An overview of Affective Models and ICT in Education

Sotiria Foutsitzi
Cultural Technology and Communication Department,
University of the Aegean
Lesvos, Greece
sofout@aegean.gr

Stylianos Asteriadis
Department of Data Science and Knowledge Engineering,
University of Maastricht,
The Netherlands
stelios.asteriadis@maastrichtuniversity.nl

George Caridakis
Cultural Technology and Communication Department,
University of the Aegean
Lesvos, Greece
gcari@aegean.gr

***Abstract*— Emotion, human intelligence and learning have inextricable connections. Making sure learners' emotions are positive during the learning procedure can increase and optimize the learning outcome. However, until recently, cognition and emotion were viewed as two separate notions. Learning materials and pedagogical strategies focusing more on how to increase and sustain the volume of knowledge, rather than how to actively engage the learner, through positive and enjoyable learning experiences, were in the focus of attention. However, in the last years, the advent of a wide variety of learning (digital) resources, such as serious games, robots, mobile devices, virtual and augmented reality, has provided the means to involve the learner in more immersive and active contexts, that place engagement and human emotions in the centre of the interaction. Moreover, the advances in artificial intelligence are now allowing for a wide availability of instruments that allow for estimating emotions based on a plethora of means, such as facial expressions, heart rate measurements, digital log files, personality analysis. The above are leading to personalized learning that tailors the learning procedure to the (emotional and cognitive) needs of the individual learner. This paper is presenting an introduction to the role of emotion in educational settings and describes influential and promising emotional models. A brief overview of ways to infer emotions follows, while examples of works intended to make use of measured emotion in learning conditions is presented at the end of this work.**

Keywords*— *ICT in education, affective computing, emotional models, e-learning, emotion recognition, personalization

I. Introduction

Emotion recognition during learning has attracted the interest of many researchers in the last years. Beyond obvious emotion expressivity signals, such as facial expressions, body posture, and voice prosody, in affect recognition, various other information channels play a significant role. These are mostly related to the learner-learning material interactions, the relation between difficulty levels of the learning material and learner's competence, as well as further contextual information, that are very important in analyzing human affective cues and emotion during learning [1]. The final goal of analyzing human emotions during learning is the personalization of the learning procedure, a timely intervention of the tutor in the procedure and, certainly, a reassurance that the learner is engaged in the whole procedure of learning, with positive emotions accompanying learning. Making sure that the learner is in a positive mood and is experiencing positive emotions while learning has been shown to have significantly beneficial impact on the final outcome of learning [2]. The major objective of this paper is to study the role of emotion in Technology-Enhanced-Learning (TEL) systems, look into existing affective models in the area and present some typical state-of-the-art works that close the loop among emotion capture, emotion analysis, mapping on emotional models and personalization in learning.

Although human emotion recognition is a field that attracts a large amount of research for decades now, most studies are focusing on the 6 basic emotions proposed by Paul Ekman [3], especially when the application involves human emotion recognition facilitated by technology. Although this representation has a very significant advantage which relates to the fact that, the underlying emotional model can be met and perceived consistently across a lot of cultures in the world, many of the involved emotions have little relation with the educational process. For instance, emotions like disgust and fear are not met very frequently (if ever) when someone is learning. In contrast to the the above, emotional cues such as interest, flow, attention, boredom, confusion, frustration, are more related [4], [5]. For example, the Theory of Flow model [4] provides a framework linking experienced affective states and their intensity, with learner competences, experiences, and difficulty levels of an interaction. With the aid of this model, the learner or the tutor can explain affective experiences but, also, intervene in the procedure, with a final goal to perform those changes that will 1. Drive the learner towards experiencing more positive emotions and 2. Optimize the pedagogically optimal outcome. Besides, a lot of studies have highlighted the correlation between cognitive and emotional processes in the human brains. For example, in [6], the relationship between memory and emotion is analyzed. In the same research, Goleman states that stress, disappointment and worry have significantly negative impacts on the learning outcome, hindering the learner from absorbing and comprehending newly acquired knowledge. On the contrary, positive emotions and cognitive states (e.g. interest, enthusiasm, curiosity) are experienced when targets and challenges are achieved, while, in this manner, the student is encouraged for further deepening into the learning process. The connection between cognitive and emotional processes during the learning procedure, is an object of research for many researchers across the globe, coming from various disciplines, beyond only pedagogy and developmental psychology. Emerging subfields in computer science, for example, such as ICT in education and affective computing conduct research in the role of emotion, looking at its impact and analyzing phenomena from varying points of view [4], [5], [7], [8], [9], [10],[11].

While in traditional learning, seeing when a learner is in a negative emotional state is usually a straightforward process, followed by timely and, in most of the cases, effective intervention by the tutor, this demand should also be satisfied

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in computer-based educational tools. In other words, while ICT has an overall positive impact on the learning outcome, the interplay between human emotion – adjustment – personalization, must be studied more profoundly. This paper is organized as follows: First, an introduction to emotional models most often used in ICT is presented. Then, emotion and affect-based learning theories are presented, focusing mainly on models that can be adopted by technology-enhanced learning. Subsequently, emotion recognition techniques are presented and, finally, some representative works in technology-enhanced-learning fueled by emotion recognition and personalization are described.

II. AFFECTIVE COMPUTING MODELS IN TEL

A. Emotional models

There have been proposed in bibliography numerous models to 'structure' emotion and put it in context. These have been drawn mainly with a view to analyzing distal cues and projecting them on emotional categories or dimensions [14]. However, as will be explained in a while, also emotional models developed for synthesizing emotions have been proposed in the literature. The two prominent directions in emotion research are the so-called basic (or label or discrete) emotion categories, and the dimensional models. There exists a lot of debate within the psychologists' research community regarding the qualitative and biological differences between the two approaches and whether they can be seen as complementary or as contradictory schools [15]. **Basic emotion models** (or discrete, label-based) theorists argue that human emotions consist of a few (5-7, usually) basic emotions. Most basic models see hardwired mechanisms in emotion generation precipitated by events. They also see stereotypical sets of emotion expressivity in facial expression, voice, blood pressure, brain activity, autonomic and peripheral nervous system. These elements of basic emotions can be enough for an observer to recognize an emotion in other humans. Moreover, many of the basic emotion models see these limited sets of emotions as the most fundamental ones that can be used as basis for building more complex ones. **Dimensional models** see emotions lying on continuous spaces, usually, along dimensions related to Valence and Arousal [16]. Dimensional model theorists do see emotions as discrete elements on those coordinate systems but see more complicated mechanisms generating emotions. These mechanisms are linked to the concept of affect, which constitutes an important aspect of emotions, however, is not identical to them. Affect is different from emotion, in the sense of it constituting the basic element providing the sense of feeling to humans and other animals. Affect is about appraising how positive/negative a stimuli and accompanying feeling is (valence) and, also, it is describing intensity (arousal). Emotions constitute higher-level concepts and their generating mechanisms involve other factors, as well, such as societal, inherent to personality, cultural, biological [17].

Below follows a presentation of some of the most influential models proposed in the literature of psychology, coming from both domains. This analysis is not exhaustive and focuses on the models that drew the attention of the ICT community. Following, a description of models dedicated to education follows.

1) Label-based emotional models

The most typical label-based model is the one proposed by Paul Ekman [3]. The Ekmanian model includes the so-called six basic emotions, namely anger, disgust, fear, joy, sadness, and surprise, while later on contempt was also added to the process. These emotions, along with the neutral one, constitute the most widely recognizable emotions across cultures. There are basic rules that every culture in the world understands and interprets them in the same manner (e.g. a smile usually means joy, across different cultures). Other sets of labels include the models proposed by: William James [18], proposing four basic emotions, namely fear, grief, love, and rage, based on bodily involvement. McDougall: Anger, disgust, elation, fear, subjection, tender-emotion, wonder, mainly related to human instincts. Oatley and Johnson-Laird: Anger, disgust, anxiety, happiness, sadness. A wide range of emotional models, label-based, is to be found in [19].

2) Dimensional emotional models

The major criticism label-based models have been receiving is related to the fact that human expressivity is much richer than simply attributing labels to it. Moreover, by labelling emotions, the dynamics and intensity of affect are hindered. The firstly introduced dimensional model was proposed by James Russell [16] and, as already mentioned before, it consists of two basic elements, namely valence and arousal or, in other words, low-high pleasure, low-high arousal. Valence accounts for the degree to which an event/object/agent/situation is attractive/good. Arousal describes the degree to which the person experiencing feels physiologically/mentally motivated, activated and triggered. For instance, surprise and anger are emotions of high arousal, however, they come from opposite sides when it comes to valence.

Robert Plutchik, based on his proposition about eight primary, bipolar emotions (joy-sadness, anger-fear, trust-disgust, surprise-anticipation), proposed the Wheel of Emotions in 1980 [20]. This is a cone-shaped model in 3D (or a wheel-based one in 2D) that describes relations among emotions, as well as how they can be combined to form new, complex ones. In 1974, Albert Mehrabian and James A. Russell proposed the Pleasure, Arousal, Dominance model [21], or, as it is more widely known, the PAD model. The PAD model considers pleasure about something/someone/a situation, the degree of arousal, but also how dominant an emotion is. This last dimension is not about how intense an emotion is but, rather, how dominant or submissive the individual feels.

B. Models in education proposed in literature

School teachers are very well aware that, recognizing their students' emotions during teaching is a very helpful procedure for adapting their strategy, their teaching activity and, even, their way of interacting with the students [13]. Knowing when the students are motivated, frustrated, engaged, or simply bored is essential for coming up with ideas that will maximize the learning outcome, according to the emotional context of the student. Technology provides a great means for that. Adapting the speed of learning, switching among different learning activities, interacting with educational games, or simply giving the students space for (online) exploration, are simple ways for keeping the student engaged and minimizing negative, non-productive emotions during the learning procedure [22]. As Rosalind Picard summarizes in [13], positive emotions and moods is not only about making someone feel better, but also induce different ways of thinking, greater creativity, and higher levels of efficiency in decision making. Similarly, negative emotions can have negative impacts on cognitive functions, with a lot of research focusing on brain activity in an effort to explain the effects of negative emotions in learning. A significant amount of research, towards this direction is dedicated to the effects of stress in learning and memory. Vogel & Schwabe in [23] have studied the effects of stress and summarize the state of the art. In particular, focusing on educational settings, stress (when not in high levels) may enhance learning. However, stress can disrupt memory retrieval and updating mechanisms, while experiencing stressful events may encourage rigid forms of memorizing knowledge, which, in turn, leads to lower levels of creativity, connection to prior knowledge and easiness to apply knowledge in real-life situations. A lot of works, focusing also on memory during learning, stress out the importance of emotionally rich material for supporting memory mechanisms [23], [25]. These materials should evoke mainly positive emotions and can come in the form of praises, or even as metaphors and representations of situations familiar to the students from their everyday life.

The presence of a mediator (i.e. a teacher) who notices negative emotions in students, takes proactive actions or involves emotional elements in teaching, has been shown to have positive outcomes in the long-run for the students [24]. This is, actually, one of major the goals of affective computing technologies, such as edutainment applications, VR, gamification: provide emotion-aware agents to the student, optimize the pedagogical experience, also from an emotional point of view and, finally, achieve sustainable results in the student. Although, today, many technologies are there, interactive tutors and ICT-based tools mainly focus on the cognitive aspects of learning [26] with, only lately, areas such as gamification, serious games and socially intelligent robots being under the spotlight of research [27], [28]. One of the main reasons for this, is that there have been proposed many emotional models, some of which also applied in education [29], [30], with research, though, still being far from proposing a concrete methodology and model building on different internal (e.g. the role of the individual) and external factors (e.g. social interactions), as well as considering a solid interplay between cognitive and affective procedures taking place during educational processes. Indeed, these mechanisms are complicated, demand a high degree of personalization, consideration of various socio-economic factors and mental models. Research is ongoing in proposing models looking into which emotions are the most important in learning, while empirical validations require reliable longitudinal studies. Such models, driven and inspired by teacher-student interactions and taking into account the above factors can open new paths, ideally can, subsequently, become materialized in the digital world and provide new paths in research in pedagogy and emotion.

The Theory of Flow [4] is attributed to Csíkszentmihályi who proposed a mapping between skill level, challenge level and experienced emotions (Fig. 1). The theory was not developed exclusively for education, but other applications may include

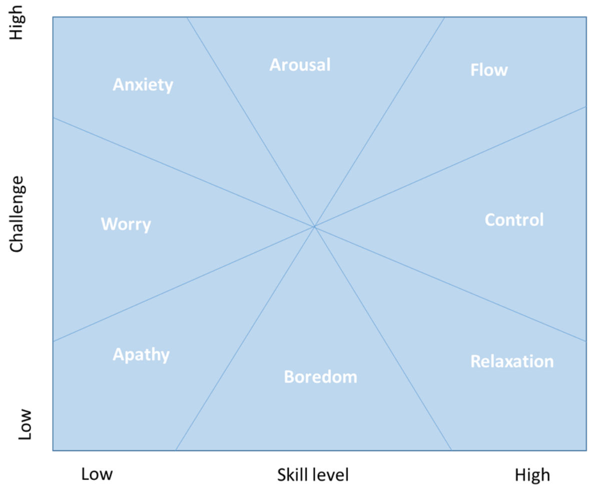

Figure 1: The Theory of Flow

games, sports, vocational training, working environments, etc [31]. Flow is defined as that situation where a person performing an activity is fully immersed in a feeling of energized focus, full involvement, and enjoyment in the process of the activity. In other words, Flow (or, the Zone) is that state where the user becomes absorbed and immersed in an activity to such an extent, that outside stimuli are of lower importance and the

focus is the task in hand. According to the Theory of Flow, different mental states are experienced, according to the skill level of the learner (user) and the challenge imposed by the (learning) material. Namely, these states are *apathy, worry, anxiety, arousal, flow, control, relaxation* and *boredom*. For instance, if the skill levels of a learner are high but the challenge imposed is low, then, the learner is expected to experience relaxation. On the other hand, high degrees of imposed challenge, accompanied with low skill levels should be expected to trigger emotions related to anxiety in the user. According to Fig. 1 the intensity of the experienced states changes in intensity, as we move away from the plot centre. Recent research in positive psychology has indicated that Flow is a state most likely to occur among humans with an autotelic personality [32], for whom the end-goal of the activity, performance and future rewards may not be the main driving factor for an activity but, rather, the activity itself. Curiosity and need for exploration are the main traits of autotelic personalities.

Most commonly, the Theory of Flow is referred to in education in its simplified form (Fig. 2). In this case, the vertical and horizontal axis still refer to the challenge levels and competence of the learner, respectively, however, there are only three states: *Anxiety*, *Boredom* and *Flow*. Nowadays, technology offers those tools that can keep the user in a state of flow: games, gamified learning materials (edutainment), role play activities, are only a few of the means that teachers can employ in their teaching procedure, in order for the students to remain engaged in the learning activity and adopt the belief that there is no other option but learning, in order to advance in the proposed material.

The largest part of criticism when it comes to the Theory of Flow, is that, as flow, by definition, requires full immersion and loss of sense of time and space, the question is how risks such as addiction can be handled. Moreover, flow in itself may not be a necessarily positive concept. It is a vehicle to learning and, as such, applications designed to lead to flow must be carefully implemented so the actual goal (learning and performance) is achieved. As also argued in [13], models like the Theory of Flow fail to help understand which emotions are the most influential in learning and how they influence it. Indeed, the Theory of Flow in education, at least, is based on the assumption that, while a user is in a state of flow, all efforts are concentrated on maximizing performance (that comes with learning) and looks into contextual factors (e.g. competences, challenge), rather that emotions as sequential experiences a learner must go through, in order to achieve effective learning.

A model that includes the notion of Flow is also the one which is based on the Yerken-Dodson Law, the so-called 'the sweet spot for achievement' [33]. This model, although more inclined towards emotions experienced at work and principles for motivating employees, has also been referred to in bibliography as part of emotions experienced in learning conditions [34]. The sweet spot for achievement is based upon *disengagement*, *frazzle*, and *flow*. Increasing performance can only commence when good stress begins to take in (optimal zone of performance), acting as a stimuli for creativity, critical thinking, combination of different fields of expertise in a person. However, overwhelming tasks may lead the brains release excessive stress hormones which, in turn, interfere with one's ability to perform well, learn, and plan. Especially if this becomes a chronic condition, stress can have severe implications on long-term memory.

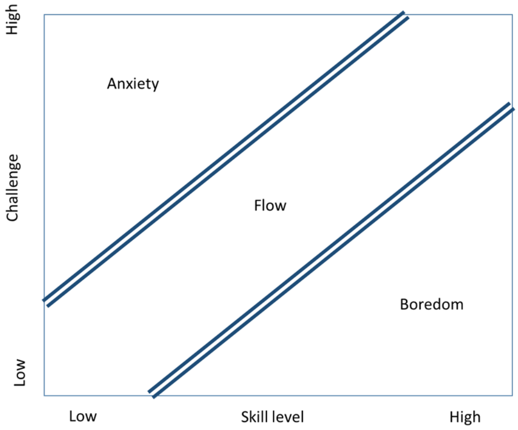

Figure 2: The simplified Theory of Flow

Kort et al., in [35] propose a model building on the interplay between emotion and learning. Similarly to the actual task of a teacher, which includes adapting the teaching style and the material, according to the emotional state of the student, this model aspired to propose a methodology to be incorporated into digital platforms, able to automatically detect and classify human emotion while learning. In particular, the proposed model is shown in Fig. 3. According to the authors, the learner would start a learning process from, either quadrant I or quadrant II, driven by curiosity and interest (quadrant I) at the beginning of the learning process, or the desire to reduce and dissolve confusion (quadrant II). Then, the student moves to quadrant III, where emotions are predominantly negative, since not all concepts are clear, something that causes frustration. The student, becoming aware of this, embarks on activities that will allow her to reduce any ambiguity and, thus, moves to quadrant IV, where the aspects of the learning material have become clear, performance is high and plans for new achievements are already under way. The most possible next quadrant becomes, then, quadrant I. The authors suggest that a typical learning experience involves the above emotions-states which, virtually, move the student along this circle, in a counter-clockwise direction. The model proposed by the authors encapsulates most common emotional experiences in learning but the lack of personalization of emotions and their sequence during learning, the role of personality traits and individualized mental models, as well as extensive longitudinal studies grounding the model, call for need for further research in it.

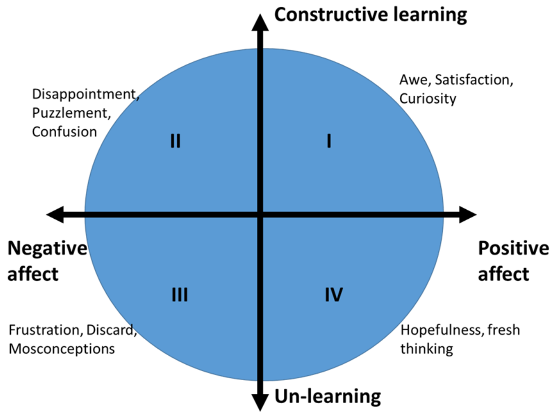

Figure 3: The model proposed in [35]

The authors in [36] studied the interplay between students' affective states, and events occurring during problem-solving activities. In particular, they studied the relationship of emotion with success, failure, positive and negative feedback, as well as the accuracy of feedback and its emotional impact. The authors studied, not only consequent triggering of emotion (e.g. following certain events or feedbacks) but incorporated cyclic patterns in their model. Annotation on emotion took place by asking participants to judge on their emotions at key points in the problem solving session, namely shortly after a problem is presented, in the middle of the session, and after feedback has been received.

In particular, the authors identify the following patterns:

1. Affective states as consequences of outcomes:

a. *Boredom, anger, disgust, frustration*, sadness are the results of providing incorrect responses and receiving negative feedback.

b. Positive emotions (*happiness, 'eureka'*) occur when a correct answer is followed by positive feedback.

c. *Surprise* is to be expected when positive impact follows incorrect answering.

d. *Frustration* and sadness are triggered when a correct answer is followed by negative feedback.

2. Affective states as antecedents to problem-solving outcomes

a. *Boredom* inhibits performance

b. *Curiosity* facilitates performance
c. *Anxiety* is detrimental to performance
d. *Eureka* facilitates problem-solving
e. *Frustration* does not give significant results when it comes to judging its possible detrimental to performance character
f. *Confusion* can lead to both positive and negative performance

3. Cyclical relationships among states

a. Vicious circle of *boredom*, followed by negative responses, followed by negative feedback and *boredom* again.
b. *Curiosity*, followed by positive answers and feedback, followed by *happiness* and further *curiosity*.
c. *Unresolved confusion* is followed by failure, negative feedback, *frustration* and more *confusion*.
d. *Resolved confusion* is followed by success, positive feedback, leading to *neutral emotions* which can go back to *confusion* as the problem evolves.
e. *Confusion* followed by failure, however, by positive feedback leads to *momentary happiness* that has the potential to lead to *curiosity* (part of a positive cycle).

As the authors in [36] note, based on c. and e. above, it may make sense to provide temporarily contradictory feedback in case confusion is followed by failure. This, however, should not be done at the expense of the learning outcome.

The Social Comparison Theory [37] states that people tend to compare themselves with other individuals, coming from different 'levels' than them, whether in terms of social status, education, financially, etc. This comparison is performed both directions: people tend to compare both upwards and downwards. It is this comparison that defines large parts of human system of values, reactions, needs, goals. Although this theory, by itself, does not imply direct links with human affective components, there is a very sensitive link, when it comes to education. Specifically, teachers must carefully look into the affective trust among individuals, in order to facilitate or not collaborative activities in which students with different competences collaborate. It may be, for instance, that students of low competence working together with high achievers lose self-confidence and they quit. Or that more competent students working with weaker ones lose motivation in becoming even better. However, a carefully designed course should cater for facilitating weaker peers in drawing inspiration from their colleagues who have higher competences in certain courses. Similarly, students who achieve better grades can take advantage of a collaborative setting so they benefit themselves through enhancing their own learning outcomes, through learning-through-teaching activities [38].

The Ortony, Clore & Collins or, as it is more widely known, the OCC model [39] has been proposed in a few research works in bibliography as a way to infer emotions while learning, driven mainly by events and external factors, rather than sensed cues [40], [41], [42]. The OCC model is an emotional computational model assuming that emotions are the result of a cognitive evaluation or appraisal of facts [43]. Such models fall into the more general category of appraisal theories. The model splits these facts into three groups: *consequences of events, actions coming from agents, appraisal of an object*. The model specifies a total of 22 typical emotions. For instance, the action of an agent, other than oneself, can lead to approval or reproach. Similarly, an aspect of an object may lead a person to loving it or hating it. The model specifies also combinations of emotions spanning more than one of the three generic categories. These are mainly related to emotions concerning consequences of events caused by actions of agents (e.g., gratitude and anger).

III. Sensing Technologies

While cognitive functions are relatively easy and straightforward to measure (e.g. it is easy to measure one's ability to recall a list of objects seen before, or apply acquired knowledge on a new application), it is not equally easy to measure one's affective state, mood and emotions [13]. A typical way to obtain feedback about one's emotions is through dedicated questionnaires, while it is also quite common to employ human observers. As both techniques have pros and cons, the ICT community, in the last years, is exploring ways to infer human emotion through dedicated sensing techniques [12]. Completing questionnaires many times involves pausing the learning experience, recalling momentary emotions that may now not be so overwhelming, while, quite often, participants may not wish to share their own emotions, due to uncertainty about how this will be perceived by the tutor. In a similar manner, observing is extremely time requiring and, especially in the case of education, it would probably require one teacher for every learner [13]. Moreover, human observation is many times biased by one's personal opinions and beliefs about a subject, and pre-existing stereotypical views stemming from the gender, age or even race of the person being observed. To solve these issues, the research community usually involves multiple observers in providing feedback about a person's emotion [44]. Such a practice, however, would be far from simply prohibitive in educational and learning contexts.

Despite the above, knowing one's own feelings during learning can be extremely helpful. A typical example is that derived from the Theory of Flow model. For instance, if a learner, trying to solve a quiz for too long, looks unease, would benefit from help. However, taking too long to answer a quiz while the student appears to be in a state of flow may mean that it would be a better strategy to offer the learner more time.

Beyond annotations, typical information sources that are used for affect detection and sophisticated artificial intelligence comprise physiology, face, and voice data, while more recent methods exploit more elaborate sources such as text, body language, posture, brain imaging, EEG, etc.

IV. Representative Works

The authors in [34] developed a system that tracks the digital interactions of students with a quiz. In this work, the authors have developed a database of 32 students coming from two different profiles: Engineering and Psychology. The quiz presented the participants with a variety of topics, namely mathematics, history, sports and geography. Moreover, the questions the participants had to answer were of varying degrees of difficulty. This variation in topics and degrees of difficulty, in combination with the fact that the participants came from different backgrounds generated varying emotions in the subjects – emotions were provided as self-annotations at the end of a package of seven consecutive questions on the same topic and of the same degree of difficulty. Emotional states were derived from the Theory of Flow (the simplified version); in particular, at the end of each

7-question session, the subjects would provide, on a Likert scale, their experienced engagement, frustration, boredom. Digital interactions (time to answer a question, time needed to finish a session, ratio of correct, wrong and skipped answers, trial number), as well as person-dependent characteristics (skill level, education background, age, gender) were used as part of an intelligent system that was able to predict experienced emotion with a final goal the adaptation of the system so the student becomes engaged.

In a similar context, the authors in [45] have proposed a technique that, taking into account, learner's emotions, proposes new learning materials, of a certain degree of difficulty to users. The authors achieve this by making use of recommendation systems [46] and, specifically, a technique called collaborative filtering. Similarly to systems existing today on the web-based market (e.g. multimedia content delivery, e-shops, etc.), the system proposed by the authors is looking into the affective state of the learner and predicts the emotion of the user, based on her/his previous interactions, as well as those of other people who experienced the same emotions.

The authors in [47] make use of information related to behavioral, visual cues and, most particularly, information coming from attention levels and levels of interest. Specifically, the authors looked into computer vision techniques collecting information from eye and head positions and movement, in order to model eye gaze directionality, head expressivity and motion. Among others, these representations provide cues regarding whether a reader is fixated on the computer screen or not. The above is useful for determining the behavioral state of the user towards a computer-based learning material, and was used along with a machine learning algorithm, in order to develop a mapping between behavioral, visual cues and emotional states. The technique was applied on videos of young students, with reading difficulties related to dyslexia, interacting with electronic documents [48]. The purpose of the experiment was to detect those time segments when students were having difficulties following the material (uttering words in the correct order, missing out words, rearranging syllables within a word). The final goal was to adapt the interface so that the readers are supported in maintaining high levels of interest in the interaction with the electronic document and also get the right feedback from the system when errors are made.

Similarly to [47], the authors in [50] utilize head and eye movements in order to identify interest or boredom in educational settings. Head rotational movements, signs of drowsiness through eye lid tracking [51] and yawning detection [52] through lip analysis are employed.

The authors in [49] have developed a multi-device platform supporting learning in different contexts, namely mainstream, special education and vocational training. The goal of their system is to bridge formal, non-formal and informal settings of learning, by making use of cloud computing and a technique allowing the integration of various devices (platform agents) coming in the form of mobile devices, laptops/desktops, robots, etc. Central role in the proposed system play the notions of emotion recognition and adaptation, following the principles of the Theory of Flow and advanced machine learning. The platform is using facial expressions, eye gaze directionality, body posture, data coming from accelerometers in mobile phones, and voice analysis. The above are used, either in isolation, or as combinations and, given the result, in combination with learners' competences on the subject matter, inferences regarding emotions are extracted and the challenge levels imposed by the learning platform are accordingly adjusted to keep the learner in a state of engagement. The learning material is organized in small chunks of knowledge and interaction, called 'Smart Learning Atoms', which are linked to a central learning goal, forming a thematic graph. According the detected emotion and performance, while interacting with material related to a specific Smart Learning Atom, its importance in the overall graph is updated, and, either strengthened or weakened to leave space for other learning atoms the learner may have more difficulties with.

The authors in [53] also employ facial expressivity in order to capture learners' emotions. In this work, the Ekmanian six basic emotions are used, although the authors mention that their model can be expanded on more emotional models, as well. Emotion annotation was performed by expert psychologists from the Open University of the Netherlands (OUNL).

One of the first works to make use of sensorial information, coupled with e-learning environments, was that presented in [54]. In that work, the authors proposed a multimodal emotion recognition system with a goal to distinguish between interest and disinterest in kids working on educational electronic puzzles. Facial expressivity and body posture were the main cues for inference, along with contextual knowledge related to the actual activity the kid is performing on the computer.

The authors in [42] are not making use of sensorial information but, instead, they propose a model that, based on probabilities, is making use of events and personality traits to estimate predicted emotions. Specifically, the model is built with a focus on distant learning sessions. The learner is initially asked to fill in a questionnaire that will allow determining prevailing personality traits and, more in particular, extraversion and neuroticism. The prevalence of each of these traits is linked to different goals while learning. Intrinsic goals are mostly linked with extrovert learners, that is, their motives are usually connected with acquiring new knowledge or improving skills, On the other side, learners with higher signs of neuroticism would be mostly performance-driven and, thus, their goals would most likely be linked with pleasing their parents or showing competence through grades and results. The above, combined with certain events (e.g. reception of a help message or experiencing difficulties) and the starting emotion during interaction, lead to the experience of certain consequent emotional states. These states are: *joy* - *satisfaction* (positive emotions) and *distress* - *disappointment* (negative emotions), derived from a subpart of the OCC model [39].

V. CONCLUSIONS

We have presented an overview of the area of affective computing and its relationship with education. Although technologies are now in a relatively mature stage for involving emotion in the learning procedure, it becomes obvious that, what is missing from the research community is a holistic framework and an emotional model that will allow to standardize these procedures and offer tools that will allow for a wide deployment of emotion sensing and personalization. The works proposed have either made use of models borrowed from other disciplines (e.g. the OCC model initially built for synthesizing digital characters) or propose models that lack a wide deployment through longitudinal studies. Moreover, what remains unexplored, is the relation between emotional models, personalization, and situational and contextual awareness, such as learner age and field of study. Future work must focus on bridging these aspects and converge towards certain areas and paths.

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