Abstract: In 2004 a group of affective computing researchers proclaimed a manifesto of affective learning that outlined the prospects and white spots of research at that time. Ten years passed by and affective computing developed many methods and tools for tracking human emotional states as well as models for affective systems construction. There are multiple examples of affective methods applications in Intelligent Tutoring Systems (ITS). This paper revises whether the white spots from the 2004 manifesto have been covered as well as explores the progress in affective tutoring systems construction. The article provides also a brief comparison of selected affective tutoring systems.

When reviewing affective computing literature in 2014 one might be impressed – there are algorithms that recognize affect from diverse input channels with accuracies reaching over 90%. There are emotional virtual characters and some of them are used in e-learning environments. However, although there is much progress in affective computing research, it seems that more white spots are found than covered, which is typical for relatively young scientific domains. Highest emotion recognition accuracies are obtained for distinguishing two emotions, which is obviously not enough for learning systems. Some of the future challenges include: improvement of both accuracy and granularity of emotion recognition, methods for emotion representation models mapping and comparison, integration of emotion recognition results from multiple input channels, effective intervention models for learning, design patterns and frameworks for affective tutoring systems, models for quantifying and integration of uncertainty related to emotional states recognition, affect-adaptive control flows and more. The thesis of this paper can be summarized as follows: Affective computing grew up from infancy, however it is still far from maturity especially when applied to learning support. During the decade of diverse investigations, affective-cognitive imbalance in ITS has changed in research, however has not changed in learning support tools.

Keywords: affective computing, affective learning, e-education, intelligent tutoring systems, affective tutoring systems

1. Introduction
Teachers know, that emotional state of a learner influences the effectiveness of educational process. Motivation and engagement foster memorization and understanding in learning. Teachers in classrooms as well as in virtual environments not only instruct and explain, but also encourage, stimulate and inspire learners, which is independent on the subject of learning. Emotional intelligence is claimed to have more influence on human educational and professional success than mathematical, lingual or spatial competence that create conventional notion of intelligence (Goleman 2010). Therefore addressing emotional aspect of learning is so important in learning environments, both traditional and electronic.

Emotional factor is rarely addressed. Intelligent tutoring systems and other e-learning environments almost always concentrate on cognitive goals, leaving affective learning aside. Current trend is to
develop methods for more natural human-computer interaction and there are also new techniques and tools for emotional interaction with computers, including emotions’ receptiveness and expression. However, there is still a gap between what we know about emotions in educational processes and what we support within tutoring systems. In 2004 a group of affective computing researchers proclaimed a manifesto of affective learning that outlined the prospects and white spots of research at that time (Picard et al. 2004). Ten years passed by and affective computing developed many methods and tools for tracking human emotional states as well as models for affective systems construction. This raises the main research question of this paper: Are affective computing methods and tools now, in 2014, mature enough to be applied in educational systems and environments?

This paper explores the progress of affective computing and its application in education. Matters linking affective learning and affective computing are described and an outline of affective computing manifesto claims is provided. This preliminary overview is followed by analysis of the literature from 2004 to 2014 both on affective computing and affective learning, especially concentrating on the combination of both. Selected Affective Tutoring Systems (ATS) are analyzed and compared to show diversity of concepts and method for affect-aware systems construction. As a result new findings are identified as well as some challenges named.

2. Affective learning and affective computing

Affective learning is a term used to describe the phenomena of emotional states’ influence on human cognition and learning (Landowska 2013a). That area was intensively explored in psychology and pedagogy, long time before affective computing developed its methods and tools. Some studies on affective learning are dated long before 2004, e.g. research on long-term memory performance depending on the level of arousal and valence (Bradley et al. 1992). There are several rules-of-thumb, that summarize the effect of emotions on learning: higher arousal levels are better than lower ones (better to be angry than bored), emotions of extremely high and very low arousal are not sufficient for educational processes, learning is fostered by concentration, engagement and the state of flow (Picard&Klein 2002) and more.

Affective learning and e-education combination can result in mutual benefits: affective learning might (and perhaps should) occur in e-learning environments and e-education provides a perfect opportunity to study the phenomena of affective learning. Affective computing research, that might be useful for learning systems includes:

- human emotion recognition based on diverse input channels (e.g. facial expressions, textual inputs, physiological parameters, posture analysis),
- emotion modelling and quantification in a computable form (ideally also understandable for human),
- control flows that can utilize information on affect,
- affective interventions that could be undertaken automatically by systems,
- personality, mood and emotional states modelling for virtual characters,
- emotion expression and visualization.

Recognition of an emotional state of a human in front of a computer can be based on several inputs, including: facial expressions, body posture and movements analysis, textual inputs analysis, voice signals processing, input devices usage patterns as well as physiological measurements interpretation. If emotion recognition is applied in e-learning environments, inputs available at home computer desks should be used, therefore video (face and posture), peripherals usage and textual inputs can be analyzed and interpreted to retrieve information on a learner’s affect. A restriction must be made, that body language and facial expressions can be controlled and even falsified (actors do this as a profession) leading to false recognition results.

As an emotional state is recognized, it must be somehow quantified or named. There are several emotion representation model types, including: label-based models (emotional states are assigned with words or phrases), discrete models (emotional states are expressed as a combination of a pre-defined emotions set), dimensional (a number of dimensions are used to quantify emotional states) and componential. There are three most common representations of emotions used in emotion recognition and affective tutoring systems, i.e. Ekman six basic emotions model (Ekman&Davison 1999), Pleasure-Arousal-Dominance PAD dimensional model (Mehrabian 1997) and OCC componential model (Ortony, Clore&Collins 1988). However, most of the emotion recognition algorithms use simple two-state label-based emotion representation (e.g. distinguishing boredom from no-boredom).

Affective intervention is a modification of standard control path or system behaviour in response to user affective state and it aims at providing effective execution of a task (Landowska 2013a). It’s important to emphasis, that affect-aware tutoring systems should make affective interventions only
when the learning process is endangered by an ineffective emotion (e.g., boredom), but refrain from intervention, when an emotional state supports learning (e.g., flow). Affective interventions of a tutoring system can be a very simple modification of control flow, as human teachers’ interventions are usually also very subtle and even though effective. Adapting a learning path, displaying an intermediary joke or adding some animation as a distractor are examples of simple automatic interventions, that may address boredom. Some tutoring systems employ more sophisticated techniques including voice messages and even virtual mentors, tutors or classmates with facial and/or postural emotion expression. The aim of this section was to introduce a set of factors for comparison of affective tutoring systems, that is provided later in section 4.3 and the following descriptive criteria might be taken into consideration: emotion recognition methods and input channels, emotion representation model, type and form of emotional intervention (definition of emotional states requiring intervention, intervention set and triggering rules), interaction type used, affect expression, affective phenomena exploited as well as expected influence on learning process. Exploited psychological phenomena.

3. Claims of affective learning manifesto 2004

In 2004 a group of affective computing researchers proclaimed a manifesto of affective learning (Picard et al. 2004) and the main claims included concerns about insufficient knowledge on emotions in learning processes as well as immature methods of affect recognition, interpretation and implementation in intelligent systems. The manifesto outlined gaps in social sciences, that provide nearly a hundred of definitions of emotion and multiple theories on how emotions are made. At the same time relatively little is known on the role of emotions in cognition, rational decision making and creation. The manifesto claimed a need for joint research from multiple fields of neurology, cognitive science, psychology and even medicine to explain emotional phenomena, its origins and implications on how people work and learn. There are multiple studies on emotion influence on learning, that include role of beliefs, self-efficacy, audience, past experience and many other factors. However the manifesto authors evaluate, that the theories are not at a level, that is suitable for implementation in an interactive machine model. The emotion theories are incompatible with computer-based processing and therefore hard to apply in e-learning environments. The manifesto authors concluded, that the extension of cognitive theory to explain and exploit the role of affect in learning is in its infancy (Picard et al. 2004).

Some other observations concerned affective computing state at the time of manifesto and they were also very critical. Automatic emotion recognition at that time was in the preliminary stage of research with few results and low accuracy. The main problem in elicitation of a person’s emotional state is that we do not know the right answer, as there is no way of determining for sure the affective state of a human. Self-reports can be intentionally biased or unintentionally misleading, as they depend on when and how the information is asked. Deduction of an emotional state from observable symptoms has also several uncertainty factors, including not only precision of recognition algorithm, but also the quality of the input channel and interpersonal variability. Moreover, observable symptoms are frequently not direct indications of an emotional state, e.g. people smile not only when they are happy, but also when they feel nervous or embarrassed (Whitehill 2011). It’s easier to recognize a smile than to resolve what it means.

Considerations on emotion recognition in the manifesto concluded with the statement, that the state of the art in affect recognition is similar to that of speech recognition decades ago (Picard et al. 2004). The affective learning manifesto intended to explore the gaps, that should be successfully resolved in order to apply affective computing methods in education and e-education. To sum up, the manifesto authors called for new research to:
- build tools and technologies that elicit and respond appropriately to affective factor,
- build new models of learning systems, that incorporate affect,
- develop resources and learning environments, that are affectively evocative and support affective learning.

The affective learning manifesto was quite critical, especially in evaluation of applicability of affective learning research in practical design of educational environments. It was also an opening for forthcoming research, showing the main goals and diversity of aspects to explore. The manifesto authors were not the only critical voice in 2004. Michael Muller questioned computers as social actors approach as well as using psychophysiological measurements of emotions without a stated theory of emotions (Muller 2004). Lindgaard expressed strong scepticism towards claims that affective responsiveness of computers can make human better-functioning and happier (Lindgaard 2004). Ward and Mardsen suggested, that a human uses intentional communicative affect while interacting with another human, which is more important than reactive affect to stimuli and this distinction might have an enormous impact on emotion recognition and understanding (Ward&Marsden 2004).
Ten years have passed by since the criticism in 2004 and affective computing is one of the most rapidly developing domain in computer science. Is this progress enough to allow for common application in educational systems?

4. Overview of the domain progress
When looking into affective computing literature in 2014 one might be impressed – there are algorithms that recognize affect from facial expressions, posture analysis, voice, textual inputs, behavioural patterns changes as well as physiology. Diverse emotional states are automatically recognized with accuracy reaching over 90% (e.g. Ko&Sim 2010). There are virtual characters, that have not only emotional states, but also moods and personalities (Nkambou 2006). The characters often express their emotional state with mimics as well as body language and voice (Sarafzadeh et al 2008). It may seem, that there are methods and technologies mature enough to be applied in diverse systems, including tutoring software. The overview of the domain progress is based on a literature review and is reported in three sections: progress of affect elicitation and response, studies on affect in learning and e-learning and a comparison of selected affective tutoring systems (as described by their authors).

4.1. Progress of tools and techniques of affect elicitation and affective response.
The mostly observable progress relates to affect elicitation from diverse input channels and, as stated before, some researchers report accuracies as high as 90% (Ko&Sim 2010). However, some restrictions must be provided: the highest accuracies are obtained for two-state analysis (for example differentiation boredom from no-boredom) and for personalized emotional reaction models, which requires baseline observation and annotation. Best results are obtained for the channels, that are rarely available at home or school computer desk: prosodic features and physiological measurements. Moreover, good results can be achieved for multimodal emotion recognition, which is sensitive to missing channels. As there is so much uncertainty related to emotion recognition, a model for its quantification is still missing (Landowska 2013a).
There are also few studies on the effects of affective feedback on student’s emotional state and performance (Robinson et al, 2009, Rodrigo et al 2012).

4.2. Studies on affect in learning and e-learning.
During the last decade multiple diverse studies have been performed on affect in learning and e-learning. An interesting study on program comprehension showed, that the higher emotional quotient of a person, the better the comprehensibility and debugging ability of any program (Savarimuthu et al 2010).
Another study of dynamics of affective state in complex learning processes emphasis, that a learner frequently and smoothly oscillates between the equilibrium of flow and other states (D’Mello, Graesser, 2012). One of the recent research reveals a surprising result, that confusion can be beneficial for learning and therefore ATS goals should be revised not to avoid that state of a learner’s mind (D’Mello et al 2014).
Another study on emotions frequency and persistence in learning environments discovered, that concentration and engagement are reported as emotional states during for about 60-65% of the interaction time with some learning environments. Boredom, confusion and frustration frequency did not exceeded 20%. The same research revealed, that boredom is the most persistent state, close to mood rather than reaction to learning experience (Baker et al. 2010).
Research conducted on a large international group of novice students (730) in Netherlands indicates that achievement emotions play an important mediator in how students engage with both on-line and face-to-face education (Tempelaar et al 2012). Another study on educational virtual world (Second Life) measured, that students’ level of enjoyment and boredom has influence on their achievement level (Noteborn et al 2012).

4.3. Studies on affective tutoring systems
An affect-aware system is defined as a program of any main functionality, that additionally recognizes emotional state of a user and has control mechanisms and application logic able to handle the information on affect (Landowska 2013b). Intelligent Tutoring System (ITS) can be an affect-aware application if provided with mechanisms to recognize learner’s affective state and somehow reacting to it (such application is also called an Affective Tutoring System, ATS). Usually intelligent tutoring software processes information on user’s performance in educational tasks in order to adapt its behaviour and learning paths to user experience and profile. Affective systems adapt not only to user experience and knowledge, but also to learner’s emotional state.
In 2011 at Gdansk University of Technology a project was started that aimed at practical implementation of affective computing science into an e-learning system called Gerda. Gerda is a virtual teacher, that questions students on operating systems and aims at both checking and consolidating their knowledge in the subject. From that point until now Gerda is being developed, still far from providing a real affective learning experience and it seems to be also true for the other analyzed affective tutoring systems. The experience of trying to build an affective tutor allowed to verify applicability of affective computing research in practical settings.

There are several characteristics, that can describe affective tutoring systems and a list of those was provided in section 2. From the features mentioned emotion recognition and representation, intervention model and expected influence on learning process is used in this paper to analyze and compare some examples of affective tutoring systems. The selection of the descriptive criteria was based on the variance of values, as the intention of the paper is to show diversity and complexity of affective tutoring systems. The ATS comparison results are presented in Table 1.

**Table 1: Affective tutoring systems comparison summary.**

<table>
<thead>
<tr>
<th>System name (source)</th>
<th>Emotion recognition and representation</th>
<th>Emotional intervention and output</th>
<th>Expected influence on learning process</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emilie-1 &amp; Emilie-2 (Nkambou 2006)</td>
<td>Emilie 2 captures learner's emotions from facial expressions. Detects: satisfaction, confidence, surprise, confusion and frustration.</td>
<td>Emilie 1 expresses emotions concerning knowledge, skills and performance history (2D or 3D virtual character expressing hope, fear, satisfaction, relief, disappointments).</td>
<td>Emilie-1 is claimed to be applicable as any tutoring agent (coaching, critiquing etc.) in order to raise students' productivity and facilitate their enjoyment or at least make positive impression.</td>
</tr>
<tr>
<td>Easy with Eve (Alexander et al 2006, Sarafzadeh et al 2008)</td>
<td>Based on video channel (posture and facial expressions). Detects: boredom, confusion, inattention and anxiety.</td>
<td>Emotional Embodied Virtual Character, that performs facial expressions as well as posture movements (body language).</td>
<td>Help to maintain the states of flow and helps to overcome states of “stuck” of any kind.</td>
</tr>
<tr>
<td>AutoTutor (D'Mello et al 2008)</td>
<td>Dialogue-based features are extracted and analyzed to identify confusion, eureka (delight) and frustration and boredom.</td>
<td>Embodied agent (facial expressions) as well as verbal response is provided.</td>
<td>Not explicitly provided.</td>
</tr>
<tr>
<td>Vicor (Grujic et al 2009)</td>
<td>Student’s emotions not recognized.</td>
<td>Embodied Conversational Agent (talking, gesturing and performing facial expressions).</td>
<td>Enhance the quality of experience for on-line students by exploiting persona effect.</td>
</tr>
<tr>
<td>Intelligent Tutor for Learning Robotics (Hernandez et al 2009)</td>
<td>Expected emotional state is predicted based on OCC theory and Five Factor Model.</td>
<td>Virtual tutor actions (animations) are chosen based on affective state and knowledge state (with affective preceding the knowledge state, as human teachers reported to do).</td>
<td>Promote a positive affective student state. Considers a trade-off between learning and affect.</td>
</tr>
<tr>
<td>EMASPEL (Ben Ammar et al 2010)</td>
<td>Face expression analysis classified into Ekman’s six basic emotions set</td>
<td>Embodied conversational agent is used, decision on intervention is made on emotional state, curriculum progress and student history.</td>
<td>Intrinsic motivation reinforcement, interventions for engagement and persistence.</td>
</tr>
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<tr>
<td>MMT (Alepis, Virvou, 2011)</td>
<td>Expected emotional state is predicted based on OCC theory, obtaining happiness, sadness, anger, fear or surprise as a result.</td>
<td>Voice communication (cartoon doctor interface agent): enthusiasm (student's doing well), anger (student seems careless), whisper (helping).</td>
<td>Students motivation for more engagement and enjoying learning process.</td>
</tr>
<tr>
<td>Gerda (Landowska 2013a, Landowska 2013b)</td>
<td>Based on student’s textual input analysis using dictionaries of affect-annotated words, provides a point in PAD model, then discretized.</td>
<td>Both textual and video response is performed and video response is chosen from a set of pre-recorded action set (performed by actor).</td>
<td>Reacts to anger (3 levels), frustration (3 levels), boredom, hilarity and idleness. Refrains from intervention in states close to neutral.</td>
</tr>
<tr>
<td>Fermat Affective ITS (Cabada et al 2012, Barron-Estrada et al 2012)</td>
<td>Face expressions and voice is analyzed to recognize: Ekman's six basic emotions and neutral state.</td>
<td>Microsoft Genie agent placed within Fermat interface can perform congratulate, confused, explain and suggest expressions.</td>
<td>Not explicitly provided.</td>
</tr>
</tbody>
</table>

5. Results summary and discussion
There are several conclusions that might be drawn from the above study on affective tutoring systems:

- there is no one standard emotion model for quantifying learner’s affective state, OCC model for emotion prediction is frequently used, but diverse emotion sets and models are also applied,
- some of the ATS concentrate on learner’s emotion recognition and some on emotion expression by embodied tutors, however most of ATS address both directions of affective interaction loop,
- facial expression analysis is one of the mostly explored affect recognition technique,
- embodied agents are frequently used, but their influence on learning performance is not explicitly evaluated,
- some of the systems are developed for research purposes and do not provide information on expected effect on learning performance,
- there are several reasons for applying ATS: increasing student’s performance in learning processes, enhancing student enjoyment and making an impression (the latter is mentioned explicitly only once, however might be a hidden cause of sophisticated embodied agents visualizations).

Most of the affective tutoring systems analyzed concern research applications only and no information is provided on any popular learning management system that employs any of the developed frameworks, designs and methods. It seems, that, typically for research, more attention is paid to emotion recognition accuracy and emotion expression realism than to the most important part – the effect on learner and learning process.

Author of the paper acknowledges, that chosen approach to literature review and analysis are not without limitations. The main limitation of the study include subjective choice of affective tutoring systems described and subjective choice of criteria for the comparison, although the selection was justified by the purpose of showing diversity of ATS. Another restriction should be provided for literature review, as it was performed by one person and on the resources available on-line only.

6. Conclusions
The paper intended to explore the progress of affective computing and affective learning domain, especially in the context of e-learning. There are issues, that were intensively explored by researchers during the last decade, such as emotion recognition on different and combined input channels, sensing without interfering, patterns of measurable external changes associated with feelings, deliberately expressed emotions versus natural expressions, emotion induction for research purposes as well as creating applications that learn about a person’s affect. However, the progress in some of the above mentioned areas resulted in identification of new challenges to be solved.

Due to neurobiologists, psychologists, sociologists as well as affective computing researchers we know more about what an emotion is, and how it could be measured. However it is still little known on
how to influence emotional states within learning environments and the effectiveness of different tutoring strategies is yet to be proved. Some of the future challenges include:

- improvement of both granularity (number of distinguishable emotional state classes) and accuracy of emotion recognition, as with raising granularity, accuracy usually suffers (Chao et al 2012) and two-state emotion recognition is not enough for learning support,
- recognizing affect form multiple channels, not relying on facial expressions only, as this input channel is dependent on: human controlling mimics, availability of camera at learner’s computer desk, quality of the camera and light conditions in the room,
- finding a model for expressing uncertainty related to emotion recognition and affective intervention,
- providing some mapping between diverse emotion representation models (PAD, Ekman’s, OCC etc) in order to either compare or integrate results coming from diverse input channels,
- defining an optimal affective learning subspace or precise emotion set, that have been proved to support learning or developing methods for retrieving such an individual space from observation and interaction with a learner.

To sum up, the thesis of this paper can be summarized as follows: Affective computing grew up from infancy, however is still far from maturity especially when it comes to learning support. In 2014 affective tutoring systems seem rather research applications than real-life learning environments. Affect-aware features are not present in the popular learning management systems. During the decade of diverse investigations, affective-cognitive imbalance in ITS has changed in research, however it has not changed in learning support tools. Although the results of 10 years of research are very encouraging and promising, we are still far from ubiquitous affective tutoring systems. Perhaps, it would be more beneficial first to perform studies on effectiveness and user experience of common learning environments and tutoring systems, and then to equip them with the most sophisticated interfaces and reasoning capabilities.

References


