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Affective Computing: A Closer View of Self-Reported Instruments in Education

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Abstract

The trends of affective computing have rapidly become an issue in educational settings. Even self-reported instruments have been the most popular class of instruments for emotional experience assessment over the past years, there are deficiencies in the in-depth literature review and classification of research based on these affective recognition instruments. For that reason, this study focused on the self-reported instruments and reviewed 18 related studies from IEEE Xplore, ScienceDirect, and Springer link databases published from 2010 to 2015, and categorized them based on affective recognition instrument, affective classification, and learning domain. Finally, this study provides insight and future direction on self-reported affective computing instruments for both researchers and practitioners.

Keywords: Self-reported instruments, Affective computing, Educational settings

1. Introduction

Emotions are considered as individual experiences which are rely on the condition in which they appear (Linnenbrink, 2006). Emotions are an essential part of daily routine, where they influence human behaviour, their thinking ability and how do they communicate with others (Subramainan, Yusoff, & Mahmoud, 2015). Research in integrating affective components to humanlike agent has increased over decade in order to improve the effectiveness of human computer/robot interactions (Ammar & Neji, 2006). Recently, Affective Computing (AC) has become one of the most interesting research topics. Outcomes from the affective states recognition are useful to analysis the user reactions to expect behavioural intentions and to create reasonable responses. Therefore, proposed systems and their user interface in potential applications can be improved (Handayani et al., 2014). Further, the incorporation of emotion detection can significantly advance the borders of educational technologies and offer some additional values to enhance the overall distance learning experience as well as providing new opportunities for the low cost delivery of teaching and learning programs (Caballé, 2015).

Educational environments provide a foundation of appearing different emotions which need to be managed. Emotions significantly affect users' learning and play a critical role in their decision making, managing learning activities, timing, and reflecting on the studies. Emotions are also vital in teaching and learning processes and usually cause different reactions with others and increase motivation in learning (Sandanayake & Madurapperuma, 2013). Therefore, to identify the relationships between emotional, cognitive and motivational features of learning, reliable methods of emotion recognition in an academic context are critical (Burić et al., 2016).

The trends of affective computing have rapidly become an issue in the education context (Wu et al., 2015) and can be recognize through different instruments such as self-report conventional text or questionnaire, skin conductance, heartbeat, facial expression, electroencephalography (EEG), electromyography (EMG) verbalization, and speech. Detecting the physical emotions requires additional hardware to recognize body gestures and positions, prosodic features and psycho-physiological data that is matched with various emotional meanings. Drawbacks of this method are obtaining large amount of data and also that hardware is disturbing and prone to failure (Muñoz et al., , 2010). Sensors are most popular used devices able to get physiological measures which need an professional on how to interpret needed information from the collected data and are usually expensive (Barreto, Zhai, & Adjouadi, 2007; Hussain, AlZoubi, Calvo, & D'Mello, 2011). Further, according to (Sandanayake, Madurapperuma, & Dias, 2011) highly confirmed, structured and controlled learning environment need to collect the biological information of a learner and the provision to practice this scenario in open and distance learning environment is somewhat difficult. Hence, some other methods and instruments should be considered in measuring such emotions. In this situation, research on the recognition of different learning emotions from self-reported instruments is worth consideration. These instruments are reliable, easy to use and manage, cheap, and independent of any special equipment. To date, most review papers have focused on the origins of affective computing, trends and challenges, models, methods, and their applications (Calvo & D'Mello, 2010; Duo & Song, 2010; Malekzadeh, Mustafa, & Lahsasna, 2015; Moridis & Economides, 2008; Wu et al., 2015). Moreover, some of them review the state of the arts related to the unique emotion like boredom (Vogel-Walcutt, Fiorella, Carper, & Schatz, 2012) or stress (Alberdi, Aztiria, & Basarab, 2016). However, much less attention has been directed towards affective detection using self-reported instruments even none with focus on education. To cover the above mention gap, this study aims to review affective detection using self-reported instruments from 2010 to 2015 in education domain.

2. Research Methodology

To find relevant papers, "emotion detection in education/learning", "affective computing in education/learning", "students' emotion", "self-reported emotion", "affective E-learning", "textual recognition in affective tutoring systems" were used as search terms/keywords. IEEE Xplore, Springer Link, and ScienceDirect were selected as appropriate online databases. To improve the quality of papers reviewed, only recent studies published from 2010 to 2015 in journals and conference proceedings were considered. Fig. 1 shows the process of selection of relevant papers. Using this approach, a total of 18 full text papers were selected and reviewed in this study.

3. Discussion

As shown in Appendix A, 18 selected papers are categorized based on affective recognition instrument, affective classification, and learning domain. The distribution of research papers by year of publication between 2010 and 2015 is shown in Fig. 2. It is obvious that, even there is a peak of 5 related papers in 2011, the number of publications decrease dramatically in 2012. However, the number of studies have steadily increased from 2013 and reached a peak of 5 papers in 2015 again. This shows the possibility for more research and improvement of self-reporting instruments in the areas of affective computing.

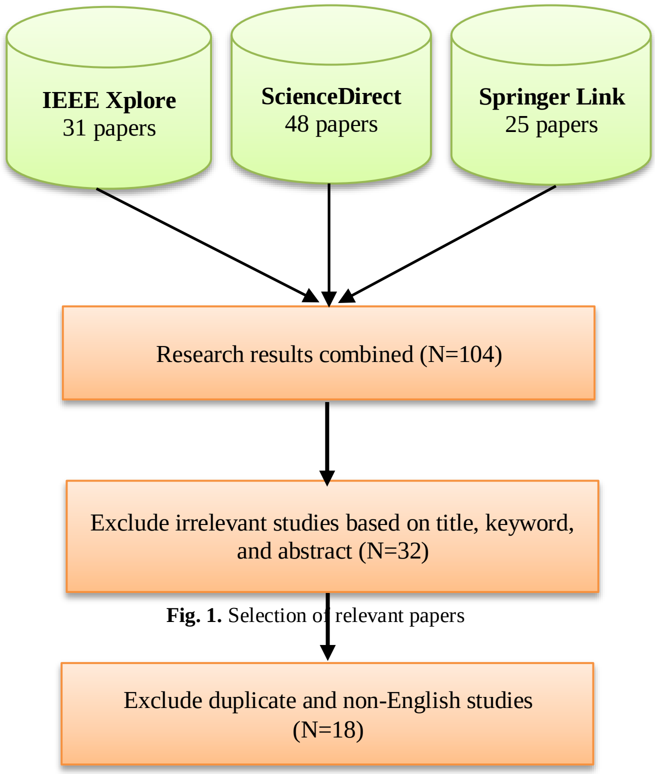

Fig. 1. Selection of relevant papers

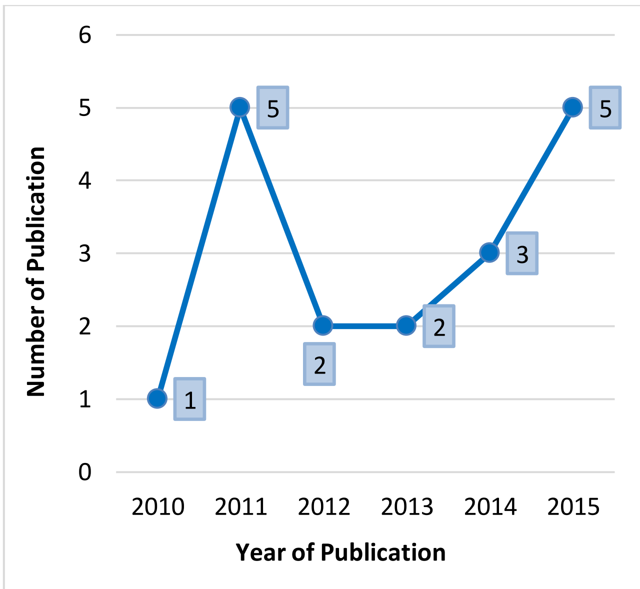

Fig. 2. Distribution of research papers by year of publication

Fig. 3. shows three kinds of self-reported instruments used for affective computing in educational settings. The questionnaire was still the most popular instrument in related studies (55%). 28% are multimodal which use mix instruments including self-reported instrument to recognize affective states of users. Additionally, using textbox/dialog

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box (17%) is also popular among related studies. According to (Lin, Wu, & Hsueh, 2014) questionnaire has the advantages collecting useful and reliable information from respondents without the need of huge amount of time and cost, and the ease of summarization and control, with the analytic results being neutral. Therefore, simplicity, reliability, and cost effectiveness are the main important reasons for high interest of researchers in applying questionnaire instrument in affective computing related studies.

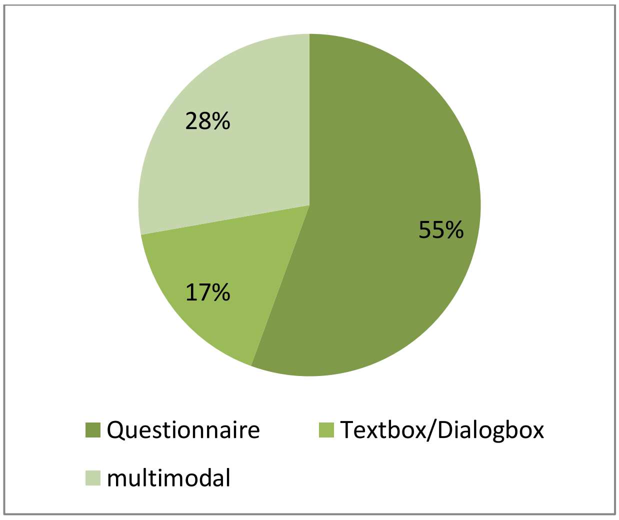

Fig. 3. Self-reported instruments used in affective computing studies

As shown in Table 1, Achievement Emotions Questionnaire (AEQ), Mini-International Personality Item Pool (mini-IPIP), Agent Response Inventory (ARI), and Self-Assessment Manikin (SAM) are different questionnaires which are used in previous affective computing related studies.

Achievement Emotions Questionnaire (AEQ): AEQ consists of 24 scales which cover nine different emotions in three different academic achievement settings: learning-related, test-related, and class-related emotions.

Mini-International Personality Item Pool (Mini-IPIP): The mini-IPIP is a 20-item version of the 50-item International Personality Item Pool-Five-Factor Model measure (Harley et al., 2015).

Agent Response Inventory (ARI): ARI consists of 76 items examining the extent to which each of the Pedagogical Agents made users feel different discrete emotions (Harley et al., 2015).

Self-Assessment Manikin (SAM): SAM allows the user to rate her valence (i.e., pleasantness of the emotion) and arousal (i.e., strength of the emotion) in a numerical scale (Salmeron-Majadas, Santos, & Boticario, 2014).

Harley et al. (2015) administrated AEQ, mini-IPIP, and ARI as self-reported instrument in order to examine the relationship between learners' trait emotions as well as personality traits and their agent-directed emotions. Salmeron-Majadas et al. (2014) collected some awkward personal information and evaluate the valence and arousal dimension of users' emotions using SAM. Among them, AEQ is the most popular questionnaire which is used by most of the researchers (Sandanayake & Madurapperuma, 2013), (Harley, Bouchet, & Azevedo, 2013), (Noteborn, Carbonell, Dailey-Hebert, & Gijselaers, 2012), (Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011), (Sandanayake et al., 2011), (Muñoz et al., 2010) to detect emotion states of users in educational settings. These results probably because AEQ construction is based on a series of preliminary empirical and exploratory investigations. Further, it is a well-known instrument which has been applied in various studies since its introduction. According to (Pekrun et al., 2011) different scales of the AEQ have successfully been used to assess relationships between achievement emotions and students' learning and academic performance. They also indicated that the scales are reliable, internally and externally valid in terms of relationships with students' control-value appraisals, academic performance, and learning.

Table 2 illustrates that the top 10 used emotion status in self-reported questionnaires and textbox/dialog box instruments are enjoyment, boredom, anxiety, proud, shame, relief, hope, anger, hopelessness, and sadness. Overall, according to this table, unpleasant and negative emotion status are more reported to be considered by previous researchers in related studies.

Table 1
Various questionnaires used in affective computing studies

	AEQ	Mini-IPIP	ARI	SAM
(Harley et al., 2015)	X	X	X	
(Salmeron-Majadas et al., 2014)				X
(Sandanayake & Madurapperuma, 2013), (Harley et al., 2013), (Noteborn et al., 2012), (Pekrun et al., 2011), (Sandanayake et al., 2011), (Muñoz et al., 2010)	X			

AEQ: Achievement Emotions Questionnaire
Mini-IPIP: Mini-International Personality Item Pool
ARI: Agent Response Inventory
SAM: Self-Assessment Manikin

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Table 2
Frequency of emotion status used in questionnaire and textbox/dialog box

Number	Emotion	Frequency
1	enjoyment	10
2	boredom	9
3	anxiety	7
4	proud	6
5	shame	6
6	relief	6
7	hope	5
8	anger	5
9	hopelessness	5
10	sadness	4
11	natural	4
12	disappointed	3
13	excitement	3
14	frustration	3
15	confusion	3
16	satisfaction	3
17	anger	3
18	fear	3
19	happiness	2
20	Curiosity	2
21	Disgust	2
22	surprise	2
23	distress	2
24	gratitude	2

Finally, as presented in Appendix A, self-reported instruments have been successfully used to assess affective states of users in different learning domains including: built environment management, math, history, digital arts, computer science, earth time zones, business, management.

4. Conclusion and Future Work

Affective computing has increasingly attracted the attention of academics and practitioners in recent years. This study reviewed affective detection using self-reported instruments from 2010 to 2015 in educational settings. This review gives the clear idea regarding the various self-reported instruments and affective classification in related studies. In total, 18 research papers were studied and reviewed. Results showed that even some papers follow similar direction, there is an increasing potential for future research and improvement of self-reporting instruments in the areas of affective computing. Further, from three classifications, questionnaire was observed to be the most popular self-reported instrument with 10 papers. Meanwhile, AEQ is the most common questionnaire which was used to detect emotion states of users in educational settings. Enjoyment, boredom, anxiety, proud, shame, relief, hope, anger, hopelessness, and sadness were top 10 used emotion status in self-reported questionnaires. Finally, evidence showed that self-reported instruments have been successfully used to assess affective states of users in different learning domains. Based on the results of review process some insights and future directions on self-reported affective computing instruments are provided for both researchers and practitioners as below:

- Increasing number of studies using self-reported instruments in affective computing process witnesses the increasing interest of researchers as well as increasing importance of these kind of instruments in affective computing studies in educational settings. Therefore, future studies are suggested to more concentrate on the usability of the self-reported instruments across different age groups, educational levels and countries.
- AEQ is reported as most popular self-reported questionnaire used in previous studies. However, since individuals in many situations cannot perceive and report their own emotions, it is suggested to the practitioners and researchers to develop new multimodal instruments combining AEQ instrument and other affective recognition methods such as facial expression, body gesture, eye tracking, heart rate, electroencephalogram (EEG), electrocardiography (ECG or EKG), and so on. Therefore, the enormous amount of information generated from both sensors and questionnaire may help to achieve more comprehensive understanding of learners' behavior in real-time environments. Meanwhile, investigation considering this category, its pros and cons, affective classifications, emotion models, and emotion recognition methods will be an interesting area for further research.
- The vast majority of reviewed studies focus on the management of negative emotions that are perceived as hindrance in an academic context. Although considering such emotions is very important, it would be recommended to practitioners and academics to focus on additional strategies aimed at managing the positive emotions, to enhance reaching the desired academic goals.
- Even self-reported instruments have been successfully used to assess affective states of users in different learning domains, these kinds of affect calculations can also be applied in the open and online education like MOOCs (Massive Open Online Courses) and M-learning (Mobile learning) to provide more personalized learning environment and build more vivid scenario. Thus, future study on emotion-sensitive computerized MOOCs and M-learning is suggested.

This study only reviewed research papers published between 2010 and 2015, and our searches were based on three databases (IEEE Xplore, ScienceDirect, and Springer link). Therefore, future research is suggested to cover different period of time and databases to provide more in-depth insights into research and development of affective computing in educational settings.

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Appendix A: Distribution of studies by self-reported instrument, affective classification, and learning domain

Research Paper	**Self-reported instrument**	**Affective classification**	**Learning domain**
(Altrabsheh, Cocea, & Fallahkhair, 2015)	Textbox	Amused, anxiety, appreciation, awkward, bored, confusion, disappointed, embarrassed, engagement, enthusiasm, excitement, frustration, happy, motivated, proud, relief, satisfaction, shame, uninterested	NS
(Caballé, 2015)	Body posture, voice intonation, eye tracking, facial expressions, eye pupil's size, heart rate, electero-dermal, keyboard events, mouse clicks, text input, verbal, pictorial	NS	NS
(Harley, Carter, et al., 2015)	Questionnaire	Enjoyment, Hope, Pride, Anger, Anxiety, Hopelessness, and Boredom, Happiness, Curiosity, Eureka, , Frustration, Shame, Fear, Contempt, Disgust, Sadness, Surprise, Confusion, and Neutral	NS
(Kaklauskas et al., 2015)	Heart rate, blood pressures, skin humidity, perspiration, temperature and conductance, voice stress analysis, EEG, self-report by questionnaires and/or textboxes	Stress, interest in learning, learning productivity	Built Environment Management
(Harley, Bouchet, Hussain, Azevedo, & Calvo, 2015)	Facial expression recognition, self-report by questionnaire (AEQ), electro-dermal activity (EDA)	Happy, enjoyment, hope, pride, curiosity and eureka, anger frustration, fear, anxiety, disgust, shame, contempt, sadness, confusion, hopelessness, boredom, surprise neutral	Math, engineering, social science, business, arts
(Feidakis, Caballé, Daradoumis, Jiménez, & Conesa, 2014)	Textbox	inspired, excited, interested, relaxed, curious, confused, anxious, embarrassed, indifferent, bored, tired, angry, desperate, neutral	Organization Management and Computer Science
(Salmeron-Majadas et al., 2014)	Keyboard and mouse interaction and Self-report by questionnaires	------	Math
(Ismaail & Mohd Zahid Syed Zainal Ariffin, 2014)	Questionnaire	Excited and bored	History
(Sandanayake & Madurapperuma, 2013)	Questionnaire	enjoyment, pride, hope and relief, anger, anxiety, hopelessness, shame and boredom	NS
(Harley et al., 2013)	Self-reported by questionnaire using Achievement Emotion Questionnaire (AEQ) Facial expression	Happy, enjoyment, hope, pride, anger, frustration, anxiety, fear, shame, confusion, sad, curiosity, eureka, contempt, disgust, hopelessness and boredom, neutral and surprise	Human circulatory system
(Noteborn et al., 2012)	Questionnaire	boredom and enjoyment	Management
(Chao, Lin, Lin, & Tseng, 2012)	Textbox/dialog box	anger, fear, disgust, surprise, joy, and sadness, normal expressionless	Digital arts
(Pekrun et al., 2011)	Questionnaire	enjoyment, hope, pride, relief, anger, anxiety, shame, hopelessness, and boredom	Psychology
(Gu, Li, & Diao, 2011)	Questionnaire	joy, anxiety, sad. angry	NS
(Jaques, Vicari, Pesty, & Martin, 2011)	Dialog box	joy, distress, satisfaction, disappointment, gratitude, anger, shame	Earth time zones
(Eyharabide et al., 2011)	Questionnaire	Satisfaction, Disappointment, Joy, Distress, Fears-Confirmed, Relief, Boredom, Surprise, Stress, Neutral	Computer science
(Sandanayake et al., 2011)	Questionnaire	Enjoyment, Pride, Hope, relief, anger, anxiety, hopelessness, shame, and boredom	Science in Information Technology
(Muñoz et al., 2010)	Questionnaire	joy, hope, hopelessness, anxiety, relief, pride, gratitude, anger, shame, sadness, frustration, boredom	Physics

NS= None Stated

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