Emotions used in Learning Analytics: a state-of-the-art review

Other

Learning Analytics Community Exchange

Emotions used in Learning Analytics: a state-of-the-art review

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Emotions play a critical role in the learning and teaching process because learners' feelings impact motivation, self-regulation and academic achievement. In this literature review of 100+ studies, we identify approximately 100 different emotions that may have a positive, negative or neutral impact on learners' attitudes, behaviour and cognition. In this review, we explore seven methods of data gathering approaches to measure and understand emotions (i.e., content analysis, natural language processing, behavioural indicators, quantitative instruments, qualitative approaches, well-being word clouds, and intelligent tutoring systems). With increased affordances of technologies to continuously measure emotions (e.g., facial and voice expressions with tablets and smart phones), it might become feasible to monitor learners' emotions on a real-time basis in the near future.

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Executive Summary

With the increased availability of large datasets, powerful analytics engines, and visualisations of analytics results, educational institutions may be able to monitor, unpack and understand the learning processes of their learners. In this LACE review, we focus on the role of emotions in learning, since an increasing body of research has found that emotions are key “drivers” for learning. Emotions play a critical role in the learning and teaching process because learners’ feelings impact motivation, self-regulation and academic achievement.

In this literature review of 100+ studies, we identify approximately 100 different emotions that may have a positive, negative or neutral impact on learners’ attitudes, behaviour and cognition. In traditional learning environments such as lectures, seminars, and tutorials. there is an increased recognition that emotions are important factors affecting students’ learning. However, in online contexts and when considering learning analytics, in particular, limited research is available on how emotions impact learning.

Using *Garrison’s* (2011) adjusted *Community of Inquiry* framework, we provide a conceptual framework for learning analytics researchers to unpack and understand the role of emotional presence in blended and online learning. *Cleveland-Innes and Campbell (2012*) defined emotional presence as “the outward expression of emotion, affect, and feeling by individuals and among individuals in a Community of Inquiry, as they relate to and interact with the learning technology, course content, learners, and the instructor”.

In this review, we focus on seven methods of data gathering approaches to measure and understand emotions. Three of these methods use existing data from common Virtual Learning Environments (i.e., through content analysis, natural language processing, and the use of behavioural indicators) and four of these methods use newly generated data approaches (i.e., quantitative instruments, qualitative approaches, well-being clouds, and intelligent tutoring systems). Each of these seven approaches has inherent strengths and weaknesses.

Measuring emotions in learning analytics brings significant epistemological, ontological, theoretical and practical challenges. Researchers’ assumptions about the nature of reality, the knower and the knowledge that guides the study of emotions and personal orientations will influence the collection and interpretation of these data (Buckingham Shum and Deakin Crick, 2012, Tempelaar et al., 2014).

With increased affordances of technologies to continuously measure emotions (e.g., facial and voice expressions with tablets and smart phones), it might become feasible to monitor learners’ emotions on a real-time basis in the near future. We hope that our review will spark new ideas and discussions amongst learning analytics researchers, managers and teachers, and we look forward to any comments and suggestions for further improvement.

> *There is no way to happiness; happiness is the way (thich nhat hanh, 2007)*

Introduction

Many educational institutions across the globe have high expectations of learning analytics to make their organisations more innovative, flexible and fit-for-purpose. Learning analytics applications are expected to provide educational institutions with opportunities to monitor, support and engage learners' attitudes (e.g., emotions, motivation, engagement), behaviour (e.g., contributions to discussion forums, clicks, likes) and cognition. In sum, these applications will, one day, enable personalised, rich learning on a large scale (Bienkowski et al., 2012, Siemens et al., 2013, Tobarra et al., 2014, Hickey et al., 2014, Tempelaar et al., 2014, Rienties et al., 2015). With the increased availability of large datasets, powerful analytics engines (*Tobarra et al., 2014*), and skilfully designed visualisations of analytics results (*González-Torres et al., 2013*), educational institutions may be able to use the experience of the past to create supportive, insightful models of primary and (perhaps) real-time learning processes (Baker, 2010, Ferguson and Buckingham Shum, 2012, Tempelaar et al., 2014).

This LACE review of 100+ studies will focus on the role of emotions of learners, as recent research indicates that emotions are key roles and drivers for learning (Artino, 2010, Kimmel and Volet, 2010, Pekrun et al., 2011, Tempelaar et al., 2014). We provide an overview of the role of emotions in learning to gain a better understanding of why collecting such data may be useful for enhancing learning analytics. In this review, we will use the (adapted) conceptual framework of Community of Inquiry (Cleveland-Innes and Campbell, 2012, Garrison, 2011), whereby we distinguish between cognitive presence, social presence, teaching presence, and emotional presence.

Although most teachers and learning designers want their learners to have a positive, "happy" and engaging learning experience (as illustrated by the Buddhist quote above), how to measure (or even adjust) such emotions seems daunting,. Such activities seem even more challenging when considering online learning environments. In this review we explore seven different approaches for gathering data on learners' emotions, in response to the following questions:

1. Using existing institutional data, which learning analytics methods and tools could institutions use to gauge learner emotions?
2. Using newly collected data, which tools for measuring learner's emotions can learning analytics researchers implement to effectively inform learners, teachers, managers and institutions?

The role of emotions in blended and online learning

Historically in Western thinking, emotions and human feeling were considered outside the sphere of rational thought. More recently, there has been a reconceptualisation of emotions as being inextricably linked to cognition and learning, and therefore of interest to educational researchers (Artino, 2012, deMarrais and Tisdale, 2002). Emotions play a critical role in the teaching and learning process (*Schutz and DeCuir, 2002*) because learners' feelings affect motivation, self-regulation and academic achievement (Chew et al., 2013, Kim et al., 2014, Mega et al., 2014). Research suggests that learners' emotions can influence their choice of study mode (Abdous and Yen, 2010, Artino, 2010, Lee, 2010) and can inform instructional design (Gläser-Zikuda et al., 2005, Meyer and Turner, 2002).

The literature on emotions and learning points to a range of human feelings associated with the learning context and academic achievement, such as anger (Baumeister et al., 2007, deMarrais and Tisdale, 2002, Dirkx, 2008, Mega et al., 2014, Pekrun et al., 2002, Strapparava and Mihalcea, 2008), boredom (Artino and Jones Ii, 2012, D'Mello and Graesser, 2011, Nett et al., 2011, Noteborn et al., 2012), desire (*Cleveland-Innes and Campbell, 2012*), enjoyment (Artino, 2010, Zembylas, 2008), happiness (*White, 2012*), pride (*Regan et al., 2012*) and yearning (*Cleveland-Innes and Campbell, 2012*).

The literature differentiates between *emotions* and *moods* by suggesting that moods are longer lasting and emotions are shorter, more intense and episodic (*Linnenbrink and Pintrich, 2002*). Other "emotions" are debated in the literature as to whether they are emotions or personal orientations, such as being interested or motivated (Buckingham Shum and Deakin Crick, 2012, Pintrich, 2003, Pekrun et al., 2002, Tempelaar et al., 2012). Some researchers assess emotions at the level of a specific emotion or even a specific facial expression or physiological/neurological response (D'Mello and Graesser, 2011, Terzis et al., 2013), while others focus on broader affective states, differentiating pleasant from unpleasant emotions (Artino, 2012, Kimmel and Volet, 2010, Mega et al., 2014, Nett et al., 2011, Noteborn et al., 2012, Shen et al., 2009). However, because they are mentioned in the literature as 'emotions' we have included them in our inventory. As such, some of these +/- 100 'emotions' listed in the Appendix may need to be considered in relation to the learners' own context to determine, say, if *happiness* is a mood or an emotion, and if *wondering* is a personal attribute or an emotion.

The development of learners' self-regulation of emotions, or *emotional intelligence*, is central to their education experience (Augustsson, 2010, Vandervoort, 2006). Substantial empirical work has been done in "traditional" face-to-face educational settings to investigate the predictive quality of emotions and emotional intelligence on their use of coping strategies (MacCann et al., 2011, Nett et al., 2011) and academic achievement (Chew et al., 2013, Hall and West, 2011, Knollmann and Wild, 2007, Mega et al., 2014). For example, in a recent experimental lab study, a strong link between emotions, physiological signs (e.g., pulse, blood pressure), learning behaviour and second language achievement is found (*Chen and Lee, 2011*). At the same time, a recent study by *Visschedijk et al. (2013*) in tactical decision-making settings with different types of behavioural cues of emotion (i.e., posture, facial expression, voice) indicated that some emotions were easy to recognise even with limited behavioural cues (e.g., anger, joy), while others were more difficult to recognise (panic, fear). In particular, in blended and online settings (Artino, 2010, Artino and Jones Ii, 2012, Tempelaar et al., 2009, Tempelaar et al., 2014), trying to understand the hidden, non-verbal or in text expressed emotions and moods of learners might be difficult for other learners and teachers to detect.

Artino (2012) claimed that although emotions play a powerful role in online education in terms of learners' learning, engagement and achievement, emotions have received little notice in educational research and learning analytics, in particular (*Tempelaar et al., 2014*). There is much to suggest that the role of emotions in online learning deserves special consideration when thinking about the nature of the learners and of the learning context. *Artino (2012*) calls for more research to be carried out that addresses: theories of emotions in online learning contexts, variance in emotions in online learning, and how online teachers can promote certain emotions in ways that enhance the learning experience. Recent studies such as Sansone et al. (2012) investigation of differences in self-regulated interest between online and face-to-face learners and Noteborn et al. (2012) study of the role of emotions in virtual education suggested there are unique differences in the evocation and influence of emotions across different learning contexts.

In a blended mathematics environment followed by 730 business students, *Tempelaar et al. (2012*) found a moderately strong relationship between feelings of enjoyment, anxiety, boredom and frustration and students' preference for online learning. In a follow-up study amongst 77 K-12 students, *Kim et al. (2014*) found that these emotions were a stronger predictor than self-efficacy and motivation, accounting for 37% of variance in student achievement. *Artino (2010*) showed that students who preferred to take online courses also reported greater self-efficacy and greater satisfaction with their current online course. Higher self-efficacy scores and higher satisfaction scores were also predictors of membership in the online group. A later study by *Artino and Jones Ii (2012*) found that enjoyment and frustration were positive predictors of self-regulation in online education. In other words, given the inherent importance of emotions in driving learning, learning analytics models need to develop sensitive approaches to understanding how learners' emotions influence their attitudes, behaviour and cognition.

Community of Inquiry and emotional presence

Garrison (2011)'s Community of Inquiry framework is commonly used as a tool for research into online learning and has been validated in subsequent studies (Akyol and Garrison, 2011, Arbaugh and Hwang, 2006, Rienties et al., 2013, Rourke and Kanuka, 2009). In the Community of Inquiry (CoI) framework, a distinction is made between cognitive presence, social presence and teaching presence. *Cognitive presence* is defined as "the extent to which the participants in any particular configuration of a community of inquiry are able to construct meaning through sustained communication." (*Garrison et al., 2000*) In other words, cognitive presence is the extent to which learners use and apply critical inquiry is a key feature of cognitive presence. *Social presence* is defined as the ability of learners to project their personal characteristics into the community, thereby presenting themselves to the other participants as ''real people''. A large body of research has found that for learners to critically engage in discourse in blended and online settings, they need to create and establish a social learning space (Caspi et al., 2006, Giesbers et al., 2013, Van den Bossche et al., 2006).

The third component of the Community of Inquiry framework is *teaching presence*. *Anderson et al. (2001*) distinguished three key roles of teachers that impact upon teaching presence in blended and online environments, namely: 1) instructional design and organisation; 2) facilitating discourse; 3) and direct instruction. By designing, structuring, planning (e.g., establishing learning goals, process and interaction activities, establishing netiquette, learning outcomes, assessment and evaluation strategies) before an online course starts (Anderson et al., 2001, Rienties et al., 2012, Rourke and Kanuka, 2009), a teacher can create a powerful learning environment within which learners can learn and interact with their peers and with a range of materials. Afterwards, a teacher can either facilitate discourse or provide direct instruction to encourage critical inquiry. According to *Anderson et al. (2001*), "facilitating discourse during the course is critical to maintaining the interest, motivation and engagement of students in active learning". Finally, direct instruction refers to teachers providing intellectual and scholarly leadership and sharing their specific domain-specific expertise with their learners.

However, recent research suggests that a fourth, separate category is needed to complement the CoI, namely *emotional presence* (Cleveland-Innes and Campbell, 2012, Stenbom et al., 2014). In a study consisting of 217 students from 19 courses, *Cleveland-Innes and Campbell (2012*) coded discourse in discussion forums and found that students expressed 17 different emotional states. Afterwards, using survey questionnaires amongst these 217 students with six specific emotional presence items in addition to 35 common CoI items, *Cleveland-Innes and Campbell (2012*) found a distinct, separate factor for emotional presence (e.g., "I was able to form distinct impressions of some course participants"; "The instructor acknowledged emotion expressed by students"). In other words, both in terms of (perceived) attitudes and actual behaviour in online environments *Cleveland-Innes and Campbell (2012*) were able to distil emotional presence. In a follow-up study in a mathematics after-school tutorial in Sweden, *Stenbom et al. (2014*) found that emotional presence was a clearly distinct, separate category in online chats that encouraged social interactions between pupils and tutors.

Social participation in online contexts presents several unique emotional challenges to learners and teachers (*Daniels and Stupnisky, 2012*). Epistemological insecurity related to the loss of the traditional classroom, fear of losing one's voice and worry of losing one's identity within an online group all create emotional tensions for learners (*Bayne and Land, 2013*). Online contexts may make it difficult for teachers and peers to ascertain learners' feelings (*Noteborn et al., 2012*) and in some contexts, silence may prevail (Cotterall, 2013, Rienties et al., 2013). Emotional presence might therefore be an important element that the learning analytics community need to take into account.

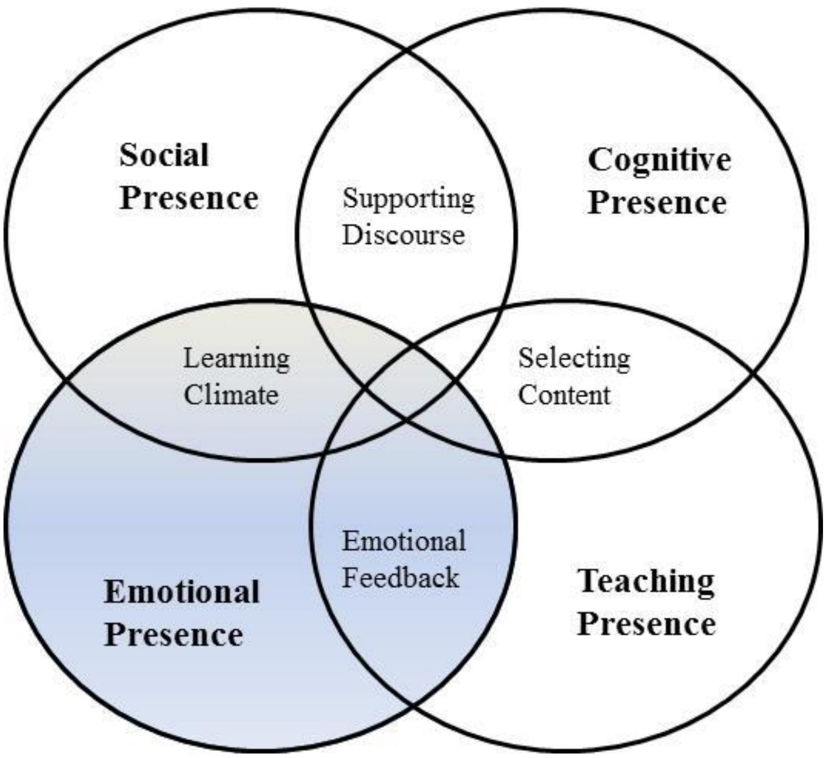

Figure 1. Community of Inquiry Framework for Online Learning (adapted from Stenbom et al. (2014)

Cleveland-Innes and Campbell (2012) defined *emotional presence* as “the outward expression of emotion, affect, and feeling by individuals and among individuals in a Community of Inquiry, as they relate to and interact with the learning technology, course content, students, and the instructor”. In line with *Stenbom et al. (2014*) we adjusted the Community of Inquiry model of *Garrison (2011*) by adding emotional presence in Figure 1.

We would like to remind the reader that emotions can occur at any stage of the learning process, at any of the four presence areas, and might be lead to completely different, even opposite, emotions for learners. For example, a rich, intensive discussion on the concerns of climate change in the Pacific in an asynchronous forum with dozens of posting (i.e., cognitive presence) might lead to positive emotions for some groups of learners (e.g., appreciation, curiosity, joy, motivation). Other learners who are not interested in climate change or have limited expertise in the particulars of climate change in the Pacific might feel disconnected or inadequate (*Rienties et al., 2012*). Finally, another group of learners might experience strong negative emotions (e.g., anxiety, depression, restricted, stupidity) as they are unable to contribute, or perhaps were told off (flamed, burned) when contributing. Similarly, a nice friendly discussion in a café forum about what peers are going to do for Christmas (i.e., social presence) might lead to completely different emotions amongst learners. Also teaching presence and (emotional) feedback in particular might lead to substantially different emotional reactions. For example, an encouraging reminder from the teacher to submit an assignment before Friday, along with a reminder that learners should not plagiarise, might lead to anxiety for some (e.g., Can I make the deadline?, How do I know whether I’ve plagiarised or not?). On the other hand, other students might be annoyed by the reminder as they were already on track to submit on time. Still, others might be completely surprised that they had to submit an assignment on Friday!. In other words, while Figure 1 illustrates emotional presence as a clear, distinct area in the Community of Inquiry model, emotions can occur as any stage of learning and teaching, and can vary significantly from learner to learner.

Measuring and understanding emotions using existing data

The burgeoning field of learning analytics offers tremendous opportunity for understanding and enhancing the learning experience (Bienkowski et al., 2012, Tempelaar et al., 2014, Tobarra et al., 2014, Ullmann et al., 2012). The possibility of collecting and mining large amounts of data from learners raises questions about which data to collect (Baker, 2010, Siemens and Baker, 2012), how to collect these data (Miller and Mork, 2013, Siemens et al., 2013), how to distil large amounts of data into meaningful representations (Thompson et al., 2013, Verbert et al., 2013, Whitelock et al., 2014) and how to use such insights to instigate enhancement of learning and teaching (Clow, 2013, Rienties et al., 2015).

Measuring emotions in learning analytics brings significant epistemological, ontological, theoretical and practical challenges. Researchers’ assumptions about the nature of reality, the nature of the knower and the knowledge that guides the study of emotions and personal orientations will influence the collection and interpretation of these data (Buckingham Shum and Deakin Crick, 2012, Schutz and DeCuir, 2002, Tempelaar et al., 2014). There are a variety of theoretical views on the nature of emotions and different methods on inquiry based on these beliefs. An additional difficulty in measuring emotions is deciding the level at which to evaluate them. In this review, we focus on three methods of data analysis of existing data to measure and understand emotions, namely content analysis, natural language processing and behavioural indicators.

Content analysis

Annotation and analysis of written text and online discourse is one method to access some existing forms of data from learners (Cleveland-Innes and Campbell, 2012, De Wever et al., 2006, Naidu and Jarvela, 2006, Strijbos et al., 2006, Strijbos and Stahl, 2007). For example, *Wiebe et al. (2005*) employed a manual technique to annotate indicators of opinions and emotions in written text. *Risquez and Sanchez-Garcia (2012*) used content analysis to code each online speech act based on 1) content—whether it was technical-methodological or participative-emotional; 2) direction—whether the speech act was coming from the mentor or from the mentee and 3) function—whether the purpose of the act was to provide information, request information or other. *Risquez and Sanchez-Garcia (2012, p. 216*) reported that "analysis of electronic records is simple, convenient and 50% more reliable than secondary sources". Others have indicated that content analysis (in particular manual analysis) can be quite cumbersome, labour intensive, and subjective unless sufficiently robust coding schemes and multiple coders are used (De Wever et al., 2006, Rienties et al., 2012, Strijbos et al., 2006, Strijbos and Stahl, 2007).

Natural language processing

Designing automated systems to derive meaning from Natural Language Processing (NLP) is another way to access some existing forms of data. Multiple studies have used automated processes to identify emotions in written text (Blikstein, 2011, Pennebaker et al., 2003, Strapparava and Mihalcea, 2008, Ullmann et al., 2012, Worsley and Blikstein, 2010). For example, *Dodds and Danforth (2010*) developed a blog analyser that identified phrases containing the words 'I feel…' across 2.4 million blogs. Data were ranked on a nine-point Happiness Scale. From these words and rankings, they developed an algorithm to calculate a net feel-good factor for each day and month. Somewhat relatedly, engines have been used to analyse text for learners' opinions (*Jeonghee et al., 2003*).

The *iTalk2Learn* project at Birkbeck College and the Institute of Education produced a system that analyses existing data related to students' emotions (*Grawemeyer et al., 2014*). This system has two components: 1) an emotion detector—which utilises speech recognition software and 2) an emotion reasoner—which attempts to reduce negative emotion by changing the environment (by aligning the task with the students' reasoning process). Systems developed at the Open University such as *OpenEssayist*, which provides automated feedback on drafts of students' essays (Alden Rivers et al., 2014), and *OpenMentor*, which analyses tutors' written feedback to students on their assessments, offer scope to consider how emotions may also be detected in these processes (*Whitelock et al., 2012*).

Identification of behavioural indicators

A third approach to measure and understand emotions is by learners' behaviour in blended and online environments. For example, existing data from learners' attitudes, behaviour and cognition may take the form of transcripts of discussion forums (Akyol and Garrison, 2011, Arbaugh and Hwang, 2006, Caspi et al., 2006, Stenbom et al., 2014, Tobarra et al., 2014), transcripts of recorded synchronous discussions (e.g., chat, videoconference, see Derks et al., 2007, Giesbers et al., 2013, Hrastinski et al., 2010, Stenbom et al., 2014), user analytics tracking learners' clicking behaviour through the virtual learning environment (Agudo-Peregrina et al., 2014, Tempelaar et al., 2014), and records of communication between learners and learner support teams, teachers and managers.

For example, *Derks et al. (2007*) asked learners to participate in online chats using text, emoticons or a combination of the two. Participants tended to use more emoticons during socio-emotional conversations than in task-orientated chats. Also, learners used more positive emoticons in positive contexts and more negative emoticons in negative discussions. The least number of emoticons were used in discussions that were negative and task-orientated. *Linnenbrink-Garcia and Pekrun (2011*) examined the effect of social loafing on the quality of small group interaction. Findings showed that negative affect (feeling tired or tense) was more strongly associated with social loafing. Neutral to deactivated positive affect (happy, calm) was directly related to positive group interactions. Deactivated negative emotions were negatively related to positive group interaction. *D'Mello and Graesser (2011*) used recordings of students' interactions with an online learning tool called AutoTutor to judge students' emotional states. By viewing two videos: 1) showing the students' faces as they carried out the learning activity; and 2) showing a screen capture of the learning environment (which showed printed text, students' responses, dialogue history and images), *D'Mello and Graesser (2011*) were able to classify students' affective states (e.g., boredom, confusion, delight, surprise). Using a longitudinal data analysis of 120+ variables from three different VLE systems and a range of motivational, emotions and learning styles indicators, *Tempelaar et al. (2014*) found that most "simple" VLE learning analytics metrics provided limited insights into the complex learning dynamics over time. In contrast, learning motivations and emotions (attitudes) and activities done by learners during continuous assessments (behaviour) provided an opportunity for teachers to help at-risk learners at a relatively early stage of their learning journey.

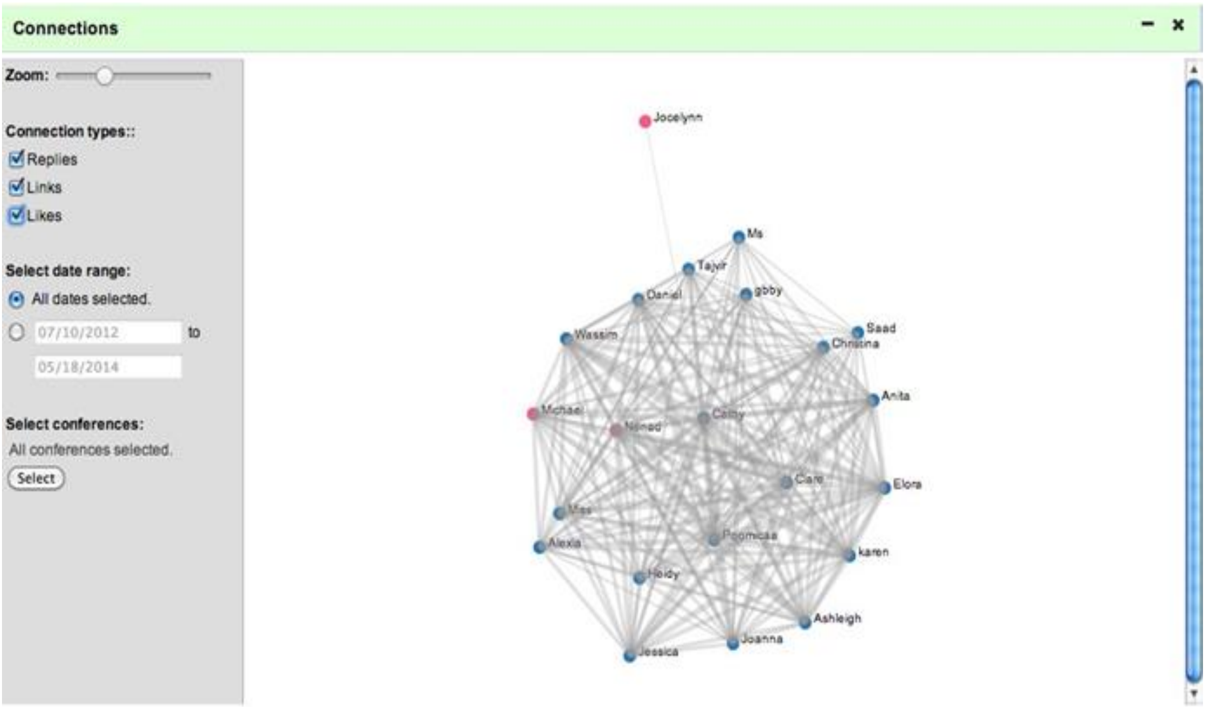

Figure 2. Online social cohesion based on use of likes, links and replies to posts (*Makos, 2014*)

Social Network Analysis (SNA) provides another behavioural tool for learning analytics researchers to analyse interaction patterns among learners (Cela et al., 2014, De Laat et al., 2007, Hommes et al., 2012, Sie et al., 2012, Rienties et al., 2012, Rienties et al., 2014). By integrating the results of content analyses or natural language processing (NLP) with SNA in order to measure participation in cognitive discourse, argumentation and social interaction patterns, a rich picture can identify which learners are actively engaging, and which learners are on the outer fringe (and potentially having negative emotions). *Rienties et al. (2014*) found that autonomous learners were more likely to develop discourse with other autonomous learners from Day One in an online economics course, while control-oriented (extrinsically motivated) learners gradually drifted towards the outskirts of the network. Similarly, *Makos (2014*) looked at how like buttons could be used to enhance social cohesion by nurturing positive feelings and encouraging deeper learning (see Figure 2). Findings from Makos's study also showed that more sophisticated pieces of writing received more likes and therefore, attracted more attention from other readers. In Table 1, we summarise the main approaches described to analyse and detect (traces of) emotions using existing data.

Table 1. Methods and tools for understanding learners' emotions based on *existing* data

Methods/tool	Link to literature
Content analysis	• Manual annotation of opinions and emotions in written text (De Wever et al., 2006, Strijbos et al., 2006, Wiebe et al., 2005) • Content analysis of emotion in online peer mentoring discussions (Risquez and Sanchez-Garcia, 2012, Stenbom et al., 2014)
Natural language processing	• Using programming code to ascertain emotions (Blikstein, 2011, Ullmann et al., 2012) • Using natural language processing to determine expression of emotion (*Worsley and Blikstein, 2010*) • Using natural language processing to gather opinions (*Jeonghee et al., 2003*) • Identifying markers of emotional states in text (Pennebaker et al., 2003, Ullmann et al., 2012) • Automatic analysis of emotions in text (*Strapparava and Mihalcea, 2008*) • Detecting learners' emotion to support their learning (*iTalk2Learn* project) • Providing automated feedback on drafts of students' essays (*OpenEssayist*, (*Whitelock et al., 2014*)) • Analysing tutors' feedback on students' assessments (*OpenMentor*, (*Whitelock et al., 2014*))
Identification of behavioural indicators	• Analysing the use of emoticons in online discussions (*Derks et al., 2007*) • Detecting active (central) and passive (outer-fringe) learners using social network analysis (Cela et al., 2014, Makos, 2014, Rienties et al., 2012, Rienties et al., 2014, Sie et al., 2012) • The effect of social loafing on small group interaction (*Linnenbrink-Garcia and Pekrun, 2011*) • Evaluating emotional states using recordings of learners' behaviour and facial expression in virtual learning contexts (D'Mello and Graesser, 2011, Giesbers et al., 2013)

Methods and tools for understanding emotions using new data

Collecting newly generated data from learners opens myriad possibilities and challenges for understanding learners' emotions (Cleveland-Innes and Campbell, 2012, Mayer et al., 2001, Pekrun et al., 2011). Several methods and tools are outlined in this section that provide scope to ascertain emotions in delayed and real-time ways. In this section, we review four approaches to collect emotions using new data gathering approaches, namely quantitative instruments, qualitative approaches, well-being word clouds and intelligent tutoring systems.

Quantitative instruments

There is an abundance of literature dealing with the design and validation of quantitative instruments for measuring emotions (e.g., Bradley and Lang, 1994, Cleveland-Innes and Campbell, 2012, Mayer et al., 2001, Mega et al., 2014, Pekrun et al., 2002, Wang et al., 2011, White, 2012). One instrument which appears to be widely used for understanding learners' emotions in blended and online environments is the Achievement Emotions Questionnaire (AEQ, Pekrun et al., 2011, Pekrun et al., 2002). The AEQ contains 24 scales to measure enjoyment, hope, pride, relief, anger, anxiety, shame, hopelessness and boredom during learning events. Previous studies have shown that the AEQ has a high degree of reliability and has been used alongside other instruments to explore relationships between emotion, task significance (*Noteborn et al., 2012*) and self-regulated behaviour (*Artino and Jones Ii, 2012*). The control-value theory of emotion rests on the notion that learners' beliefs about their ability to produce desired results and prevent unwanted outcomes (control) and their beliefs about the importance of their actions and of the outcomes of learning (value) are the primary antecedents for "achievement emotions" (Dettmers et al., 2011, Daniels and Stupnisky, 2012, Pekrun et al., 2002, Pekrun et al., 2011).

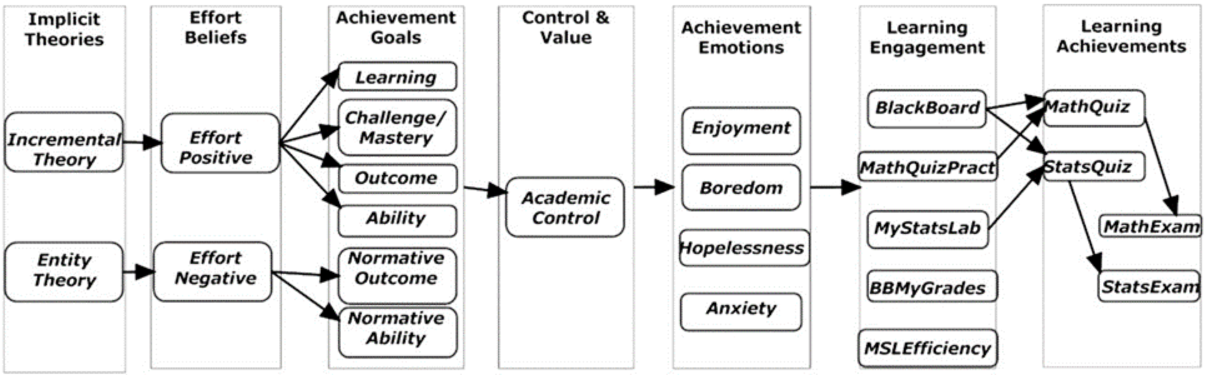

Figure 3. Control-value theory of achievement emotions (*Tempelaar et al., 2012*)

Tempelaar et al. (2012) used the control-value theory testing the relationship between a students' own learning goals (or goal-setting behaviour) and their emotions. *Tempelaar et al. (2012*) developed the model shown in Figure 3 to reflect their hypotheses that students' beliefs about effort (underpinned by their implicit beliefs of intelligence) influences their goal-setting behaviour, which then influences their beliefs about control and value. Four emotions (anxiety, boredom, enjoyment, hopelessness) were measured using the 43 items of Pekrun's Achievement Emotion Questionnaire. Follow-up structural equation modelling indicated a moderately strong relationship between feelings of enjoyment, anxiety, boredom and frustration and students' behaviour and cognition in online learning (Figure 4).

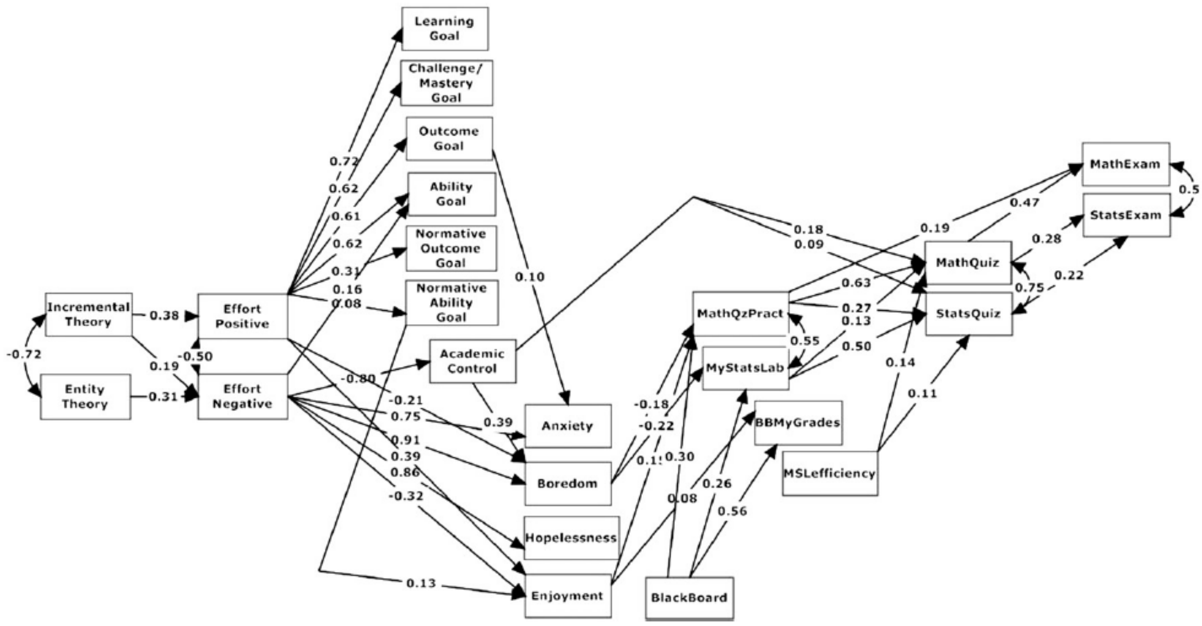

Figure 4. Path model of emotions and learning analytics behaviour and cognition (*Tempelaar et al., 2012*)

Offline interviews and purposeful online conversations

Qualitative research has a long tradition in trying to understanding how people think and feel. For example, *deMarrais and Tisdale (2002*) reported on the use of phenomenological interviews to study anger in female students. While qualitative methods may not be ideal for understanding emotions in large groups of learners, it may be possible to create discursive events in online spaces that can serve as corpora for automated analysis. For example, *Risquez and Sanchez-Garcia (2012*) used online peer mentoring discussions as a corpus for analysing emotional feelings. In many of the quantitative studies on emotions in learning, there are examples of how qualitative studies have been used as part of a multi-method approach (e.g., Mega et al., 2014, White, 2012).

Wellbeing word clouds

Wellbeing word clouds are dynamic visualisations of learners' self-reported feelings. For example, Edith Cowan University included a word cloud initiative in their Connect 4 Success programme to enhance learner progression (*Edith Cowen University, 2011*). Another Australian university—University of New England—implemented a swirling work cloud called 'The Vibe' (Figure 5), which is used as part of an early alert and student engagement tool (Nelson and Creagh, 2013, University of New England, 2012). Alternatively, institutions may just collect emotions using simple emoticons of students' experience on a daily/weekly/monthly basis.

Figure 5. 'The Vibe' wellbeing word cloud (*University of New England, 2012*)

Intelligent tutoring systems

Studies spanning more than fifteen years have explored the use of intelligent tutoring systems (Ahmed et al., 2013, Baylor, 2011, Fitrianie et al., 2003, Hawkins et al., 2013, Koedinger and Aleven, 2007, Lehman et al., 2012, Robison et al., 2010). For example, AutoTutor tracks students' cognitive and emotional states and adapts its responses based on these human attributes. AutoTutor engages users in a naturalistic dialogue with an on-screen agent (see Figure 6 for an example). The agent responds to the learner's speech, intonation, facial expressions and gestures. There is a particular version of AutoTutor that focuses more specifically on learners' emotions. *Lehman et al. (2012*) used AutoTutor to promote students' ability to cope with confusion. Like AutoTutor, many of these systems rely on multimodal biophysical feedback such as facial expression, eye movement and voice recognition (Bashyal and Venayagamoorthy, 2008, Shen et al., 2009). In Table 2, we summarise the main approaches to collect new data purposefully for learning analytics.

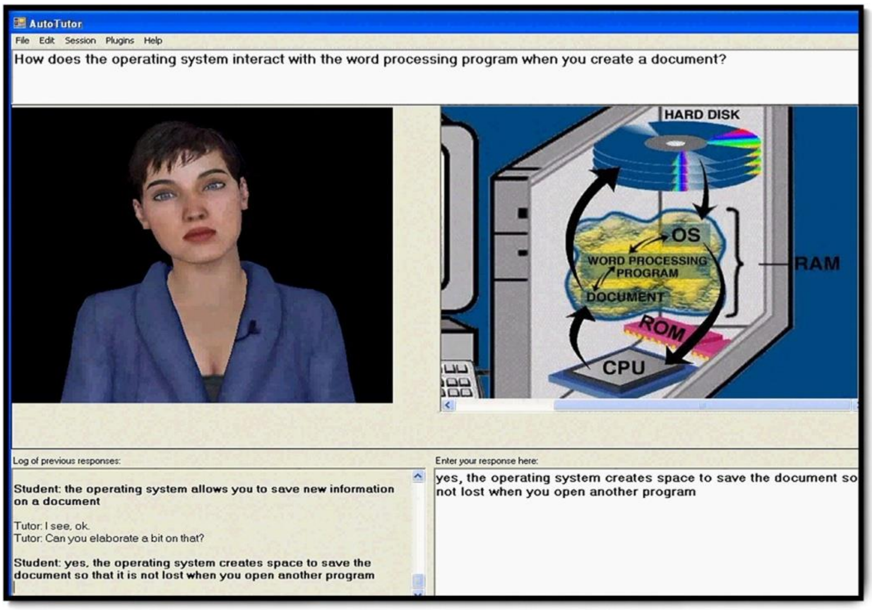

Figure 6. An application of AutoTutor (*Lehman et al., 2012*)

Table 2. Methods and tools for understanding learners' emotions based on new data

Methods/tool	Link to literature
Quantitative instruments	• Self-assessment Manikin to measure subjective experience of emotion (*Bradley and Lang, 1994*) • Widener Emotional Learning Scale (*Wang et al., 2011*) • Achievement Emotions Questionnaire (*Pekrun et al., 2011*) • Higher Education Emotions Scale (*White, 2012*) • Self-regulated Learning, Emotions, and Motivation Battery (*Mega et al., 2014*)
Offline interviews and purposeful online conversations	• Use of phenomenological interviews to study anger in female students (*deMarrais and Tisdale, 2002*) • Use of online peer mentoring discussions as a corpus for analysis of emotion (*Risquez and Sanchez-Garcia, 2012*)
Well-being word cloud	• Word cloud initiative (*Edith Cowen University, 2011*) • 'The Vibe' early alert and student engagement tool (swirling word cloud) (University of New England, 2012, Nelson and Creagh, 2013)
Intelligent tutoring systems, agent engines and avatars	• On developing empirically based student personality profiles for affective intelligent feedback (*Robison et al., 2010*) • Using AutoTutor to promote students' ability to cope with confusion (*Lehman et al., 2012*) • Developing machine emotional intelligence (*Picard et al., 2001*) • Recognising student emotion in an agent-based emotion engine (*Ahmed et al., 2013*) • On designing motivational agents and avatars (*Baylor, 2011*) • Computer recognition of facial expression (*Shen et al., 2009*) • Multi-modal bio-feedback for emotion recognition and student profiling (*Bashyal and Venayagamoorthy, 2008*)

Conclusions

With the increased availability of large datasets, powerful analytics engines and skilfully designed visualisations of analytics results, stakeholders (e.g., institutions, teachers, students) may be able to monitor, unpack and understand emotions from learners. In this LACE review we focussed on the role of learners' emotions, as an increasing body of research has found that emotions are key drivers for learning. Emotions play a critical role in the teaching and learning process because learners' feelings affect motivation, self-regulation and academic achievement (Chew et al., 2013, Kim et al., 2014, Mega et al., 2014, Tempelaar et al., 2012). In this literature review of 100+ studies, we identified approximately 100 different emotions that may have a positive, negative or neutral impact on learners' attitudes, behaviour and cognition. In "traditional" learning environments there is an increased recognition that emotions matter. However, *Artino (2012*) argued that emotions have received little notice in educational research in online settings and learning analytics, in particular.

Using an adjusted Community of Inquiry framework, we provided a conceptual framework that might be useful for learner analytics researchers to understand the complex, dynamic impact of emotional presence on cognitive presence, social presence and teaching presence. We would like to stress that emotions can occur at any stage of the learning process, at any of the four presence areas, and might lead to completely different, even opposite, emotions for different learners. Measuring emotions for learning analytics (either from existing or new data) brings significant epistemological, ontological, theoretical and practical challenges. Researchers' assumptions about emotions will influence the collection and interpretation of these data (Buckingham Shum and Deakin Crick, 2012, Tempelaar et al., 2014). There are a variety of theoretical views on the nature of emotions and different methods on inquiry based on these beliefs. An additional difficulty in measuring emotions is deciding the level at which to evaluate them. Thus, learning analytics algorithms trying to monitor, measure and unpack emotions from learners' behaviour need to be flexible enough to recognise that learners' emotions might vary significantly between students.

In terms of our second research question, we focussed on three methods of data analysis using existing data which can measure and understand emotions, namely content analysis, natural language processing, and behavioural indicators. Annotation and analysis of written text and online discourse is one method to access some existing forms of data from learners (Cleveland-Innes and Campbell, 2012, De Wever et al., 2006). A natural extension of content analysis (which can be labour intensive) is natural language processing (NLP). NLP uses automated systems to derive meaning from natural language input. Multiple studies have used automated processes to identify emotions in written text (Blikstein, 2011, Ullmann et al., 2012). Although substantial progress has been made in this field, at present most NLP approaches find it rather difficult to analyse fine-grained nuances in tone, expression and subtle emotions. While humans are quite capable to "read between the lines" to understand unwritten messages, NLP algorithms need further fine-tuning to understand the complex subtle discourses people engage in. Particularly, this is true for learners who come from diverse backgrounds (e.g., culturally, linguistically, socio-economically). A third option for unpacking emotions is to look at learners' behaviour. For example, transcripts of discussion forums, recorded synchronous discussions, records of communication between learners, learner support teams, teachers and managers, and user analytics tracking learners' clicking behaviour through the virtual learning environment (Agudo-Peregrina et al., 2014, Tempelaar et al., 2014) provide a large treasure trove to mine the four forms of presence and their interactions.

In terms of our third and final question, collecting new data from learners opens myriad possibilities and challenges for understanding learners' emotions (Cleveland-Innes and Campbell, 2012, Pekrun et al., 2011). We reviewed four approaches, namely quantitative instruments such as questionnaires, qualitative approaches, well-being word clouds, and intelligent tutoring systems. Each of these four approaches has inherent strengths and weaknesses. For example, quantitative instruments for measuring emotions (*e.g., Pekrun et al., 2002*) seem to provide a relatively accurate and valid depiction of emotions when learners complete the questionnaire, which is linked to learning processes and achievement (Noteborn et al., 2012, Tempelaar et al., 2012). Furthermore, implementing a survey questionnaire is relatively straightforward in most VLEs and a cost-effective approach. Nonetheless, not all learners may be willing to complete a 50+ item questionnaire on a frequent basis, and this approach might be vulnerable to non-response bias and self-selection bias when response rates drop below a particular benchmark (*Rienties, 2014*).

Offline interviews and purposeful online conversations can provide insightful accounts of learners' learning and emotions on a fine-grained level. However, as is the case with quantitative surveys, collecting a rich but all-encompassing dynamic understanding of learners' emotions in large-scale modules might be challenging. Wellbeing word clouds are dynamic visualisations of learners' self-reported feelings, which have been implemented recently by several Australian universities. The simplicity of the idea is probably the most important affordance. It is similar to Twitter and Facebook, whereby learners can post what they are thinking or feeling at a particular point in time. The word cloud application takes these postings and represents them in an aggregated well-being word cloud. A potential weakness of this approach is linked to general disadvantages of word clouds, which aggregate most frequently used words without an inherent and fine-grained understanding of the underlying narratives. Similarly, the aggregation of well-being might give a very positive or negative picture at a particular time, but due to the aggregation of data some learners who experience different emotions might be ignored. Finally, a promising field of research in terms of measuring and understanding learners' emotions is intelligent tutoring systems (Ahmed et al., 2013, Baylor, 2011, Hawkins et al., 2013, Lehman et al., 2012). However, the complexities of such tutoring systems and requirements to adapt the tutoring to local needs might make this option cost-ineffective unless implemented on a large scale.

With increased affordances to continuously measure facial and voice expressions with tablets and smartphones, it might become feasible to monitor learners' emotions on a real-time basis. Although Picard et al. (2001) discussion paper on machine emotional intelligence is now already a decade old, we feel that the five factors identified for emotional data collection are still relevant for educational research and learning analytics, in particular (see Table 3).

Table 3. Five factors that influence affective data collection (Picard et al., 2001)

Factor	Research Question
Spontaneous versus posed	Is the emotion elicited by a situation or stimulus that is outside the subject's control of the subject is asked to elicit the emotion?
Lab setting versus real-world	Is the data recording taking place in a lab or in the usual environment of the subject?
Expression versus feeling	Is the emphasis on external expression or on internal feeling?
Open recording versus hidden recording	Is the subject aware that s(he) is being recorded?
Emotion-purpose versus other-purpose	Does the subject know that s(he) is a part of an experiment and that the experiment is about emotion?

Further Reading

We recommend the following articles for further reading to get an overview of the affordances and limitations of measuring and unpacking emotions in learning analytics contexts:

- ARTINO, A. R. & JONES II, K. D. 2012. Exploring the complex relations between achievement emotions and self-regulated learning behaviors in online learning. *The Internet and Higher Education,* 15**,** 170-175.
- CLEVELAND-INNES, M. & CAMPBELL, P. 2012. Emotional presence, learning, and the online learning environment. *The International Review of Research in Open and Distance Learning,* 13.
- TEMPELAAR, D. T., NICULESCU, A., RIENTIES, B., GIESBERS, B. & GIJSELAERS, W. H. 2012. How achievement emotions impact students' decisions for online learning, and what precedes those emotions. *Internet and Higher Education,* 15**,** 161–169.
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Appendix: Inventory of learners' emotions

Emotion	Reference
Admiration	*Pekrun et al. (2002)*
Alienation	*Zembylas (2008)*
Aggression	*Visschedijk et al. (2013)*
Anger	*Baumeister et al. (2007); Dirkx (2008); deMarrais and Tisdale (2002); Kim et al. (2014); Mega et al. (2014); Pekrun et al. (2002); Pekrun et al. (2011); Strapparava and Mihalcea (2008); Visschedijk et al. (2013); White (2012)*
Annoyance	*White (2012)*
Antipathy	*Pekrun et al. (2002)*
Anxiety	*Chen and Lee (2011); Cleveland-Innes and Campbell (2012);Gläser-Zikuda et al. (2005); Kim et al. (2014); Marchand and Gutierrez (2012); Mega et al. (2014); Pekrun et al. (2002); Pekrun et al. (2011); Regan et al. (2012); Tempelaar et al. (2012); White (2012)*
Appreciation	*Cleveland-Innes and Campbell (2012); Pekrun et al. (2002)*
Apprehension	*Regan et al. (2012)*
Assuredness	*Regan et al. (2012); White (2012)*
Belonging	*Regan et al. (2012); White (2012)*
Boredom	*Artino and Jones Ii (2012); D'Mello and Graesser (2011); Kim et al. (2014); Nett et al. (2011); Noteborn et al. (2012); Pekrun et al. (2002); Pekrun et al. (2011); Tempelaar et al. (2012); White (2012)*
Calm	*Linnenbrink-Garcia and Pekrun (2011); White (2012)*
Challenged	*White (2012)*
Comfortable	*White (2012)*
Communication anxiety	*Regan et al. (2012)*
Competent	*White (2012)*
Confident	*White (2012)*
Confusion	*D'Mello and Graesser (2011); Lehman et al. (2012); White (2012)*
Connectedness	See belonging
Contempt	*Pekrun et al. (2002)*
Contentment	*Zembylas (2008)*
Convenience	*Regan et al. (2012)*
Curiosity	*Arnone et al. (2011)*
Delight	*Cleveland-Innes and Campbell (2012); D'Mello and Graesser (2011)*
Depressed	*White (2012)*
Desire	*Cleveland-Innes and Campbell (2012)*
Devalued	*Regan et al. (2012)*
Disappointment	*Pekrun et al. (2002); Cleveland-Innes and Campbell (2012); White (2012)*
Disconnectedness	*Regan et al. (2012); Zembylas (2008)*
Disgust	*Strapparava and Mihalcea (2008)*
Dislike	*Cleveland-Innes and Campbell (2012)*
Elation	*Dirkx (2008); Linnenbrink-Garcia and Pekrun (2011)*
Embarrassment	*Baumeister et al. (2007); Kim et al. (2014); Pekrun et al. (2002); Pekrun et al. (2011); Mega et al. (2014); Turner et al. (2002); White (2012)*
Empathy	*Pekrun et al. (2002)*
Emphatics	*Cleveland-Innes and Campbell (2012)*

Encouraged	See assuredness
Energetic	*Linnenbrink-Garcia and Pekrun (2011)*; *Pekrun et al. (2002)*; *Zembylas (2008)*
Engaged	See belonging
Enjoy	*Artino and Jones Ii (2012)*; *Chen and Lee (2011)*; *Cleveland-Innes and Campbell (2012)*; *Kim et al. (2014)*; *Pekrun et al. (2002)*; *Pekrun et al. (2011)*; *Mega et al. (2014)*; *Noteborn et al. (2012)*; *Strapparava and Mihalcea (2008)*; *Tempelaar et al. (2012)*; *Visschedijk et al. (2013)*; *White (2012)*; *Zembylas (2008)*
Enthusiasm	See energetic
Envy	*Pekrun et al. (2002)*
Excitement	*Cleveland-Innes and Campbell (2012)*; *White (2012)*; *Zembylas (2008)*
Fear	*Cleveland-Innes and Campbell (2012)*; *Strapparava and Mihalcea (2008)*; *Visschedijk et al. (2013)*; *White (2012)*
Flow	*D'Mello and Graesser (2011)*
Frustration	*Artino and Jones Ii (2012)*; *Cleveland-Innes and Campbell (2012)*; *Dirkx (2008)*; *D'Mello and Graesser (2011)*; *Marchand and Gutierrez (2012)*; *Regan et al. (2012)*; *White (2012)*
Gratitude	See appreciation
Guilt	*Regan et al. (2012)*; *White (2012)*; *Zembylas (2008)*
Happiness	*Cleveland-Innes and Campbell (2012)*;*White (2012)*
Hate	See antipathy
Helplessness	*Regan et al. (2012)*
Hope	*Cleveland-Innes and Campbell (2012)*; *Kasworm (2008)*; *Marchand and Gutierrez (2012)*; *Mega et al. (2014)*; *Pekrun et al. (2002)*; *Pekrun et al. (2011)*; *White (2012)*
Hopelessness	*Kim et al. (2014)*; *Pekrun et al. (2002)*; *Pekrun et al. (2011)*; *Tempelaar et al. (2012)*
Humiliated	See embarrassment
Humour	*Cleveland-Innes and Campbell (2012)*
Inadequacy	*Regan et al. (2012)*
Insecurity	*Linnenbrink-Garcia and Pekrun (2011)*; *Regan et al. (2012)*
Interested	*Gläser-Zikuda et al. (2005)*; *White (2012)*
Intrigue	*Regan et al. (2012)*
Irony	*Cleveland-Innes and Campbell (2012)*
Joy	See enjoy
Liberty	*Regan et al. (2012)*
Like	*Cleveland-Innes and Campbell (2012)*
Love	*Pekrun et al. (2002)*
Motivated	*White (2012)*
Need for connectedness	See disconnectedness
Nervous	See anxiety
Neutral	*D'Mello and Graesser (2011)*; *Visschedijk et al. (2013)*
Overwhelmed	*Regan et al. (2012)*
Panic	*Visschedijk et al. (2013)*
Passion	*Cleveland-Innes and Campbell (2012)*
Peace	*Chen and Lee (2011)*
Pleasure	*Regan et al. (2012)*
Preference	*Cleveland-Innes and Campbell (2012)*
Pressure	*Linnenbrink-Garcia and Pekrun (2011)*; *White (2012)*; *Zembylas (2008)*

Pride	*Kim et al. (2014)*; *Mega et al. (2014)*; *Pekrun et al. (2002)*; *Pekrun et al. (2011)*; *Regan et al. (2012)*; *Cleveland-Innes and Campbell (2012)*; *Zembylas (2008)*
Rejuvenated	*Regan et al. (2012)*
Relaxed	See calm
Relieved	*Pekrun et al. (2002)*; *Pekrun et al. (2011)*; *White (2012)*
Restriction	*Regan et al. (2012)*
Sadness	*Cleveland-Innes and Campbell (2012)*; *Pekrun et al. (2002)*; *Strapparava and Mihalcea (2008)*
Sarcasm	See irony
Satisfaction	*Regan et al. (2012)*
Scared	See fear
Shame	See embarrassment
Stress	See pressure
Stupidity	*White (2012)*
Surprise (positive and negative)	*Cleveland-Innes and Campbell (2012)*; *D'Mello and Graesser (2011)*; *Pekrun et al. (2002)*; *Strapparava and Mihalcea (2008)*; *Zembylas (2008)*; *White (2012)*
Sympathy	*Pekrun et al. (2002)*
Tense	See pressure
Thankfulness	See appreciation
Thrill	See elation
Tired	*Linnenbrink-Garcia and Pekrun (2011)*
Uncertainty	*Regan et al. (2012)*; *White (2012)*
Unease	See insecurity
Unhappiness	See sadness
Validation	*Regan et al. (2012)*
Wonder	*Cleveland-Innes and Campbell (2012)*
Worn out	See tired
Worry	*White (2012)*
Yearning	*Cleveland-Innes and Campbell (2012)*

About ...

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