose a variety of solutions for this art of detection, or of guessing, whichever may be the case. A variety of works on education-related FER can be found in both scholarly and scientific literature, varying, as far as is known, only in terms of *technology types* and *application*-related criteria. In this study, these two categorisations took place when a FER was recognized as belonging to a class based on certain technology-related or application-related criteria. For instance, when a FER is described on the basis of its methodology, a category ”methodology” is established as the class encompassing FER solutions that share a description by their technological characteristics. Further categorisation allowed for grouping tools that utilize comparable technological frameworks or mechanisms. Similarly, for descriptions of education-related FER from the viewpoint of FER applications in education, another category ”applications” was formed, representing FER solutions that serve particular educational purposes, organised in subcategories, such as student engagement assessment, student interest detection, student attention surveillance [43], etc. This section organizes FER solutions in these two broad and predefined categories, recognising that the listing is by no means definitive or exhaustive, its purpose being solely that of expanding discussion about FER teacher-users, the meaningfulness of which is heavily dependent on understanding existing classifications.

4.1.1 Categorisation patterns by *technology type*

There are many different categorisation studies related to FER, in general, [46–55], and [25], reviewed FER for education, in particular. Because the technology behind FER is common to all sectors of application, the listing provided here makes no distinction between *FER* and *FER for education* in terms of the technology available. This categorisation is designed to help non-specialists navigate through existing and emergent types of FER, grouped into: methodology, implementation, analysis and ownership.

A. Methodology

A.1. Algorithms

A.1.1. Traditional machine learning pipeline

A.1.1.1. Pre-processing (face detection and localisation, dimension reduction and normalisation)

A.1.1.2. Feature extraction (e.g. local binary patterns (LBP), histogram of oriented gradients (HOG), facial landmark detection)

A.1.1.3. Traditional machine learning (e.g. Support Vector Machines (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), Gaussian Mixture Models (GMM))

A.1.2. Deep learning (e.g. Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM))

A.1.3. Decision fusion (e.g. combining results from multiple classifiers, weighted voting and probabilistic fusion)

A.1.4. Uncertainty estimation (e.g. confidence scores and uncertainty quantification, identifying ambiguous expressions)

A.2. Data

A.2.1. Data collection (e.g. in-laboratory, controlled settings, in the wild)

A.2.2. Data modality

A.2.2.1. Image/video capture hardware (e.g. webcams, smartphone, cameras, RGB/infrared/depth cameras, 3D scanners, eye-tracking devices, wearable devices)

A.2.2.2. Input data (e.g. image-based, video-based)

A.2.2.3. Dimensionality (2D, 3D)

A.2.3. Facial expression databases (e.g. CK+, JAFFE, AffectNet, RaFD, MMI, FER2013, TFD, Multi-PIE, SFEW, Oulu-CASIA, MUG, EMOTIC)

A.2.4. Synthetic data

A.3. Data anonymisation/encryption

A.3.1. End-to-end

A.3.2. Homomorphic

A.3.3. Secure multiparty computation

A.3.4. Differential privacy

B. Implementation

B.1. Connectivity (e.g. online, offline)

B.2. Integration (e.g. unimodal, multimodal)

B.3. Flexibility of model (e.g. adaptive, fixed)

B.4. Real-time processing (e.g. low-latency processing for real-time applications, optimization for resource-constrained devices)

B.5. Timing of analysis (e.g. real-time, post-analysis)

C. Analysis

C.1. Emotion interpretation

C.1.1. Categorical approach (e.g. isolated emotions, positive, neutral, negative)

C.1.2. Multiple dimensions (e.g. congregated emotions, arousal-valence)

C.2. Visualization (e.g. facial landmarks, heatmaps, AU activation maps, facial expression morphing, LIPnet, 3D facial models)

C.3. Duration of analysis (e.g. short-term, long-term)

C.4. Temporal context (e.g. static, dynamic, continuous/conditional monitoring)

C.5. Scope of analysis (e.g. localized, global, hybrid)

D. Ownership and access (e.g. proprietary, open source)

Obviously, the choice between FER technological approaches ultimately depends on resources and requirements.

4.1.2 Categorisation patterns by *technology application in education*

Although the present study did not identify any FER taxonomies based on technology application in the field of education, most proposals for FER in education, mentioned earlier in this paper, are accompanied by statements regarding the application for which they were designed. It is beyond this paper's scope to provide an exhaustive list of all possible types of FER education-related applications, the purpose being simply to contour the application grounds for FER in the realm of education. The contrasts listed below are patterns found in or deduced from the literature, as well as models that are not covered by other studies, listed in no particular order.

A. Student target (e.g., individual, collective, selective)

B. Educational level (e.g., pre-school, primary education, secondary education, tertiary education)

C. Class format (e.g., synchronous, asynchronous, online, offline, hybrid)

D. Teaching/learning approach (e.g., traditional, interactive, adaptive)

E. Emotion focus (e.g., general emotions, learning-related emotions)

F. Affective objective (e.g., student discipline, attention, well-being, satisfaction, engagement, interest, emotional intelligence)

G. Content creation (e.g., emotion-driven content creation, curriculum customization, educational design / guidance)

H. Assessment improvement (e.g., assessment enhancement / accuracy / personalisation, traditional / adaptive assessment)

I. Various accommodation (e.g., support for special needs, inclusive education)

J. Adoption model (e.g., top-down, bottom-up)

K. User target (e.g., user-specific, generalized)

These categories collectively shape the decisions for applying FER in educational settings, considering the unique requirements and goals of each scenario.

As noted above, the categorisation approach in this study goes beyond these two stated or implied criteria, to introduce a new category dedicated, in general, to the users of education-related FER and, in particular, to teacher-users. When tools are sorted into this user-centric category of ”users”, by acknowledging the different users subcategories, such as teachers, education administrators, parents, students themselves, researchers etc., allows one to distinguish tools that cater to different user needs and wants. Finally, the study hones its focus on a single but significant subset within the user subcategories, *the teachers*, further classifying them based on theoretical traditions in education and related fields.

4.2 Synthesis of Primary Data From Teacher Surveys

For the purpose of this study a short survey was conducted on a sample of 80 diverse teachers from Japan, Romania and Zambia, ranging from elementary to university level, asking the following question:

”In your teaching practice, are you also interested in student affect (how a student feels about the lesson) or only in student cognition (how much knowledge a student acquired from the lesson)?”

Answer choice:

- Yes, I am interested in what the student feels about what I taught.
- No, I am not interested in what the student feels about what I taught. I am only interested in what he learnt from what I taught.

Only 3 teachers out of 80 answered ”No”.

The result of this micro-investigation supports the previously posited hypothesis that there are teachers who do not need or want to use a FER. This small finding alone implies that a top-down decision to adopt such technology may hinder teacher autonomy, face resistance, squander resources etc.

In the same survey, the following question was also asked:

”As a parent, would you agree to FER monitoring your child’s face in class?”

Answer choice:

- Yes.
- No.

34 out of 80 teachers answered ”No”.

Teachers who answered ”No: to this question may justifiably be considered, on the one hand, likely to reject FER on principle, and on the other, unlikely to assume the responsibility of using FER in their teaching practice.

The same short survey also asked the following question:

”As a teacher would you choose to use FER or would you rather rely on your natural ways of detecting emotions on your students’ faces?”

Answer choice:

- Yes, I would use it.
- No, I would rather rely on my natural ways to detect emotion on each student face.

28 out of 80 teachers answered ”No”, which indicates on the one hand, that most teachers value the detection of emotions on their students faces, and on the other, that they would be willing to adopt tools that can assist this detection.

5. NEW CATEGORISATION

Although understanding user needs is critical to the success of all automation, both proponents and critics of FER in education seem to have omitted two fundamental questions:

a) What categories of FER-users exist in educational settings; and
b) What are the needs of the FER end user.

This section presents a categorisation attempt intended to provide general help to those concerned with FER in education, by highlighting the distinction between teacher-users and non-teacher users, as well as making better sense of the variety of teacher approaches to visual detection of student emotions from the face.

5.1 General Categorisation by *User Types*

The purpose of presenting a list of potential education-related FER users is not only to provide context for narrowing the focus down to teacher-users, but also incipient criteria for user-centred FER design thinking processes and standardisation initiatives. It is a broad overview of the main potential categories of FER users which may be conceived in ignorance of their specific particularities, needs and preferences. Neither is this listing in a particular order, nor does it purport to include all conceivable categories of FER users in educational settings. It is also beyond the aim of this paper to enter into specific subcategories or provide detailed explanations of user needs for each category in this simple 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. Counsellors
N. Curriculum designers
O. Talent scouts

5.2 Categorisation by *Teacher-User Types*

Teachers obviously teach differently, which is what the principle of teacher autonomy is built upon. One teacher's art of teaching is not (easily) reproducible, and any one art of teaching is not generally applicable. Ideally, before a FER is used in a school, it should be clear that teachers there would be willing, able and content using it. These personal and professional characteristics, to which hardly anyone draws attention in studies related to computers in education in general, and FER in particular, might be usefully classified based on teacher orientation, condition and preference (though some overlap), as follows:

A. Orientation

- A.1. Teaching philosophy
  - A.1.1. Teachers interested in student affect
  - A.1.2. Teachers not interested
- A.2. FER-related principles
  - A.2.1. Teachers who do not oppose FER
  - A.2.2. Teachers who do
- A.3. Opinion on automated FER methods related to education
  - A.3.1. Teachers who believe recognition of student facial emotions can be automated
    - A.3.1.1. Teachers who believe FER can work for all age/education levels of students
    - A.3.1.2. Teachers who believe FER can work only for some
      - A.3.1.2.1 Teachers who teach students in the age/education level range that they believe FER can work for

A.3.1.2.2 Teachers who do not

A.3.2. Teachers who do not believe recognition of student facial emotions can be automated

A.4. Ethical perspective

A.4.1. Privacy-oriented teachers

A.4.1.1. Teachers who believe data encryption methods can protect privacy

A.4.1.2. Teachers who do not

A.4.2. Transparency-oriented teachers

A.5. Attitudes on student affective response

A.5.1. Attitudes on education-related affective response from students

A.5.1.1. Student discipline-oriented teachers

A.5.1.2. Student satisfaction-oriented teachers

A.5.1.3. Student attention-oriented teachers

A.5.1.4. Student interest-oriented teachers

A.5.1.4.1. Teachers who work to elicit student interest in everything that is being taught

A.5.1.4.2. Teachers who work to elicit student passion for one or several subjects

A.5.1.5. Student emotional intelligence-oriented teachers

A.5.1.6. Student engagement-oriented teachers

A.5.1.6.1. Teachers interested in student (general) engagement

A.5.1.6.2. Teachers interested in student (intrinsic) engagement

A.5.2. Attitudes on student general emotional well-being

A.5.2.1. Teachers who believe that teacher intervention to improve student general emotional well-being is good

A.5.2.2. Teachers who believe their intervention to improve student general emotional well-being may do more harm than good

A.6. Teaching focus

A.6.1. Individual-oriented teacher

A.6.2. Collective-oriented teacher

A.7. Views on emotion classification and detection

A.7.1. Teachers who believe that categorical emotions (negative/positive, happy/sad etc.) are indicative of student affective state related to learning

A.7.2. Teachers who believe that emotional transitions (analysing congregated emotions) are more important

B. Condition

B.1. Familiarity with technology

B.1.2 Teachers who can use FER

B.1.2. Teacher who cannot

B.1.2.1. Teachers willing and able to learn

B.1.2.2. Teachers unwilling, but able to learn

B.1.2.3. Teachers unable to learn

B.2. Adaptability

B.2.1. Teachers willing and able to adapt to any FER

B.2.2. Teachers who need a FER to replicate, at least to some extent, their natural methods

B.2.2.1. Teachers willing and able to take part in FER personalisation

B.2.2.2. Teachers unable take part in FER personalisation

B.3. Adoption decision models

B.3.1. Teachers comfortable with top-down approaches to FER adoption

B.3.1.1. Teachers responsible for FER use

B.3.1.2. Teachers not responsible

B.3.2. Teachers uncomfortable with top-down approaches to FER adoption

B.4. Technical literacy

B.4.1. Teachers who can program FER (partially or entirely)

B.4.1.1. Teachers with FER ownership preferences (open-source or proprietary FER)

B.4.1.2. Teachers with technical preferences

B.4.1.3. Teachers with hardware preferences

B.4.2. Teachers who can use FER (by themselves)

B.4.3. Teachers who need support (occasional or permanent)

B.5. Familiarity with students

B.5.1. Teachers who know their students very well

B.5.2. Teachers who do not (yet) know their students very well

B.6. Teaching methods

B.6.1. Direct interaction (e.g. experiments, discussions, case studies, workshops, simulations, role playing)

B.6.2. Content delivery (e.g. lectures, presentations, reading, demonstrations)

B.7. Class format

B.7.1. Online (synchronous, asynchronous)

B.7.2. Traditional (conventional, flipped)

B.7.3. Hybrid (online, offline)

C. Preference

- C.1. Choice of emotion recognition methods
  - C.1.1. Teachers who choose to use FER
  - C.1.2. Teachers who choose to rely on their own traditional (natural) emotion recognition methods
- C.2. Disposition for adaptive teaching
  - C.2.1. Teachers willing and able to tailor educational experience for each student
  - C.2.2. Teaching unwilling
- C.3. Curriculum-related use
  - C.3.1. Teachers who intend to use FER feedback for curriculum adjustments
  - C.3.2. Teachers who do not
- C.4. Student assessment-related intent
  - C.4.1. Teachers who intend to include FER feedback in student assessment
  - C.4.2. Teachers who do not
- C.5. Feedback preferences
  - C.5.1. Teachers who prefer to receive feedback regularly
  - C.5.2. Teachers who prefer to receive feedback when significant change was detected.
- C.6. Non-affective objectives
  - C.6.1. Teachers who wish to use FER for student identification (for roll-call, exams etc.)
  - C.6.2. Teachers who wish to use FER for student surveillance
  - C.6.3. Teachers who wish to use FER for data collection
- C.7. Detection duration preferences
  - C.7.1. Teachers who prefer FER analysis at specific intervals
  - C.7.2. Teachers who prefer FER continuous analysis

A first conclusion that may be drawn from this classification is that, unless persuasion and/or training efforts are invested, teachers in categories A.1.1., A.2.1., A.3.1.2.2., A.3.2., A.4.1.2., B.1.2.2., B.1.2.3., B.5.2. and C.1.2. might not become FER users because they would not, cannot and/or prefer not to use FER in their classroom.

It is hoped that this long list would serve FER proponents in improving the quality of their proposals, FER critics to better assess the implication, and FER users to formulate more informed opinions and requirements.

6. DISCUSSION

The proposition that an element of a school population should be subjected to FER experimentation without declaring exactly whose efficiency it enhances, with what scope, and by what means, seems insensitive, to say the least, as many critics pointed out [56–58]. By the same token, to criticise FER without declaring what is expected of it, seems futile.

In subsection 2.3., this study pointed to the fact that it is unlikely that a FER can distinguish general emotions from learning-related emotions on a student's face. Let us, nevertheless, assume that it can. If a FER that can detect only general emotions on a student's face is used by teachers in schools, it follows that teacher-users are both willing and able to react to FER-generated negative feedback on student affect. In reality, however, the typical teacher is neither trained nor constituted as a mental health professional or as an entertainer. Teachers are concerned only with certain aspects of the personal and intellectual development of their students and, in that role, each student's general emotional state is a datum from which they start. It is neither a teacher's duty to change it, nor reasonable to attempt during teaching hours because it is not changeable within measurable time. Teacher intervention to change student general emotions, not only goes beyond the scope of standard education, but may also do more harm than good. Therefore, FER tools designed to detect general emotions may be more suitable for categories of users other than teachers.

Conversely, if a FER can detect student emotional reactions to the educational content being taught, i.e. *learning/academic emotions*, it follows that the machine-generated feedback ought to make sense to the teacher-users. Many teachers assume the moral duty to creatively intervene in order to elicit and/or maintain students' interest, cultivate their innate emotional intelligence etc., in freedom, by trial and error, rather than in textbook fashion or by imposition. Such teachers may find useful a FER that offers insight into student emotional responses, provided these are aligned with affective educational objectives that teacher-users themselves are familiar with. The details of these objectives vary with theoretical persuasions, teaching experiences, educational traditions in a teacher's country of origin, teacher's age etc.

Although FER users are generally presumed to be teachers, the envisioned model for FER adoption in educational settings is top-down, as if nothing could or should empower teachers to have, by their own accord, a FER in the classroom. This approach may have obscured the need for categorization by user types. If research on FER focused on user needs it may have escaped being ridiculed as "a solution in search of a problem" [59], or perceived as a monolithic top-down approach. In Japan, for instance, decisions on the adoption or rejection of AI in schools seem to have been taken without thorough consideration for or consultation with teachers [60]. The problem with the top-down approach is, first, that it takes the focus away from differences between users in general, and teacher-users in particular; and secondly, that it promotes a standardisation process which, by reducing the number of different tools used, in effect reduces the number of different arts of teaching. Unlike more limited forms of technology, AI is highly adaptable and can support as well as enhance teaching practice diversity.

The considerations above call on proponents of FER in education to consider:

a) acknowledging that the distinction between general and academic emotions can hardly be formulated as an algorithm;

b) declaring to which of the two broad and distinct streams of professional practice within schools (educational and non-educational) their FER applies; and

c) being guided less than some have been [24, 41–43, 46, 61–66], by oversimplifications which a machine translates into categories (such as *compatible with learning* and *incompatible with learning*) and more by empirical insights directly from education practitioners.

7. CONCLUSION, LIMITATIONS AND FUTURE PERSPECTIVES

If it is true that every human being has an intellectual appetite, then its discovery can be a crucial moment in one's life. This paper showed that knowledge specific to the field of computer vision can be made clear to outsiders in terms of both means (technology) and ends (application). It also identified a number of fallacies that have misguided education-related FER research focus away from teachers. In an attempt to provide remedy, it proposed a categorisation of teacher-users based on teacher orientation, condition and preference, which further classified teacher-users into 96 categories and subcategories, each with its contrasting characteristics. Teachers and other potential users, can refer to these classification schemes to better understand FER technology and its application in education, as well as determine their user requirements. The proposed "teacher-users" category can also enable developers and other proponents to gain a broader view of teachers as FER users. This work may also be of value for reviewers and critics of FER in education.

One limitation is that the categories presented herein are consistent mainly with a classical taxonomy of affective educational objectives. Another problem is that, in studies on affective educational objectives, including the ones which have guided this study, speculation and argument may take the place of sound theory and evidence. Because FER is far from common in schools, and empirical data for analysis is hardly obtainable, this paper could only provide a starting point for understanding the relationship between FER and teachers-users.

The proposed categorisation needs to be tested based on comprehensive coverage of teacher characteristics, case studies, and data on teacher experiences with FER, as they become available. The classification schemes need revision and extension as analytical models of affective educational objectives become more complex and the FER technology advances.

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