Predicting Learner Engagement during Well-defined and Ill-defined Computer-Based Intercultural Interactions

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Abstract. This article reviews the first of two experiments investigating the effect tailoring of training content has on a learner's perceived engagement, and to examine the influence the Big Five Personality Test and the Self-Assessment Manikin (SAM) mood dimensions have on these outcome measures. A secondary objective is to then correlate signals from physiological sensors and other variables of interest, and to develop a model of learner engagement. Self-reported measures were derived from the engagement index of the Independent Television Commission-Sense of Presence Inventory (ITC-SOPI). Physiological measures were based on the commercial Emotiv Epoc Electroencephalograph (EEG) brain-computer interface. Analysis shows personality factors to be reliable predictors of general engagement within well-defined and ill-defined tasks, and could be used to tailor instructional strategies where engagement was predicted to be non-optimal. It was also evident that Emotiv provides reliable measures of engagement and excitement in near real-time.

Keywords: learner engagement, well-defined tasks, ill-defined tasks, EEG

1 Introduction

Simulation-based training environments, although potentially powerful, suffer from the same weaknesses as other computer-based training methods; they lack individualized guidance and feedback. The effectiveness of adaptation in state-of-art computer-based training is limited and is far from producing comparable benefits to those seen in human-to-human instruction. However, incorporating the application of dynamic cognitive-state assessment of a learner can be used to provide additional cues to a training system to facilitate personalized self-directed learning. Emerging evidence suggests that enabling a training system to access affective and cognitive states can enable it to adapt an individual student's learning experience and improve learning outcomes [1]. Personalizing instructional content on the individual level requires real-time cognitive state assessments that aim to interpret the attentional resources a particular student is devoting to a task and to determine a student's "readiness" to learn [2]. Ultimately, this can lead to enabling training systems to better diagnose student errors and improve learner engagement.

This paper presents the results of an initial study which observed whether and to what degree tailoring of training content (e.g., clarity and flow of task) in a computer-based cultural negotiation trainer had on self-reported levels of engagement. It also evaluated if specific sensors are practical for gathering data for cognitive-state modeling. Engagement is a state of interest. It reflects processes that involve information gathering, visual scanning, and periods of sustained attention [3]. A secondary research objective is to correlate signals from physiological sensors and other variables of interest to arousal leading to development of a model of learner engagement. Longer-term, the results of this study could contribute to establishing the validity of using commercial off-the-shelf (COTS) cognitive-state sensors for manipulations designed to improve engagement and provide inputs sufficient for enabling engagement modeling.

2 The Link of Engagement to Learning

Developing reliable methods to measure and classify learner engagement, as well as better understand its connection to learning has been a research focus within the computer-based tutoring community [4]. A number of empirical studies have shown student engagement to be a critical predictor of learning and personal development [4][6]. Carini et al. [6] found student engagement to be positively correlated with desirable learning outcomes such as critical thinking skills and grades; however, the magnitude of this connection was fairly weak because engagement is only one of a variety of variables which contribute to these particular learning outcomes. Similarly, Rowe et al. [4] found, independent of students' prior domain knowledge and experience, a strong positive relationship between learning outcomes and increased engagement. Thus, engaged interest towards an instructional task can influence cognitive performance, thereby facilitating deeper learning [4][7].

The methods for detecting engagement levels across individuals in real-time rely primarily on physiological sensors. A number of sensors have been empirically tested for detecting engagement levels, including: electrocardiogram (ECG) [18], galvanic-skin response (GSR) [8], and EEG. EEG is the prominent variable of interest for this research because commercial EEG systems have been used to track and model user attention in real time [5]. Fairclough and Venables' [17] experiment revealed EEG measures to reliably correlate with engagement levels and explained 26-42% of the variance for self-reported levels of distress (e.g, tension and confidence associated with negative affect) across prolonged task interaction. By comparison, Stevens, Galloway & Berka [2] found EEG indices of engagement to negatively correlate with experience. They consider the metric is responding to the appearance/format of the content rather than the actual content presented.

Results from these studies show a number of variables have an impact on a learner's engagement, and time on task and presentation characteristics of instructional content are directly related. Adaptive tailoring of content can mitigate this effect and extend the time before the onset of disengagement. The primary goal of this effort is to identify predictive influencers of engagement so as to adapt content, flow and feedback, in real-time, when a classified cognitive state is deemed to have a negative impact on learning.

3 Methodology

Twenty-one adults volunteered to participate in the experiment with seventeen providing usable data. Of the 17 participants, 11 were males (age M = 34, SD = 9.5) and 6 were females (age M = 40, SD = 12). Each participant interacted with the Cultural Meeting Trainer (CMT), a web-browser-based training system prototype in which the learner engages in bilateral conversations with virtual characters representative of Middle Eastern culture. Participants interact with CMT characters through static dialogue choices. No subjects reported experience in inter-cultural conversations or negotiations prior to participating in the study.

A counterbalanced within-subjects experimental design evaluated the effectiveness of an EEG-based cognitive-state sensor during three conversations of (a) varying clarity (one well-defined and two ill-defined) and (b) the presence or absence of interruptions. A well-defined task was one which followed an unambiguous series of steps, where success was clearly defined. An ill-defined task was one in which the task was vague or ambiguous, where objectives are not clearly stated and there are many possible paths to success.

The second manipulation measured the effect of disruption on engagement, using self-report measures of engagement. In the context of the experiment, participants and characters take turns speaking or acting. Having the character speak unpredictably is a disruption to the pattern of expectancy. This type of disruption occurs in one of the two ill-defined conversations. This manipulation enables the assessment of whether or not there are detectable differences in reported levels of engagement with the inclusion and exclusion of disruptions.

3.1 Procedure

Participants were first given an overview of the research, signed a consent form, were fitted with the EEG recording Emotiv EPOC, and given a demographics questionnaire. Next, initial interaction with the CMT interface is provided through an introductory conversation with a virtual character. Then there were three conversation tasks presented to the participants in random order. Before each conversation, participants observed a relaxation video for 1-2 minutes in order to place them in a state of calm before conducting the next conversation. This video was intended to mediate the mood state experienced in the previous scenario. At the start of each conversation, participants were given a background briefing on the character they would be conversing with along with guidelines and the purpose of the meeting.

For this study, the participant conversed with three hospital employees soon after a nearby insurgency attack. The well-defined no interruption (WDNI) task required participants to maintain casual small talk with an in-house physician. The two ill-defined scenarios included an Ill-Defined No Interruption (IDNI) task with the lead physician and an Ill-Defined with Interruption (IDI) task with the hospital administrator. The objective of the conversation with the lead physician was to gather information on the attack without making commitments directly to the doctor. The discussion with the administrator was intended to gain U.S. support and identify what the hospital needed to function efficiently. This conversation with the hospital administrator was designed with an interruption in task flow where the character spoke out of turn. Each meeting was approximately 5-6 minutes in duration.

3.2 Dependent Measures

A demographic questionnaire was administered to each participant. Information included age and education level, prior experience in inter-cultural conversation and negotiation, personality (Big Five Personality Test [9]), and current mood (SAM). The Big Five Personality Test provides percentile scores on the dimensions of Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. Research suggests these dimensions provide insight into how an individual governs their cognitive resources [20].

Subjects' self-reported engagement levels were collected following each conversational task. A 2-part instrument was administered to assess engagement. The first part included fourteen "engagement-specific" (α=.89) questions derived from the Independent Television Commision-Sense of Presence Inventory (ITC-SOPI). The engagement index assesses a subject's attention and involvement during task interaction [12]. This survey was selected because attention signals have been shown to be highly correlated with "presence", which is reasonably correlated with engagement in virtual environments [10, 11]. The second part of the post-conversation survey is the SAM [15], a validated non-verbal graphical approach for evaluating Mehrabian's three dimensions of mood: pleasure, arousal and dominance [16].

Real-time measures of engagement were derived from sensors placed directly on the participant. Data was collected via the Emotiv EPOC Neuroheadset, a commercial-off-the-shelf EEG brain-computer interface. The Emotiv EPOC is composed of 14 electrodes with locations following the American EEG Standard [14]. This device provided rolling continuous measures of associated states, including: short term excitement (STE), long-term excitement (LTE) and engagement. The Emotiv has previously been used to capture engagement levels within computer-based entertainment games [19]. Collection of sensory data provided concurrent physiological information allowing assessment of dynamically changing cognitive states instead of only evaluating static labels from the administered self-report instruments [13]. Data collected with the initial questionnaire was used to correlate demographic variables with EEG and self-reported data to generate subgroups.

This research evaluated the influence of personality, mood and EEG measures on the prediction of engagement. The following hypotheses were addressed: (1) Assessed measures of personality via Big Five Personality Test and mood via the SAM will correlate with self-reported measures of engagement, (2) Aggregate physiological data (STE, LTE and Engagement from EMOTIV) will correlate with self-reported engagement levels. (e.g., *feeling of not just watching)*, (3) Self-reported measures of engagement will be significantly higher in the interruption condition (IDI) when compared to scenarios with no interruption (WDNI and IDNI), and (4) Self-reported measures of engagement will be significantly higher in the ill-defined scenarios (IDNI and IDI) when compared to the measures of engagement in the well-defined scenario (WDNI) due to unspecified routines for achieving task objectives. It is believed an interruption in scenario flow will produce higher engagement scores because the expected interaction routine is broken, resulting in more focused attention to dialogue selections.

4 Results

Analysis was conducted to observe the relationship personality and mood dimensions have on self-reported engagement levels following interaction with a web-based training system. The following tables present Pearson's coefficients for the Big Five personality and the SAM mood dimensions in relation to measures derived from the engagement index of the ITC-SOPI (See Table 1, 2, and 3). Separate analysis was conducted for all conditions and was based on each of the 14 individual items as well as their mean to produce an overall engagement score. Individual items were examined to gauge causal relationships between variables.

Table 1. Big Five and SAM correlations with reported Engagement scores for individual items within the Well-Defined Conversation Scenario.

Engagement Item	Big Five Dimension	Correlation
'I paid more attention to displayed environment than I did my own thoughts'	Openness Agreeableness	$r(16) = -.564, p = .023$ $r(16) = -.498, p = .049$
'I felt myself being drawn in'	Agreeableness	$r(16) = -.524, p = .037$
'I felt involved'	Agreeableness	$r(16) = -.527, p = .036$
'I feel I wasn't just watching something'	Agreeableness	$r(16) = -.547, p = .028$
'I responded emotionally'	Agreeableness	$r(16) = -.546, p = .029$
Average Score for All Items	Agreeableness	$r(16) = -.767, p = .001$
'I felt the characters were aware of me'	SAM Pleasure	$r(16) = .516, p = .041$
'I feel I wasn't just watching something'	SAM Dominance	$r(16) = .596, p = .015$

Table 2. Big Five and SAM correlations with reported Engagement scores for individual items within the IDNI Conversation Scenario.

Engagement Item	Big Five Dimension	Correlation
Average Score for All Items	Agreeableness	$r(16) = -.612, p = .012$
Average Score for All Items	Neuroticism	$r(16) = .535, p = .033$
'The experience was intense'	SAM Pleasure	$r(16) = .617, p = .011$

Table 3. Big Five and SAM correlations with reported Engagement scores for individual items within the IDI Conversation Scenario.

Engagement Item	Big Five Dimension	Correlation
'I felt involved'	Agreeableness	$r(16) = .499, p = .049$
'I paid more attention to displayed environment than I did my own thoughts'	Agreeableness SAM Pleasure	$r(16) = -.566, p = .022$ $r(16) = .621, p = .010$
'I felt that interacting with the character was difficult'	SAM Dominance	$r(16) = -.512, p = .043$

Examining the reliability of the assessed personality/mood measures and their influence on self-reported engagement, all variables were accounted for in regression analysis. Variables were trimmed based on coefficients found to not have a significant influence on the prescribed outcome. The results illustrated "*agreeableness and arousal*" to explain a significant portion of variance in *Self-Reported Engagement* scores for the WDNI scenario, adjusted $R^2 = .66$, $F(2, 13) = 15.68$, $p < .001$. The following linear regression model was developed:

$$\textit{Self Reported Engagement} = 4.374 - 0.013 * \textit{agreeableness} - 0.099 * \textit{arousal} \tag{1}$$

Furthermore, results suggest a significant amount of variance in *Self-Reported Engagement* scores (IDNI scenario) is explained by "*agreeableness and neuroticism*", adjusted $R^2 = .54$, $F(2, 13) = 9.89$, $p = .002$, producing the linear regression model shown below:

$$\textit{Self Reported Engagement} = 3.295 - 0.007 * \textit{agreeableness} + 0.010 * \textit{neuroticism} \tag{2}$$

In the interruption scenario (IDI), "*agreeableness*" explained a significant portion of variance in *"feeling of being involved"* scores, adjusted $R^2 = .20$, $F(1, 14) = 4.65$, $p = .049$; and in "*more attention to environment"* scores, adjusted $R^2 = .20$, $F(1, 14) = 6.59$, $p = .022$. Based on these findings, the two models were formed:

$$\textit{Feeling of being involved} = 2.566 + 0.014 * \textit{agreeableness} \tag{3}$$

$$\textit{More attention to environment} = 4.598 - 0.020 * \textit{agreeableness} \tag{4}$$

Subsequently, aggregate physiological data (STE, LTE and Engagement) was analyzed against self-reported engagement scores to identify correlations (See Table 4). This analysis incorporated Resting Engagement (RE) data collected during the two minute phases prior to each individual scenario.

Table 4. Emotiv STE, LTE, and Engagement correlations with reported Engagement scores for individual items within all Conversation Scenarios (WDNI, IDNI and IDI).

Engagement Item (WDNI, IDNI, IDI)	Emotiv Dimension	Correlation
'I feel I wasn't just watching something' (WDNI)	STE LTE	$r(16) = -.523$, $p = .019$ $r(16) = -.436$, $p = .046$
'I felt the character was aware of me' (WDNI)	STE LTE	$r(16) = -.563$, $p = .012$ $r(16) = -.450$, $p = .040$
'I felt that interacting with the character was difficult' (WDNI)	STE	$r(16) = .485$, $p = .029$
'I responded emotionally' (WDNI)	LTE	$r(16) = -.428$, $p = .049$
'I was surprised by something the character did or said' (WDNI)	Resting Engagement (RE)	$r(16) = -.516$, $p = .020$
'I feel I wasn't just watching something' (IDNI)	RE	$r(16) = -.455$, $p = .038$
'I lost track of time' (IDNI)	RE	$r(16) = -.542$, $p = .015$
'I paid more attention to displayed environment than I did my own thoughts' (IDNI)	RE	$r(16) = -.436$, $p = .046$
'I felt myself being drawn in' (IDI)	STE LTE	$r(16) = -.447$, $p = .041$ $r(16) = -.473$, $p = .032$
'I felt that interacting with the character was difficult' (IDI)	Engagement	$r(16) = -.457$, $p = .037$
'I lost track of time' (IDI)	RE	$r(16) = -.569$, $p = .011$
'I feel I wasn't just watching something' (IDI)	RE	$r(16) = -.440$, $p = .044$

Examining the reliability of self-reported engagement measures in predicting physiological outputs for the WDNI scenario, analysis showed *"surprised by character actions"* to explain a significant portion of variance in RE scores, adjusted $R^2 = .21$, $F(1, 14) = 5.08$, $p = .041$ and "f*eeling that character was aware of you*" explained a significant portion of variance in STE scores, adjusted $R^2 = .27$, $F(1, 14) = 6.49$, $p = .023$. The following linear regressions were developed from these results:

$$STE = 0.677 - 0.091 * \textit{feeling that character was aware of you} \quad (5)$$

$$RE = 0.702 - 0.057 * \textit{surprised by character actions} \quad (6)$$

Within the two ill-defined scenarios, two linear regression models that explain significant variance in self-reported scores were found. The item *"lost track of time"* explained a significant portion of variance in RE scores for both the IDNI and IDI scenarios, adjusted $R^2 = .24$, $F(1, 14) = 5.82$, $p = .030$ (IDNI); adjusted $R^2 = .28$, $F(1, 14) = 6.69$, $p = .022$ (IDI). The following linear regression models were developed:

$$RE \text{ (IDNI)} = 0.722 - 0.063 * \textit{lost track of time} \quad (7)$$

$$RE \text{ (IDI)} = 0.714 - 0.065 * \textit{lost track of time} \quad (8)$$

The next statistical test evaluated if engagement scores will be significantly higher in the interruption condition (IDI) when compared to scenarios with no interruption (WDNI and IDNI). A non-directional t-Test ($\alpha = .05$) was used to compare the average “interruption” scores with the average “no interruption” score. Only the *“feeling that interaction was difficult”* item, a self-reported measure of engagement, was shown to have a significant difference in the averages within subjects for the WDNI (M = 2.188, SD = 1.05) and the IDI groups (M = 2.875, SD = 1.02), t = -2.63, p = .019. All other self-reported measures of engagement failed to show any significant differences between the “interruption” and “no interruption” conditions.

In addition, analysis examined if engagement scores were significantly higher in ill-defined scenarios (IDNI and IDI) when compared to the measures of engagement in the well-defined scenario (WDNI). A non-directional student’s t-Test ($\alpha = .05$) was used to compare the ill-defined (both with and without interrupts) average scores with the average well-defined score for all ten self-reported measures of engagement.

For *“feeling that interaction was difficult”*, significant differences in the averages of the IDNI group (M = 3.063, SD = 1.12) and the WDNI group (M = 2.188, SD = 1.05), t = 3.12, p = .036 were identified. As well, there were significant differences in the averages of the IDI group (M = 2.875, SD = 1.02) and the WDNI group (M = 2.188, SD = 1.05), t = 2.68, p = .017. For *“surprised by character actions”,* there was no significant difference in averages for the IDI and the WDNI groups, but there was a significant difference between the IDNI (M = 3.375, SD = 1.09) and the WDNI groups (M = 2.75, SD = .93), t = 2.29, p = .036, with a higher mean for the ill-defined task. For *“lost track of time”*, there was no significant difference in the averages of the IDNI group and the WDNI group, but there was a significant difference between the IDI group (M = 2.56, SD = .89) and the WDNI group (M = 3.13, SD = 1.09), t = -2.52, p = .023, with the well-defined scenario showing the larger mean.

5 Discussion

The manipulation of task clarity and sequence of task interaction has shown reliable differences in self-reported scores of engagement. In terms of clarity this conveys that more attentional resources are required for task execution when steps for successful performance are ambiguously defined. As well, it was hypothesized that the interruption scenario would show reliably higher engagement scores when compared to non-interruption conversations. Analysis illustrates that subjects reliably reported the interaction to be more difficult when an interruption in the expected task flow was present. This suggests tailoring training content to incorporate ill-defined rules along with interactions that break expectations can produce visible increases in engagement.

In addition to assessing the effect tailoring of content has on engagement, personality factors, mood factors and physiological factors were evaluated to observe their predictive power in terms of estimating self-reported ITC-SOPI scores. The resulting analysis expressed multiple approaches for reliably predicting learner engagement through static and dynamic assessment techniques. Specifically, the personality dimensions of extraversion, agreeableness, and neuroticism along with the mood dimension of arousal were found to be reliable predictors of engagement when analyzed within individual tasks. For all post-scenario metrics, the dimension of agreeableness (cooperative vs. suspicious) was the only variable to demonstrate predictive power independent of task definition, with the majority displaying negative correlations. This suggests that individuals who are classified with low 'agreeableness' engage in training content on a higher scale due to their preference of questioning events and content they experience.

Furthermore, the specificity of the Emotiv system for predicting engagement scores was evaluated. Specificity defines how precisely a specific cognitive state can be inferred. The protocol attempted to evaluate specificity by comparing self-reported levels of engagement to aggregate states (e.g., STE, LTE) classified by the Emotiv. The results validated relationships between the RE and STE metrics provided by Emotiv with self-reported states of engagement. The RE finding conveys that those subjects exhibiting high engagement in rest states are less apt to be drawn in when training continues due to their attentional resources already being in use.

6 Conclusion and Recommended Future Research

The results of this study show that personality factors (agreeableness, neuroticism) were predictors of general engagement and could easily be used to tailor instructional strategies where engagement was not predicted to be optimal. It was also evident that Emotiv provided significant near real-time measures of engagement and excitement where head movement (and thereby signal noise) is restricted. Emotiv would have significant limitations in predicting engagement (or other states) in any interactions where head movement was significant (e.g., natural interfaces like Xbox 360 Kinect).

Following this initial study a more expansive experiment that includes Emotiv and BioPac (ECG and GSR measures) systems will be conducted. ECG and GSR measures have aided EEG in the establishment of an engagement index in order to predict engagement [19]. For future research we recommend continued efforts to find passive sensors that are portable, durable and indicate the learner's cognitive and affective states to provide a clearer decision point for adaptive instructional strategies.

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