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Abstract. This chapter reports how affective computing (in terms of detection methods and intervention approaches) is considered in e-learning systems. The goal behind is to enrich the personalized support provided in online educational settings by taking into account the influence that emotions and personality have in the learning process. The main contents of the chapter consist in the review of 26 works that present current research trends regarding the detection of the learners’ affective states and the delivery of the appropriate affective support in diverse educational settings. In addition, the chapter discusses open issues regarding affective computing in the educational domain.

1 Introduction

Literature reports interplay between the cognitive aspects of learning and affect, which implies the need to detect and then intelligent manage (through appropriate feedback based on affect-related strategies) the affective dimension of the learner within educational systems (Blanchard et al., 2009). In this way, an affective-based personalized learning experience can be provided. In fact, over ten years ago it was already suggested that the “new” technologies (that can develop new sensors and interfaces such as intelligent chairs, gloves and mice, as well as new signal processing, pattern recognition and reasoning algorithms) can help to measure, model, study and support learners affectively, the less intrusive as possible the better (Picard et al., 2004). Nevertheless, it is still not clear which affective features are to be considered in the learner models that drive the adaptation pathways (Vandewaele et al., 2011).

Affective computing research explores how affective factors influence interactions between humans and technology, how affect sensing and affect generation techniques can inform our understanding of human affect, as well as the design,
implementation, and evaluation of systems involving affect at their core (Calvo et al., 2014). Detecting and modelling affect is an open research topic that is to be addressed from a psychological perspective (Calvo and D'Mello, 2010). Readers interested can consult other chapters of this book for a more psychology-based background on emotions and personality (i.e., see Chapter 3 for personality models (\ref{3-personality-models})), Chapter 4 for affect acquisition (\ref{4-affect-acquisition}); Chapter 5 for personality acquisition (\ref{5-personality-acquisition}); Chapter 9 for available datasets with personality and affective parameters (\ref{9-corpora}).

In turn, this chapter reports how affective computing is considered in e-learning systems to enrich the personalized support provided in them by taking into account the influence that emotions and personality have in the learning process. Nonetheless, for the sake of context, a brief overview of non-specific educational issues on emotions and personality research is provided in this section. The situation can be summarized as follows: since personality is considered much more stable than emotions, research efforts to adapt systems responses to the users’ needs have mainly focused on automatically detecting emotional changes during learners’ interactions while personality has usually being modeled with standardized psychological instruments. Anyway, there still exist many challenges both for the automatic detection of the user state and the delivery of the appropriate personalized intervention.

The chapter is structured as follows. After this introduction, a review of 26 e-learning systems that take advantage of affective computing (where emotions and/or personality traits are considered) is reported. This review serves to identify the current research trends in the field. Then, other open issues that might worth be explored are discussed. Finally, main contributions are wrapped up.

### 1.1 Overview of Emotions

Emotions are complex. They represent sort reactions (i.e., a matter of seconds) to the perception of a specific (external or internal) event, accompanied by mental, behavioral and physiological changes (Mauss and Robinson, 2009). They have been defined in a huge variety of ways and there is no agreed theory that explains them. Within the affective computing field, the aim is to automatically detect and intelligent respond to users’ emotions in order to increase usability and effectiveness (Calvo and D’Mello, 2010).

As discussed in Chapter 4 (\ref{4-affect-acquisition}), there exist many modalities for affect detection (e.g., spoken and written language, video including facial expression, body posture and movement, physiological signals, tactile interaction data), which can either use a discrete (in terms of specific emotions) or a continuous (in terms of degrees of valence and arousal) representation model. Detecting emotions in contexts of extensive information use can pose several methodological challenges (Lopatovksa, 2011): 1) defining the phenomena (affect, emotion,

mood, feeling, etc., as well as the way to structure it, either as a discrete or a continuous manifestation; 2) selecting the methods for the study (control of variables, emotions elicitation, naturalistic setting, participants’ engagement), the data collection (standardized measures, level of obtrusiveness of the emotional source used, objectiveness of the emotional labelling, cost of the data collection, researchers’ skills) and the data interpretation (pilot data, time interval); 3) preparing and integrating data (quantity, quality and compatibility with other data); and 4) deriving meaning from data (to make computers more attuned to users’ needs and making users’ experience more pleasant). The use of multiple methods for emotions detection would increase reliability of findings and more comprehensively cover multiple facets of emotions (Scherer, 2005). In addition, multimodal detection approaches that combine emotional information from diverse sources seem to improve the classification accuracy of the emotions detected, but there are still several open issues to be researched (D’Mello and Kory, 2015).

Despite existing challenges regarding the automatic detection of emotional states, there are also research efforts aimed to close the so called affective loop (Conati et al., 2005) by developing solutions that dynamically respond to the emotions recognized and are aimed at influencing the user’s affective state. Some application domains where emotions are taking into account are tackled in other chapters of this book, such as conversational systems (Chapter 11 - conversational-system); music information retrieval (Chapter 13, 13-affective-mir, Chapter 15, 15-emotion-places and Chapter 17, 17-emotions-colors), and recommender systems (Chapter 10, 10-affective-recsys). This chapter focuses on the educational domain.

1.2 Overview of Personality

Regarding personality, affective computing follows the trait approach, which focuses on finding empirically psychological differences among individuals and how these differences might be conceptualized and measured, and thus, modelled and implemented in computers (Nunes et al., 2012). Personality traits are dispositions towards action, belief and attitude formation, differ across individuals and influence behavior (Matthews and Campbell, 2009). Personality is much more stable than emotions (normally considered stable over years (Soldz and Vaillant, 1998)), but can influence emotions directly (Rusting and Larsen, 1997). Thus, personality needs to be considered when personalizing a system to the users’ needs (Nunes et al., 2012), especially when affective issues are taken into account.

In addition, as discussed in Chapter 5 (ref{5-personality-acquisition}), people do not always behave the same way due to the natural variability of behavior in concrete situations. To deal with this behavioral variability, personality states have been proposed, which can be defined as behavioral episodes having the same contents as traits (Fleeson, 2001).
Typically, personality traits are identified using questionnaires containing descriptive items that accurately reflect the traits of interest (Allport, 1937). As acknowledged in Chapter 3 (ref{3-personality-models}), the so-called Big Five model, or Five Factor model (FFM), has become standard in Psychology to describe personality. The FFM is a multi-factorial approach which labels the following five traits: i) extraversion, ii) agreeableness, iii) conscientiousness, iv) neuroticism, and v) openness to experience.

Nonetheless, proposals are being made to automatically detect users’ personality from cues left in daily life activities (Gosling et al., 2011) or inferred from speech (Gosling et al., 2006), text-mining (Mairesse et al., 2007), mining interactions in social networks (Ortigosa et al., 2014) and keyboard and mouse usage (Khan et al., 2008). In this respect, Chapter 5 (ref{5-personality-acquisition}) reviews sources of data and methods to automatically detect personality. In fact, as surveyed in (Vinciarelli and Mohammadi, 2014) and despite open issues and challenges regarding data, methodological issues and applications, technologies are being capable of dealing with personality in three ways: i) automatic personality recognition (inference of the true personality of an individual from behavioral evidence), ii) automatic personality perception (inference of personality others attribute to an individual based on her observable behavior), and iii) automatic personality synthesis (generation of artificial personalities via embodied agents).

2 Affective Computing in Educational Scenarios

Affect detection in educational scenarios is even more challenging than in other domains, since emotions usually do not change too much during learning (Shen et al., 2009) and have lower intensity than in other domains (Salmeron-Majadas et al., 2015). Even though there is not yet a single theory that fully explains how emotions influence learning, computers can be given some ability to recognize and respond to affect, and this can also help to understand the phenomenon (Picard et al., 2004). In this respect, different modelling approaches have been used in the educational domain, such as the OCC model (Ortony et al., 1988), the basic emotions (Ekman, 1992), the Learning Spiral Model (Kort et al., 2001), and the model of achievement emotions linked to academic performance based on the AEQ (Pekrun et al., 2009).

Since affect recognition in educational scenarios is still at an early research stage, human labelling of learners’ affect by trained observers (e.g., using the BROMP protocol (Ocumpaugh et al. 2015)) is needed to identify student learning behaviors and suggesting how emotions impact on learning (Woolf et al., 2009). To aid the study of learners’ affect and inform the design of affective computing educational systems, knowledge elicitation methods can be used, which differ in what instruments are available, who generate the emotional reports and when the elicitation is undertaken (Porayska-Pomsta et al., 2013). In any case, detecting learners’ affective states can be helpful not only in adapting the tutorial interaction
and strategy, but also in contributing to the understanding of affective behavior and its relation to learning, thereby facilitating an optimal learning experience (Afzal and Robinson, 2010).

In addition, as commented in the previous section, the personality traits of a person can also influence emotions, and thus, could have an impact on the learner’s affective state (Denis et al., 2015). In particular, personality can be used as a predictor of affective state, when coupled with performance related to a learning goal (Conati and Zhou, 2002; Robison et al., 2010).

With this context in mind, a literature review (compiled in Table 1) has been done to collect approaches for detecting the learners’ affective state and reacting to them by delivering some affective intervention in diverse educational scenarios, considering emotions and personality traits. This review does not aim to be an exhaustive analysis of the state of the art in the field. In turn, it aims to illustrate the state of the art of affective computing in educational scenarios. This selection of 26 works is biased towards recent papers (more than half of them are from this year or the past one, i.e., 2014 and 2015) that summarize the progress towards the current state of the art, and which can serve as reading pointers for researches that want to get familiarized with the field. Thus, they can also serve to discuss the current trends and open issues in the field.

For each work analyzed, the following information is compiled in Table 1 (in addition to the bibliographical reference): i) the type of educational setting, including the number of participants involved in the evaluation studies reported, ii) the personality traits considered (if any), iii) data source(s) used to extract the (emotional) information, iv) the emotional labelling used as well as the labeler (learner vs. educator/researcher), v) the detection technique(s) used to model the emotions, and vi) the intervention applied (when done) to feed the learner back with affective support.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Educational setting (&amp; #participants)</th>
<th>Personality traits</th>
<th>Data sources</th>
<th>Emotional labeling (and labeler)</th>
<th>Emotion modeling</th>
<th>Affective intervention,</th>
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</thead>
<tbody>
<tr>
<td>Afzal and Robinson, 2010</td>
<td>Computer-based learning tasks N=8</td>
<td></td>
<td>camera (facial expressions, head gestures)</td>
<td>bored, confused, happy, interested, neutral, surprised (researcher)</td>
<td>Classification (Hidden Markov Models)</td>
<td>Hints (not using the affective model)</td>
</tr>
<tr>
<td>Conati and Maclaren, 2009</td>
<td>Math Educational game (Prime Climb) Zhou, 2002 N=41</td>
<td>FFM (from electromyography)</td>
<td>OCC (joy, distress, pride, model (dynamic decision network) + valence (learner)</td>
<td></td>
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<tr>
<td>Reference</td>
<td>Educational setting (&amp; #participants)</td>
<td>Personality traits</td>
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<tr>
<td>Dennis et al., 2015</td>
<td>Conversation- al agent N=+1000</td>
<td></td>
<td></td>
<td>conversational cues, pressur es (posture features), camera (facial features)</td>
<td>boredom, con- Multimodal clas- sifier</td>
<td>Emotional support mes- sages</td>
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<tr>
<td>D’Mello &amp; Graesser, 2012</td>
<td>Multi-domain interactive intelligent system (Affective AutoTutor) N=+1000</td>
<td></td>
<td></td>
<td>galvanic skin resistance</td>
<td>anger, disgust, Only statistical analysis of labelled data</td>
<td>Emotional feedback + synthesis of emotional expressions in the agent</td>
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<tr>
<td>D’Mello, 2014</td>
<td>Multi-domain intelligent tutoring system (ALEKS) N=3</td>
<td></td>
<td></td>
<td>keystrokes, camera (facial expressions) + interaction logs</td>
<td>flow, surprise, Wizard of Oz</td>
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<tr>
<td>Felipe et al., Affective intelligent agent for programmin N=6</td>
<td>mathematical learning environment for children N=26</td>
<td></td>
<td></td>
<td>supervised classification (some Weka algorithms)</td>
<td></td>
<td></td>
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<tr>
<td>Grawemeyer et al., 2015</td>
<td>Math exploratory learning environment for children N=26</td>
<td></td>
<td></td>
<td>screen, voice</td>
<td>flow, surprise, Wizard of Oz</td>
<td>Varied types of feedback (prompts, detailed instructions, hints…) including motivational messages</td>
</tr>
<tr>
<td>Gutica and Conati, 2013</td>
<td>Agent-based educational game for Math (Heroes of Math Island) N=15</td>
<td></td>
<td></td>
<td>screen</td>
<td>neutral, boredom, convergence, confusion, boredom (learner, researcher; + retrospective)</td>
<td>Progressive hints provided by monkey character (neutral, happy and confident, sad and</td>
</tr>
<tr>
<td>Reference</td>
<td>Educational setting (&amp; #participants)</td>
<td>Personality traits</td>
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<tr>
<td>Harley et al., 2015</td>
<td>Self regulating FFM (mini-questio-naires) (AEQ, ARI)</td>
<td>AEQ (enjoyment, hope, pride, anger, anxiety, hopelessness, and boredom)</td>
<td>Only statistical analysis of labelled data</td>
<td>Audible assistance with agent directed emotions</td>
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<tr>
<td>Jaques et al., 2014</td>
<td>Eye tracking boredom, curiosity (learner)</td>
<td>Superviced classi-fication (some algorithms from Weka)</td>
<td>Suggested to increase task success, engagement, and user satisfaction</td>
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<tr>
<td>Janning et al., 2015</td>
<td>Voice</td>
<td>Supervised classi-fication</td>
<td>Task sequencing</td>
<td></td>
<td></td>
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<tr>
<td>Jraidi et al., 2014</td>
<td>Electroencephalography, galvanic skin resistance + heart rate, help requested, mouse movements, performance</td>
<td>Hierarchical probabilistic methods (dynamic bayesian network) vs. supervised classification</td>
<td>Suggested approaches; no intervention, challenging task, help, different activity</td>
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<td>Reference</td>
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<tr>
<td>Kai et al., 2015</td>
<td>Exploratory game on physics (Physics Playground) N=137</td>
<td></td>
<td>camera (facial expression), interaction logs</td>
<td>boredom, confusion, engagement, frustration (researcher)</td>
<td>Supervised classification (RapidMiner and Weka algorithms)</td>
<td></td>
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<tr>
<td>Khan et al., 2013</td>
<td>System to teach programming to children (Alice) N=16</td>
<td></td>
<td>mouse, keyboard, galvanic skin resistance</td>
<td>arousal (labeled with galvanic skin resistance)</td>
<td>Multiple regression analysis</td>
<td></td>
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<tr>
<td>Leontidis et al., 2009</td>
<td>Web-based adaptive educational system (MENTOR) N=43</td>
<td>FFM (NEO-questions asked by system)</td>
<td>joy, satisfaction, pride, hope, gratification, distress, disappointment, shame, fear, reproach</td>
<td>Ontology-based Bayesian network affective tactic</td>
<td>Non-specified</td>
<td></td>
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<tr>
<td>Paquette et al., 2015</td>
<td>Serious game on tactical combat casualty care (vMedic/TC3Sim) N=119</td>
<td>interaction logs, Kinect (head movements posture shifts), Q-self (not used)</td>
<td>boredom, confusion, engagement classification algorithms</td>
<td>(manual labeling not required)</td>
<td></td>
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<tr>
<td>Rodriguez et al., 2014</td>
<td>Adaptive e-learning systems (CoMoLE) N=1</td>
<td>text</td>
<td>joy, anger, sadness and fear</td>
<td>Sentiment analysis</td>
<td></td>
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<tr>
<td>Sabourin and Lester, 2014</td>
<td>Microbiology game-based learning (Crystal Island)</td>
<td>student answers</td>
<td>anxious, bored, confused, curious, excited, focused, frustrated,</td>
<td>Probabilistic model (dynamic bayesian network)</td>
<td>Activity selection, feedback message (not implemented)</td>
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<table>
<thead>
<tr>
<th>Reference</th>
<th>Educational setting (&amp; #participants)</th>
<th>Personality traits</th>
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<th>Emotion modeling</th>
<th>Affective intervention,</th>
</tr>
</thead>
<tbody>
<tr>
<td>Salmeron-Majadas et al., 2015</td>
<td>Math Intelligent tutoring system N=2</td>
<td></td>
<td>heart rate, breath volume, skin conductance focused, concerned and temperature, frustration, logs and camera</td>
<td>emotions vs. no emotion + anxiety, concentration, familiarity, happy, shame or surprise, as well as none (learner; + retrospectively)</td>
<td>supervised classification (Weka algorithms)</td>
<td>task-based, parallel emphatic and reactive emphatic</td>
</tr>
<tr>
<td>Santos et al., 2013b</td>
<td>Web-based learning environment (dotLRN) N=71</td>
<td></td>
<td>mouse, keyboard, text, Kinect (not used)</td>
<td>valence and arousal (learner, researcher; dictionary)</td>
<td>Sentiment analysis, classification</td>
<td>Formative feedback will be defined with TORMES methodology</td>
</tr>
<tr>
<td>Santos et al., 2014</td>
<td>Web-based learning environment (dotLRN) N=77 (learners) +18 (educators)</td>
<td>FFM, GSE</td>
<td>screen + facial expressions &amp; body movements</td>
<td>confusion, doubt, distracted, nervous, shame, anxious (researcher)</td>
<td>Wizard of Oz</td>
<td>Diverse types of emotional support via text messages</td>
</tr>
<tr>
<td>Santos et al., 2015</td>
<td>Language learning N=6</td>
<td>FFM, GSE</td>
<td>heart rate, skin temperature, skin conductance, camera (facial expressions), voice</td>
<td>stress (researcher)</td>
<td>Wizard of Oz</td>
<td>Sensorial signal (light, sound, movement) to calm down</td>
</tr>
<tr>
<td>Shen et al., 2009</td>
<td>Online and offline content to study programming N=1</td>
<td></td>
<td>skin conductance, heart rate, electroencephalography</td>
<td>engaged, con- Classification methods</td>
<td>Rules that recommend contents, examples, music and videos</td>
<td></td>
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<tr>
<td>VanLehn et al.</td>
<td>Agent-based</td>
<td></td>
<td>camera (face good model)</td>
<td>Regression modelMotivational</td>
<td></td>
<td></td>
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</tbody>
</table>
Table 1. Selected works on affective computing in educational settings

<table>
<thead>
<tr>
<th>Reference</th>
<th>Educational setting (&amp; #participants)</th>
<th>Personality traits</th>
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<th>Emotional labeling (and labeler)</th>
<th>Emotion modeling</th>
<th>Affective intervention,</th>
</tr>
</thead>
<tbody>
<tr>
<td>al., 2014</td>
<td>affective Meta-Tutoring system (AMT) N=several studies with 40-50 each</td>
<td>cial expression, posture-sensing chair</td>
<td>ing, engaged, new understanding, inconsistent, guessing, flustering/confused/lost, boredom</td>
<td>and meta-cognitive spoken messages</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Woolf et al. 2010</td>
<td>Agent-based Math tutoring system (Wayang Outpost) n=35,29,29</td>
<td>camera (mental state), skin conductance, bracelet, pressure sensitive mouse, pressure sensitive chair</td>
<td>frustration, interest, confidence, and excitement (learner)</td>
<td>Linear regression</td>
<td>Empathetic learning companions; agents</td>
<td></td>
</tr>
</tbody>
</table>

The 26 works compiled in Table 1 aim to provide an overview of the current research trends and open issues regarding the application of affective computing in e-learning systems. Emotions, personality traits or both are considered.

From a quick look, it can be noticed the diversity in the educational settings. They can be classified in game based learning systems (Conati and McLaren, 2009; Gutica and Conati, 2013; Kai et al., 2015; Paquette et al., 2015; Sabourin and Lester, 2014), intelligent tutoring systems (D’Mello, 2014; Janning et al., 2015; Salmeron-Majadas et al., 2015), dialogue system (Litman and Forbes-Riley, 2014), agent-based systems (Dennis et al., 2016; D’Mello and Graesser, 2012; Felipe et al., 2012; Gutica and Conati, 2013; Harley et al., 2015; Jaques et al., 2014; VanLehn et al., 2014; Woolf et al. 2010) and non-specific (or non-specified) learning environments (Afzal and Robinson, 2010; Jraidi et al., 2014; Khan et al., 2013; Leontidis et al., 2009, Rodriguez et al., 2014; Shen et al., 2009; Santos et al., 2015; Santos et al., 2013b; Santos et al., 2014; Grawemeyer et al., 2015).

Usually the number or participants involved in the evaluation studies is large in order to account for statistical validity across subjects. However, in some works, intrasubject studies have been carried out over several months (D’Mello, 2014; Shen et al., 2009; Rodriguez et al., 2014).

Although the final goal of the research is the same in all the works (i.e., build educational systems that provide personalized affective support), the focus of the research reported in the selected papers is diverse. Some papers mainly focus on improving emotions detection, either by exploring the potential of single data source (Conati and McLaren, 2009; Jaques et al., 2014; Afzal and Robinson, 2010;
D’Mello, 2014; Janning et al., 2015) or the combination of several input sources (Felipe et al., 2012; Kai et al., 2015; Khan et al., 2013; Paquette et al., 2015; Shen et al., 2009; Salmeron-Majadas et al., 2015; Santos et al., 2013b). Other works focus on improving the affective intervention, avoiding the challenges in automatic affective detection by simulating the detection process by using the Wizard of Oz method (Dahlbäck, Jönsson, & Ahrenberg, 1993) as in (Grawemeyer et al., 2015; Forbes-Riley and Litman, 2012; Santos et al., 2015; Santos et al., 2014). In addition, a third group of papers focus on analyzing the affective states reported (D’Mello, 2014; Gutica and Conati, 2013; Jraidi et al., 2014), the influence of the personality (Denis et al., 2016; Harley et al., 2015; Leontidis et al., 2009) or assessing the impact of the affect support in the learning process (Litman and Forbes-Riley, 2014; D’Mello and Graesser, 2012; Sabourin and Lester, 2014; VanLehn et al., 2014; Woolf et al. 2010).

Data sources considered are also diverse. In particular, the following have been reported: 1) cameras for facial expressions and/or body movements (Afzal and Robinson, 2010; D’Mello and Graesser, 2012; Felipe et al., 2012; Kai et al., 2015; VanLehn et al., 2014; Woolf et al. 2010; Santos et al., 2015; Salmeron-Majadas et al., 2015; Santos et al., 2014); 2) pressure sensor/posture sensing chairs (D’Mello and Graesser, 2012; VanLehn et al., 2014; Woolf et al. 2010); 3) Kinect sensor (Paquette et al., 2015) – in (Santos et al., 2013b) it is used to collect data, but analysis not reported; 4) physiological signals such as electro dermal activity (D’Mello, 2014; Jraidi et al., 2014; Khan et al., 2013; Shen et al., 2009; Woolf et al. 2010; Santos et al., 2015; Salmeron-Majadas et al., 2015); electromyography (Conati and McLaren, 2009); skin temperature (Santos et al., 2015; Salmeron-Majadas et al., 2015); breath rate (Salmeron-Majadas et al., 2015); electroencephalography (Jraidi et al., 2014; Shen et al., 2009); heart rate (Jraidi et al., 2014; Shen et al., 2009; Santos et al., 2015; Salmeron-Majadas et al., 2015); 5) behavioural information such as keystrokes (Felipe et al., 2012; Khan et al., 2013; Santos et al., 2013b); mouse movements (Jraidi et al., 2014; Khan et al., 2013; Santos et al., 2013b) and pressure (Woolf et al. 2010); interaction logs (Felipe et al., 2012; Kai et al., 2015; Paquette et al., 2015; Salmeron-Majadas et al., 2015) and performance features (Jraidi et al., 2014); 6) eye-tracking (Jaques et al., 2014); 7) speech features (Litman and Forbes-Riley, 2014; Santos et al., 2015; Janning et al., 2015, Grawemeyer et al., 2015) and conversational cues (D’Mello and Graesser, 2012); 8) Text (Rodriguez et al., 2014, Santos et al., 2013b); 9) participant’s screen (Grawemeyer et al., 2015; Gutica and Conati, 2009; Santos et al., 2014); and 10) learners’ answers to questions (Harley et al., 2015; Lentidis et al., 2009; Sabouring and Lester, 2014). In addition, quantified-self sensors such as a wearable arm bracelet have also been used to collect data – but not analysed due to errors in the collection process (Paquette et al., 2015), which in addition to electrodermal activity and skin temperature, can measure participant’s orientation through a built-in 3-axis accelerometer.

This diversity in the data collection sources follows existing approaches in the affective computing field, which among others, include facial expression, voice
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(paralinguistic features of speech), body language and posture, physiology and brain imaging, as well as multimodal combinations (Calvo and D’Mello, 2010), keyboard and mouse interactions can also be considered as affective information sources (Kolakowska, 2013) and, when the educational context is taken into account, interaction logs that can consider lexical, semantic and contextual cues, as well as the interactive features of the environment (hints or information buttons) (Mavrikis et al., 2010).

With respect to the techniques used for detecting emotions, supervised classification techniques are mainly used (Afzal and Robinson, 2010; D’Mello and Graesser, 2012, Felipe et al., 2012; Jaques et al., 2014; Kai et al., 2015; Litman and Forbes-Riley, 2014; Paquette et al., 2015; Shen et al., 2009; Salmeron-Majadas et al., 2015; Janning et al., 2015; Santos et al., 2013b), as well as probabilistic models (Conati and McLaren, 2009; Jraidi et al., 2014; Sabourin and Lester, 2014; Leontidis et al., 2009) and regression analysis (Khan et al., 2013; VanLhen et al., 2014; Woolf et al., 2010). This requires emotionally labelling learners’ interactions and behavior (Woolf et al. 2009; Mavrikis et al., 2010). To this respect, methodological decisions need to be taken regarding methods, instruments and informants for the labelling process (Porayska-Pomsta et al., 2013). These decisions can compromise the ecological validity of the detection process, for instance, if learners are asked to verbalize their affective states while interacting with the e-learning system or attached physiological sensors are used, but these decisions are necessary for deriving models that can be introduced and evaluated subsequently in more ecologically valid situations (Mavrikis et al., 2010).

Practice shows that the labeling is either performed by the learner during the interaction with the system (Conati and McLaren, 2009; D’Mello and Graesser, 2012; D’Mello, 2014; Grawemeyer et al., 2015; Jaques et al., 2014; Jraidi et al., 2014; Sabourin and Lester, 2014; Shen et al., 2009; Woolf et al. 2010; Salmeron-Majadas et al., 2015; Santos et al., 2013b), by the learner retrospectively (D’Mello and Graesser, 2012; Grawemeyer et al., 2015; Salmeron-Majadas et al., 2015; Janning et al., 2015), or by the researcher during (D’Mello and Graesser, 2012; Grawemeyer et al., 2015; Kai et al., 2015; Paquette et al., 2015; Janning et al., 2015; Santos et al., 2014) or after the interaction (Afzal and Robinson, 2010; D’Mello and Graesser, 2012; Felipe et al., 2012; Gutica and Conati, 2013; Santos et al., 2013b). With respect to emotional labeling by the researcher while the learner interacts with the system, BROMP standardized procedure is used (Grawemeyer et al., 2015; Kai et al., 2015; Paquette et al., 2015). In most cases, the labelling is done in terms of a set of predefined categories, being boredom, confusion, frustration, engagement/flow and delight/pleasure/happiness/joy/excitement the most commonly used ones, which except for the lower cases of curiosity, is consistent with findings reported elsewhere (D’Mello 2013). In few cases, a dimensional labelling (in terms of valence (Conati and McLaren, 2009; Sabourin and Lester, 2014; Santos et al., 2013b) or arousal (Khan et al., 2013; Santos et al., 2013b) is done. In one work, the physiological signal (i.e., electodermal activity) was used as the emotional labeler (Khan et al.,
In one work, labels are mapped to the specification W3C EmotionML (Salmeron-Majadas et al., 2015).

Few systems consider personality traits. When done (Conati and McLaren, 2009; Dennis et al., 2016; Harley et al., 2015; Jraidi et al., 2014; Leontidis et al., 2009; Sabourin and Lester, 2014; Santos et al., 2014; Santos et al., 2015), standardize questionnaires following the FFM are used (e.g., IPIP-NEO, mini-IPIP, NEO-PI-R). Other personality traits, such as the general self-efficacy scale (Schwarcer, 1993) have been collected in (Santos et al., 2014 and Santos et al. 2015). No works have been found to automatically detect the personality from the learners’ interactions.

Regarding affective interventions, not many systems provide them (although some give suggestions about how to deliver them (e.g., Conati and Maclaren, 2009; Felipe et al., 2012; Jaques et al., 2014; Jraidi et al., 2014; Leontidis et al., 2009; Robinson et al., 2012; Salmeron-Majadas et al., 2015; Janning et al., 2015; Santos et al., 2013b), but when done, it is either delivered through different kinds of feedback depending on the learner’s personality (Dennis et al., 2016) or emotional states (Gravemeyer et al., 2015; Litman and Forbes-Riley, 2014; Shen et al., 2009; Santos et al., 2014; Rodriguez et al., 2014) and/or by synthesizing affective elements through the generation of facial expressions, the inflection of speech, and the modulation of posture in the case of embodied conversational agents or learning companions (D’Mello and Graesser, 2012; Gutica and Conati, 2013; Harley et al., 2015; VanLehn et al., 2014; Woolf et al. 2010). Another way to respond to the learners’ affective state is through the physical ambient in which the learner is embedded, exploring the use of the different sensorial channels with ambient intelligence (Santos et al., 2015).

In this respect, determining in an automatic way the best tutoring response to specific learners’ affective states (including when to intervene and what affective support to provide) is a difficult task, but might not require a very robust diagnosis of learner affect (Porayska-Pomsta et al., 2008). Anyway, experiments have shown that affective-based interventions do change the learners behavior, but the appropriate strategy has to be applied, as well as the appropriate time and type of feedback to success on the intervention (for instance, mirroring the student emotion might not be the right response for all emotions) (Woolf et al., 2009).

From this review, it can be concluded that there is no a clear approach regarding emotions detection in terms of data sources, labelling and modelling. In turn, personality features are statically used (when considered). And intervention opportunities are still to be explored. Hence, there is still a large way to go for affective computing research in educational scenarios. Nonetheless, other issues that might worth also to be explored are discussed in the next section.
3 Open issues

Additional open issues regarding emotions and personality in e-learning systems that have not emerged during the review carried out in the previous section, and which might worth be explored in future research, are commented here.

3.1 Learning styles and affective states

In the educational domain, learning styles can be considered a specific personality trait, being the Index of Learning Styles (ILS)\(^1\) by Felder and Solomon the most commonly used. In fact, it seems to be some correlation between personality traits and learning styles (Kim et al., 2015). However, no evidence has been found in the literature that learning styles influence affective states, even when both are computed in the same system (Leontidis and Halatsis, 2009; Khan et al., 2010). Thus, the field requires experimental studies that can provide some insight into this question, including (if appropriate) dynamic detectors of learning styles as their stability is controversial (El-Bishouty et al., 2014).

3.2 Emotions and personality in collaborative learning

Emotions can emerge in collaboration scenarios and influence learning (Järvenoja and Järvelä, 2009). They can be very motivating and rewarding for learners (Jones and Issroff, 2005), and transferred among them (Barsade, 2002). Thus, they have to be considered when managing the collaboration in e-learning scenarios. For instance, in order to design group learning activities, a framework that integrates techniques for affect recognition using physiology and text has been proposed (Calvo, 2009). Another proposal is to suggest collaborative activities to groups of students according to the group members’ emotions (Rodriguez et al., 2014). In addition, personality traits also play a key role in social and collaborative scenarios since personality can modulate the way the student participates in a given situation (Solimeno et al., 2008).

However, still little attention has been paid on understanding the role of affective and social factors when learning collaboratively online, and there is still a need for further development of methodological approaches. To provide some background on social emotions, see Chapter 2 (\ref{2-social-emotions}).

\(^1\) http://www4.ncsu.edu/unity/lockers/users/f/felder/public/ILSpage.html
3.3 Emotions and personality in inclusive learning

While learning should be an engagement experience, this is more critical when students have learning disabilities, which might imply additional efforts on the learners to develop the required learning strategies (Murray et al., 2007). Thus, emotional states such as frustration are more likely to happen, and thus, more important to be detected in these situations.

Emotional management is also very relevant in autism spectrum disorders and other developmental problems (El Kaliouby et al., 2006). Affective states of children with autism spectrum disorders have already been experimentally detected via physiology-based affect recognition technique (Liu et al., 2009). The use of embodied conversational agents can help to understand and influence the affective dynamic of learning and improve the social and emotional functioning of children with autism spectrum disorders (Messinger et al., 2014).

In addition, people with bipolar disorders can also benefit from emotion detectors as they require mechanisms to get insight in their own emotional state (Khan et al., 2013).

Moreover, there exist diverse challenges for inclusive emotions detection in educational scenarios, especially when recording facial expressions and analyzing the typing behavior in visually impaired learners (Santos et al., 2013a). The former refers to eye and head blindisms (repetitive, self-stimulating mannerisms made by blind people unconsciously), which should be taken into account when processing the data. The later implies detecting the purpose of each keystroke (data input vs. content navigation), and processing it accordingly.

Personality computing is also likely to play a major role in detecting disorders like paranoia and schizophrenia (Vinciarelli et al., 2014) that typically interfere with personality (Warren, 2009) and can impact learning (Dugan, 2014).

3.4 Gathering affective data in a non-intrusive way

In addition to the low intrusive hardware sensors already reported by Picard et al. (2004) (i.e., camera, posture analysis seat, pressure mouse and wireless skin conductance sensor), current technological advances on wearable devices (Mukhopadhyay, 2015) and e-textiles (Fleury et al., 2015) can facilitate the low-cost and low-intrusive gathering of physiological and behavioral data that can be used to infer learners’ affective states. In this respect, as commented in Chapter 8 (8-experience-sampling), mobile devices allow in-situ sampling of human behavior, and provide researchers with ecologically valid and timely assessments of a person’s psychological state at previously unimaginable granularity and scale.
Nonetheless, sensor-free affect detection should also be explored, as recent research in educational data mining shows that some emotions such as frustration can be recognized from log data (Wixon et al., 2014).

### 3.5 Big data processing of affective multimodal flows

Since affective computing requires a large computational infrastructure for data processing and analysis, big data on cloud computing should be considered (Hashem et al., 2015). Big data technologies provide an opportunity to extract insightful multimodal emotional information flows continuously gathered from mobile devices as it can deal with the processing of data that is potentially unstructured, needs to be processed at high velocity, and is growing so big in size that it becomes impractical to handle by using traditional data processing systems (Bambetov et al., 2015). In fact, the potential of big data in education is large due to its ability to mine unstructured and informal connections and information produced by students, including sensors and location based data, which can allow educators to uncover useful facts and patterns they were not able to identify in the past (Daniel & Butson, 2014).

### 3.6 Providing more interactive and contextual affective feedback

As learning takes place in diverse and rich environments, the incorporation of contextual information about the learner when providing personalized feedback can improve the system response to the learner’s needs (Verbert et al., 2012). Thus, the challenge here is to identify the appropriate affective support that can take advantage of contextual information, not only for detecting the learners’ affective states, but also to deliver the affective feedback.

To advance in this issue, some steps have been carried out applying TORMES elicitation methodology (Santos and Boticario, 2015) to analyze the feasibility of interactive context-aware affective educational recommendations using ambient intelligence (Santos et al., 2015). In particular, as commented in Section 2, stressful situations have been detected (using the Wizard of Oz user centred design method) from physiological signals, facial expressions, body movements and speech and affectively managed by delivering sensorial feedback to the learner through different sensorial channels (e.g., sight, hearing, touch).

3.7 Interoperable support for ubiquitous affective learning

Affective detection technologies and intervention support algorithms embedded into mobile infrastructures should provide in a near future ubiquitous learning experiences affectively. For this, interoperability between the components involved in the affective adaptation process needs to be supported, as in non-affective educational scenarios (Santos and Boticario, 2011).

In this sense, there exist description languages to model emotions (i.e., the W3C Emotion ML (Schröeder et al., 2012)) and personality (PersonalityML 2.0 (Nunes et al. 2012). Other specifications that might be of interest are the Attention Profiling Mark-up Language (APML)\(^2\) and the Contextualized Attention Metadata (CAM)\(^3\). They need to be integrated with educational specifications such as those proposed by the IMS Global Learning Consortium\(^4\) as well as with the standards and specifications used in big data infrastructures.

3.8. Affective Support in Psychomotor Learning

According to psycho-educational theories, learning not only involves cognitive and affective aspects, but also psychomotor aspects, which are related to actions and require the acquisition of motor skills (Bloom, 1956). In fact, there are some kind of learning activities such as playing a musical instrument, doing a medical operation, playing sports, etc. that require learning motor skills in order to properly perform them. Adaptive e-learning systems can be built to support psychomotor learning (Santos, 2016a).

These smart learning environments should provide a holistic personalized support to learners involving cognitive, affective, and psychomotor aspects, and thus, be able to deal with learners’ movements, both to reinforce cognitive learning and to support motor skills acquisition, and where affective issues are also supported to keep motivation and engagement (Santos, 2016b).

Considering the affective state of the learner while learning motor skills is critical in order to deal with the trade-off between learning and performance (Soderstrom and Bjork, 2015). In particular, actions that can produce relatively permanent changes in behaviour with long-term retention and transfer introduce more performance errors, and thus, might frustrate the learner. Performance errors are reduced if the activity is reproduced over and over, but this also increases boredom. Hence, special attention to the affective state is needed also when learning motor skills.

\(^2\) APML: [http://apml.areyoupayingattention.com/](http://apml.areyoupayingattention.com/)
\(^3\) CAM: [https://sites.google.com/site/camschema/home](https://sites.google.com/site/camschema/home)
\(^4\) IMS: [http://www.imsglobal.org/](http://www.imsglobal.org/)
4. Concluding remarks

The review carried out in this chapter (consisting in a detailed analysis of 26 publications) has illustrated how affective computing has been applied to develop diverse e-learning systems. Emotions are more widely considered than personality traits, and they are also more diverse. Emotions are usually detected during the learner interaction using supervised classification methods from a wide variety of emotional sources that are manually annotated by learners or researchers, while personality, when considered, is statically gathered with FFM questionnaires. Few works report the delivery of interventions, as they require the existence of accurate affective (and personality) detectors (and this still has many open issues regarding data sources, labelling and modelling). Nonetheless, learner’s direct input or user centered design methods like the Wizard of Oz are being used in parallel to explore intervention opportunities and thus, advance the research on the impact on the learners of the affective support provided.

Thus, from the current trends, many challenges exist to provide affective support in educational scenarios. In addition, there are other issues not emerging from this review that might also be relevant to explore. Some of them have been discussed in this chapter. On the one hand, from the learners’ perspective, future research could focus on investigating if learning styles (which can be considered a kind of personality trait in the educational domain) influence somehow the affective state of the learner. It could also focus on providing a collaborative and inclusive affective learning experience since i) the learner might not be learning alone, and ii) learners are functionally diverse, and some might have impairments. On the other hand, from a technological perspective, there are several open issues regarding the gathering data in a non-intrusive way, processing (with big data techniques) multimodal flows of affective data, and providing more interactive and contextual affective feedback through interoperable infrastructures in order to support ubiquitous affective learning experiences.

Finally, in addition to those open issues, and in line with affective computing research in general (D’Mello & Kory, 2015), further efforts are also required in this domain to support naturalistic learning experiences into the wild by assuring authenticity (naturalness of training and validation data), utility (states detected are relevant in the real-world contexts of use) and generalization (maintain its level of accuracy when applied to new individuals and new or related contexts).

Acknowledgments. The research carried out to produce this chapter is partially supported by the Spanish Ministry of Economy and Competence under grants numbers TIN2011-29221-C03-01 (MAMIPEC project: Multimodal approaches for Affective Modelling in Inclusive Personalized Educational scenarios in intelligent Contexts) and TIN2014-59641-C2-2-P (BIG-AFF: Fusing multimodal Big Data to provide low-intrusive AFFECTive and cognitive support in learning contexts).

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