ENGAGING LEARNERS THROUGH EMOTION IN ARTIFICIALLY INTELLIGENT ENVIRONMENTS

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Abstract

Academic Emotion (AE) as defined by Pekrun (2006) [24], can significantly influence student learning and achievement (Villavicencio & Bernard, 2013) [33]. We propose the concept of Extensive Academic Emotion (EAE), which extends AE to include emotional factors considered by Human Computer Interaction (HCI) researchers in the design of interactive systems. We argue that EAE can positively or negatively affect student engagement and success. This paper outlines a brief history of the convergence of the Artificial Intelligence (AI) and eLearning systems, with a particular focus on Intelligent Tutoring Systems (ITS). Where used appropriately, Artificially Intelligent Education (AIEd) models can be used in ITS to positively influence student motivation (Luckin et al 2016) [20]. The Mobile Adaptive Personalised Learning Environment (MAPLE) model (Mehigan & Pitt, 2013) [21] is assessed in light of its strengths and weaknesses for achieving optimal learner engagement. MAPLE is compared to a descriptive and simplified educational technology driven by AIEd. This technology comprises core models designed to support the social, emotional, and meta-cognitive aspects of learning. Appraisal of MAPLE as an AIEd-driven model could inform the extension of existing ITS to achieve optimal mediated AIEd to meet the emotional needs of the learner.

Keywords: Emotion, Affect, HCI, ITS, Artificially Intelligent Education, AI.

1 INTRODUCTION

Emotion, particularly Academic Emotion (AE) (Pekrun, 2006) [24], can significantly influence student learning and achievement (Villavicencio & Bernard, 2013) [33]. The inclusion of enjoyable and interesting activities for example, can lead to positive emotions and therefore increased student engagement (Frenzel, Pekrun & Goetz, 2007) [12]. Learner effort can also be influenced through personalization, consideration of cognitive variables (for example such as Working Memory Capacity (WMC)) etc. HCI can take account of both emotional affect and the fact that interacting with a system may require extensive cognitive processing on the part of a user. Human Computer Interaction (HCI) can also determine motivation sentiment (Brave & Nass, 2000) [3]. AIEd models can be used to influence student motivation for a positive result in ITS when considering the social, emotional, and meta-cognitive aspects of learning. Ideally, both academic and HCI emotions should be considered simultaneously in the development of an AIEd-based ITS.

We propose the concept of EAE to combine both academic emotion, and emotion and affect arising from interaction with a system. Where EAE is negative it can result in reduced student motivation, interaction and consequently a poor learning outcome. Consideration of EAE when developing AIEd models can potentially improve overall student engagement and success. While there exists an extensive body of research literature in the area of ITS, little advancement has been made in extending ITS to facilitate improved student experience and learning through a reduction of negative emotional factors. Cognitive variables, content and learning outcome and context should be considered alongside EAE to create optimal AIEds. The application of these combined variables could lead to the development of improved mediated models that overcome negative EAE during the learning experience, for improved student achievement.

We examine MAPLE (Mehigan & Pitt, 2013) [21] with regard to its potential for accommodating EAE within an AIEd-based ITS. MAPLE is an ITS model. It is designed for use with any eLearning or mLearning platform to facilitate the intelligent detection of user learning-styles based on two dimensions of the Felder-Silverman Learning Style Model (FSLSM) [8]. Based on user interaction, automatic adaptation based on personalization to suit the learning style needs of the user is facilitated. Such appraisal of MAPLE as to an AIEd driven model, could inform the extension of existing ITS models to achieve optimal mediated AIEd to meet learners’ emotional needs.
2 THE CONVERGENCE OF AI AND ELEARNING

E-Learning involves intensive usage of Information and Communication Technology (ICT) to serve, facilitate, and revolutionize learning processes. “It is self-evident that the history of technology in education extends back to the clay tablets, slate drawing boards, and handmade paper of pre-Gutenberg education” (Garrison & Anderson 2003) [13]. The development of Computer Aided Instruction (CAI) in the early years of the 1960s, led both psychologists and educators to see an opportunity for computers to act as a supplement to teaching as an existing field. This idea has been extended to the application of artificial intelligence to education which has been a focus of researchers in the field for more than 30 years.

In the 1970s the first indications of the use of AI emerged with the development of the SCHOLAR system (Carbonell 1970 as cited by Welham 2008) [34]. The system saw a surge in development of ITS including BUGGY (1978) and Sophie (1982). These systems were in essence AI-based systems providing the facility to analyse students’ methods in solving Algebra problems (BUGGY), with SOPHIE acting as a domain expert specializing in system design. The Alvey program (1983) focused on how AI could be used in a knowledge-based system. According to O’Connell (2011) [22], many other AI-based languages emerged including LISP and PROLOG. “These languages allowed developers to manipulate symbols instead of numbers and facilitated the creation of the first learning systems” (Welham, 2008) [34]. These developments in the 1980s enabled the development of educational applications of AI focusing on a knowledge-based approach (Sleeman and Brown,1982) [30]. To date, ITS has seen the highest level of research in the space (Wooff 2009) [35].

In recent years, the focus of development of ITS has moved toward the generation of learning analytics, reasoning capabilities and educational data mining (EDM) that facilitate the ITS to collect real-time input and maintain historical data from learner behavior and interaction. This in turn is used to create a didactic model of the learner to allow for automatic adaptation to meet the needs of individual learners (see Mehigan & Pitt 2013, Luckin et al 2016: Drigas and Ioannidou, 2012) [21][20][5].

According to Shaw (2008) [29] “AI might be simplistically described as an attempt to use computers to mimic the functioning of human intelligence and may include knowledge acquisition, reasoning and adaptation to experience”. This sentiment can be transferred to the learning space through the use of ITS where Al is used for real-time learning analytics and educational datamining to recognise and adapt user exposure based on human emotions (BenAmmar et al 2010) [2]. “It is important to incorporate the emotions of students in the learning process because recent learning theories have established a link between emotions and learning, with the claim that cognition, motivation and emotion are the three components of learning” (Frasson et al 2010; Baker et al 2010) [11][1].Thus, there is a move toward the development of Affective Tutoring Systems (ATS) that recognise learner frustration, happiness and motivation etc. associated with extensive academic emotion.

3 EMOTIONS AND AFFECT FOR AIED-BASED ITS

3.1 Academic Emotion (AE)

Emotions can significantly influence student learning and achievement (Villavicencio & Bernard, 2013) [33]. Pekrun presents an integrated framework for antecedents and consequences of students’ emotional experiences relating to learning, achievement, and other activities within an educational setting. The control-value theory of academic emotions (Pekrun, 2006; Frenzel et al, 2007) [11][12] includes definition and dimensions of academic emotions where “emotions [are] directly tied to achievement activities or achievement outcome.” (Frenzel et al 2007) [12]. The three-dimensional taxonomy of achievement emotions (see Table 1) highlights how these can be divided into both positive and negative emotions when focused on achievement. In relation to subjective values of both activities and outcomes, Pekrun makes a distinction between intrinsic and extrinsic values, where extrinsic values relate to the instrumental utility of activities to produce outcomes which are subsequently used to produce further outcomes and, intrinsic values are linked to appreciation of activity and consequently relevant outcomes. On this basis Brave & Nass, (2000) [3] identify that there are two generally agreed-upon aspects of emotion: emotion as a reaction to events deemed relevant to the needs, goals, or concerns of an individual; and emotion that encompasses physiological, affective, behavioral, and cognitive components. Where AE is negative it can result in reduced student motivation, interaction and consequently a poor learning outcome. The inclusion of enjoyable and interesting activities for example, can lead to positive emotions and therefore increased student engagement (Frenzel et al 2007) [12]. Learner effort can also be influenced through personalization, contemplation of cognitive variables, etc.
3.2 Emotional Affect and Cognition in HCI

HCI can encompass emotional affect and the fact that interacting with a system may require extensive cognitive processing on the part of a user. HCI can also determine motivation sentiment (Brave & Nass, 2000) [3]. The first evidence of the importance of emotion in HCI comes from Picard's fundamental publications on affective computing (1997) which had a major effect on both the AI and HCI fields. Stemming from neurology, medicine, and psychology, affective computing implements a bio-logic perspective on emotion processes in the brain, body, and thus interaction with others and with machines. User emotions are identifiable states based on Picard's first principles. When measured successfully they can be used to facilitate the construction of an individual's cognitive model. Based on first principles, the aim is to achieve a human-like interaction that adapts to the user's emotional state. The user is then influenced through the system adaptation. This can be achieved through the application of rules for example Ortony et al's OCC model from (1988) [23].

3.3 Extensive Academic Emotion (EAE)

Extensive Academic Emotion (EAE) at a very basic level reflects academic emotion as extended to include emotion and affect as defined by HCI Research. The relationship between academic and HCI emotions should be considered simultaneously in the development of an AIEd-based ITS. Where EAE is negative it can result in reduced student motivation, interaction and consequently a poor learning outcome. Students' results can be improved with the right encouragement and support (Kort et al., 2001) [19] therefore, the aim of an AIEd-based ITS is to assess the overall user emotion based on both AE and HCI-based Emotion to motivate the learner toward a positive EAE. This is enhanced where consideration is also given to both cognitive variables, such as WMC, and user context, i.e. the learning environment for example in mobile contexts, where the learner is located, their time availability, noise and distractions etc. Consideration of contextual factors are significant when looking at group-based, collaborative and individual learning scenarios.

4 DEVELOPING AN INTELLIGENT ITS FOR IMPROVED LEARNER ENGAGEMENT

Luckin et al [20] present a description of what a piece of simplified AIEd-based technology could look like (see Figure 1). Larkin's AIEd system is comprised of three core models, these being the Domain, Pedagogy and Learner Models. In addition to these, Larkin et al state that "AIEd researchers have also developed models that represent the social, emotional, and meta-cognitive aspects of learning. This allows AIEd systems to accommodate the full range of factors that influence learning".
Figure 1. AIEEd system showing a simplified picture of a typical model-based adaptive tutor (Luckin et al 2016[20]).

The authors present an ITS model called MAPLE [21] designed for use with any mLearning platform to facilitate the detection of user learning-styles (based on dimensions of the FSLSM) from user interaction for the automatic provision of adapted content display to suit the learning- style needs of the user. Luckin’s three core models are addressed within MAPLE. The Learner Interface provides adaptive content based on the needs of the individual learner in that adaptive content is provided based on interaction-based data capture and analysis for pattern recognition. However, while MAPLE has many strengths, in reflection of Luckin’s model it also shows weaknesses in that real-time data capture does not provide for achievement or emotion. The model is examined in terms of its Strengths, Weaknesses, Opportunities and Threats (SWOT) when compared to the model proposed by Luckin et al (2016) [20].

4.1 Maple

MAPLE facilitates the intelligent and automatic detection of user learning-style based on biometric interaction pattern data. The model is suitable for use with any electronic or mobile learning environment. The model can be implemented for any platform and any device category including, for example, Apple’s iOS, Google’s Android OS and web-based applications. The MAPLE model [2] facilitates intelligent learning systems through a structure that comprises a number of stages as indicated in the model (Figure 2). The model comprises three main components, the adaptation engine, the learning environment and user interaction facilities. Each component has associated rules which are applied at each stage of the model’s implementation. The adaptation engine is the backend and intelligent aspect of the model. It holds learning object templates designed to match the required display to learners depending on the adaptation engine’s assessment of their learning-style on completion of the adaptation processes. These processes are based on the data obtained from the user's interaction with a system through the learning environment associated with it.

The stored templates comprise learning objects specific to the learning topic and course requirements. The templates include a range of learning content from which the system selects material for individual learners in accordance with their learning-style, for example, visual learning objects can be included for display to Visual learners. The visual content can comprise pictures, graphs, flowcharts, timelines, video and demonstrations. Verbal learning objects are included suitable for display to verbal learners including
for example text and auditory (verbal) explanations. This content meets the requirements for content presentation outlined in Felder & Silverman’s (1988) [8] teaching-styles as prescribed by the FSLSM. Display content can be combined: for example, for the Visual / Verbal dimension the templates could include a balance of visual and verbal content displayed where a student is deemed (by a system employing the MAPLE model) to be balanced on the dimension in question.

The processes gather and interpret user interaction data obtained from the ‘Learning Environment’, including the amount of attention paid by users as to content as revealed through their interaction with the learning objects displayed to them. For example, the total user interaction time on particular learning objects (Visual / Verbal learners) could be used by the processes to detect the learning-style of the user on the Visual / Verbal dimension of the FSLSM (Popescu 2008 & Cha et al. 2006) [28][4]. A user’s maximum vertical speed when viewing displayed content could be applied to detect Global / Sequential learners (Spada et al. 2008) [31]. The outcome of the processes determines the template to be displayed to the user as part of the overall learning environment.

The learning environment comprises the user interaction aspects and the front end of any system based on the MAPLE model. The learning environment displays learning-object-based content to users. The system initially displays an assessment screen and a subsequent display of adapted content to suit the needs of the specific learner based on the outcome of the adaptation engine’s processes. User interaction is facilitated via biometric technologies. These can include, but are not restricted to, the accelerometer and / or eye-tracking technologies. User attention reflects the overall attention and focus of a learner on a specific learning object within the displayed content.

4.1.1 FSLSM

The FSLSM (Felder & Silverman, 1988) [8] is a widely employed model for inferring learner characteristics in the area of adaptive eLearning. For example, the model is used in the CS383 System (Howard et al 1999) [17] and by Graf and Kinshuk (2008) [15] for their adaptive LMS system. The FSLSM was formulated to provide the best basis for instructors in the engineering field for the delivery of educational content and has since had a multi-disciplinary adoption. The model attempts to capture the most important learning-style differences among students to enable the delivery of content in a manner that suits all students. Felder and Silverman’s work was based on the belief that the matching of a student’s learning-style with the teaching style of their professor would lead to better learning-outcomes for students. Where a mismatch occurs, Felder & Spurlin (2005) [10] suggest that students are likely to lose interest, leading to an inferior educational outcome. “Learners are characterised by values on the four dimensions. These dimensions are based on major dimensions in the field of learning-styles and can be viewed independently from each other” (Graf, 2007) [15]. The measurement instrument associated Felder Silverman Index of Learning Styles (FSILS), develops the preference profile of a student on four of the learning-style dimensions. Based on the original Felder & Silverman paper (1988)
[8], there is a discrepancy between the FSLSM and the FSILS, in that the FSILS, in assessing preferences on the four scales of the FSLSM provides for a higher number of possible combinations when considering the high, moderate and balanced style levels across a scale.

4.2 MAPLE SWOT; Toward an AIEd System

4.2.1 MAPLE’s Strengths and Weaknesses

The strength of the MAPLE model lies in that the learner interface provides adaptive content based on real-time interaction-based data capture and analysis for pattern recognition. The development of a learner model on this basis provides for the needs of the individual learner in that adaptive content is provided based on their learner-style.

While this provision is currently indicative of individual learning scenarios it could also be applied to collaborative and group settings to facilitate successful matching and/or mismatching of diverse individuals to enhance the mix of learner dynamics in such settings depending on the required outcomes of assigned tasks and projects. As an algorithmic-based user model is generated it could be extended from its current manifestation to incorporate other features such as emotional, social, and meta-cognitive aspects of learning. MAPLE’s incorporation of user attention could be extended to consider Pekrun’s idea of user focus, and on outcomes based on the theories of Picard’s Affective computing. In doing so the needs associated with inclusion of user emotion could be enhanced as a consideration of EAE. Detection of user emotion could be used to adapt the user experience based on real-time data analysis to assess the level of positivity/negativity of that emotion and, in turn influence the user toward positive response through relevant content provision.

As the Model currently facilitates interaction based on biometric user data (including accelerometer and/or eye-tracking input) it could be extended to include real-time data streams from sensor-based wearable devices. For example, Electroencephalogram (EEG) and Galvanic Skin Response (GSR) data inputs could be included for real-time analysis by the system.

The area of accessibility could also be incorporated to meet the needs of learners with special needs who exhibit learning disabilities such as Dyslexia, sensory impairments such as sight or hearing loss or other impairments or disadvantages. Thus, a properly structured AIEd could address the lack of social considerations to allow diverse groups of students to work together collaboratively whilst achieving individual milestones in different learning contexts.

As indicated MAPLE’s weakness lies in its lack of consideration of social, emotional, and meta-cognitive aspects of learning. When real-time data is captured it does not in its current format provide for the capture and measurement of emotion through its data gathering or analysis algorithms. There is currently no consideration as part of the user attention component or processes to use behavior data to adapt content in reflection of the learner’s emotional state and/or to motivate them toward a different emotional state other than through provision of content matched based on their learning-style. While matching content provision in regard to how a learner processes data is a step forward toward motivation to learn, it doesn’t stimulate the learner toward positive activity/outcome focus where a negative object focus exists. There is an element of social exclusion and while consideration is provided for meta-cognition via provision of adaptation based on learning-style, cognitive variables such as WMC are not considered at this time.

4.2.2 Opportunities and Threats,

There are opportunities to further strengthen the MAPLE Model through extension of its current components to accommodate real-time data gathering for measurement of EAE. The inclusion of biometric measurement tools such as brain Computer Interfaces and other wearable devices measuring EEG and GSR in future studies could examine both academic stress and interaction-based stress at an individual level. Potentially the current manifestation of user interaction within the MAPLE model could be extended to gather emotion-based data for the inclusion of an EAE-based process. This could be achieved through signal gathering using devices such as the Emotive Insight headset [6] and the Empatica E4 wristband [7].

A user study could be conducted to investigate if Felder-Silverman’s visual learners exhibit more or less stress/emotional response than verbal learners. It could also be assessed if there are any differences across the other dimensions of the FSLSM. Results from this type of study based on meta-cognitive factors such as learner-style emotion and stress would provide a good starting point in the facilitation of a real-time adaptive ITS to emotionally motivate learners toward positive focus. Further studies could
combine data gathered via eye-tracking technology to measure arousal through pupil dilation etc. for further analysis and modelling of learner data. Reduction of stress and increase in arousal should help with moving toward activating a positive object focus in both activity and outcome tasks.

The main threat towards furthering MAPLE’s facilitation of emotional consideration for students is the immediate financial and physical restrictions cause by the use of technologies such as eye-trackers, headsets etc. While these technologies are reducing in cost they still represent a significant expenditure for users. Also, some of these devices, including the Emotive Insight Headsets are cumbersome to wear. This could cause problems for some system users. Wearing such devices can also result in students standing out from others depending on the context and environment of the wearer.

5 CONCLUSIONS

It is necessary to extend Academic Emotion (AE) as defined by Pekrun (2006) [24] to include emotional factors considered by Human Computer Interaction (HCI) researchers in the design of interactive systems. The concept of Extensive Academic Emotion (EAE) as outlined in this paper, can positively or negatively affect student engagement and achievement when considered within the context of AIEd-based ITS. Through appropriate adaptation AIEd-based models can positively influence student motivation. MAPLE (Mehigan & Pitt, 2013) [21] is compared to a descriptive and simplified educational technology driven by AIEd designed to support the social, emotional, and meta-cognitive aspects of learning (Luckin et al 2016) [20]. We have appraised MAPLE in light of its strengths and weaknesses for achieving optimal learner engagement. We conclude that MAPLE as an AIEd-driven model could inform the extension of existing ITS to achieve optimal mediated AIEd to meet the emotional needs of the learner.

REFERENCES


