Proceedings of the Twenty-Third International Florida Artificial Intelligence Research Society Conference (FLAIRS 2010)

An Empirical Examination of the Relation Between Attention and Motivation in Computer-Based Education: A Modeling Approach

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Abstract

Attention is considered a pre requisite to achieve greater motivation in the classroom. However, empirical evidence of this relationship in educational setting is scarce since the measurement of attention requires specialized equipment such as clinical electroencephalograms (EEG) or fMRI. With the advent of portable, consumer oriented EEG it is now possible to estimate levels of attention and shed light onto this relationship in the context of a computer based educational setting. To that end, students (N 40) interacted for an average of 9.48 minutes (SD .0018) with an assessment exercise in a virtual world. Participants' attention levels were monitored via a portable EEG and incorporated into an attention model capable of deciding on strategies to correct low levels of attention. The participants' motivation was assessed using a self reported motivation questionnaire at pre test and post test times. The results indicated that students with higher self reported motivation and self reported attention answered significantly more correct answers. However, no direct evidence was found of a relation between EEG readings and self reported attention or self reported motivation. This suggests student's own perceptions of motivation and attention influence performance. Future work consists of defining new models of attention considering self perceived attention and motivation as baseline as well as improving the model of attention combining EEG reading with an indication of the students' gaze.

Introduction

This paper addresses the relationship between attention and motivation in computer-based education. The relevance of this research lies in that it analyses how attention impacts upon motivation and vice versa. These analyses might inform the design of models of motivation to aid personalization of educational technology. The idea that attention and motivation are related is proposed by some motivation researchers who see attention as a prerequisite to achieve greater levels of motivation in educational settings (Song and Keller 1983, del Soldato and du Boulay 1995, Keller 1983). Detecting lack of attention and deploying techniques to cope with low levels in classroom-based situations is an strategy that can be learnt by teachers (Keller 1987) by considering students' verbal and non-verbal cues. However, in computer-based settings, estimating attention and motivation is a complicated task and models are normally employed to construct beliefs about the learner's attention and motivation (Rebolledo-Mendez and de Freitas, 2008, Rebolledo-Mendez, du Boulay and Luckin 2005). Until recently, analyzing physiological readings of attention was difficult as it was restricted to clinical settings because of the intrusiveness of Electroencephalograms (EEG), functional magnetic resonance imagining fMRI or near infrared scanners (NIRS). However, with portable electroencephalograms (EEG) systems such as NeuroSky's ThinkGear, it is possible to have real-time estimates of Beta waves (13 – 30 Hz) associated with waking consciousness or attention (Linden, Habib and Radojevic 1996). The use of this device makes possible the fusion of physiological and interaction data to develop more complex models of attention (Rebolledo-Mendez and de Freitas, 2008). The aims of this paper are 1) to investigate the relationship between self-reported motivation and various measurements of attention including EEG readings and 2) assess students' performance in a computer-based exercise considering measurements of attention and motivation. The approach taken is to examine Beta waves generated during brain activity as an indicator of the levels of attention a student has while interacting with educational technology and analyze them in the light of self-reported motivation and self-reported attention. To explore this issue, a series of hypotheses have been defined dealing with relationships between variables. Hypotheses 1 to 4 analyze readings of attention at three different points in the experiment. Hypotheses 5 to 10 look at the relationship between motivation and reading of attention. Finally, Hypotheses 11 and 12 look at performance in light of the different readings of attention. The paper is organized in five sections. Section II presents the theoretical background of this work. Section III describes the experimental setting, materials, participants and methodology employed in the study. Section IV presents the results of a series of statistical analyses aimed at answering the research questions. Section V discusses the implications of the results in the light of the literature and the research objectives as well as future work in this area.

Background

Motivation is an important aspect both in real world and computer-based educational settings as it is assumed more motivated student will have a better performance in the learning process. The ARCS model (Keller 1983) is an example that considers attention as a fundamental component of motivation. To date, however, there is scarce empirical evidence of this relationship. This might be because of the intrusiveness of technology used to measure attention consisting of clinical EEG and fMRI. To shed light onto this relationship an experimental situation was design to measure real-time levels of attention and calculate their relation to self-reported motivation and attention in a virtual world assessment exercise. This approach considers a portable Brain Computer Interfaces (BCI) based on electroencephalogram (EEG) readings of real-time brain activity. A model of attention was defined (Rebolledo-Mendez and de Freitas 2008) which considers physiological inputs in combination with interaction data. The combination of inputs or data fusion is not new (Manske and Conati 2005, Amershi, Conati and McLaren 2006). The model of attention utilizes Beta waves (13-30 Mhz) associated to being awake or paying attention. To this end, a portable EEG device (NeuroSky's ThinkGear) was used to read Beta waves. The ThinkGear is a headphone-like device with 3 sensors, two located beneath the ear and one located on the left hand-side of the forehead. The frontal sensor is used to read frequencies originated on the left pre-frontal lobe while the two posterior sensors are used to control for other frequencies (noise) associated to muscular activity. The ThinkGear is capable of reading other frequencies (i.e. Alpha, Theta waves) but this work focuses exclusively on Beta waves. A scale (0 to 100) has been developed by NeuroSky to estimate values of attention based on raw Beta wave readings (13-30 Mhz). The values are calculated at a pace of approximately one per second; a value of 0 indicates low attention and greater values indicate increasingly higher levels of attention with the highest value set at 100. The closer to 100 a particular reading is the greater the magnitude of the associated Beta waves for that person. Because of the dynamic nature of the readings and the potentially large data sets, the model of attention (Rebolledo-Mendez and de Freitas 2008) is built dynamically while the learner answers one question in the virtual world assessment exercise. To calculate attention for a specific question-answer episode in the assessment, the mean of all ThinkGear readings that occur during the formulation of individual answers is obtained and divided by one hundred. This is a simple measurement but is a first step on building an attention model based on physiological inputs. The model also considers clues from the interaction which might indicate learner's attention such as time taken and errors made (de Vicente and Pain 2002) and whether the student gave-up, see Table 1. To calculate the attention associated to a particular question, binary values (high = 1, low = 0) for all the variables except the EEG readings are averaged out together with value of the EEG readings at the end of every question.

TABLE I. ATTENTION MODEL

	Low	High
Portable EEG readings	< .50	> .50
Quality	Errors made	No errors made
Speed	More than 1 minute	Less than 1 minute
Give up	Yes	No

This mean value is a measurement of attention associated to a question-answer episode for which the model selects a type of reaction (see Table II). The model of attention not only detects varying levels of attention but also provides corrective feedback to improve or sustain learner's attention. These reactions were inspired by previous work on motivation (Keller 1983) since it provides clear guidance on how to improve or sustain learner's attention.

TABLE II. REACTIONS FOR THE ATTENTION MODEL AND ASSOCIATED VALUES OF ATTENTION

Reaction	Values of attention	Strategy
1	0 .1666	To increase attention, use novel, incongruous and paradoxical events. Attention is aroused when there is an *abrupt* change in the status quo.
2	.1667 .3333	To increase attention, use anecdotes and other devices for injecting a *personal, emotional element* into otherwise purely intellectual or procedural material.
3	.3334 .50	To arouse and maintain attention, give people the opportunity to learn more about things they *already know about* or believe in, but also give them moderate doses of the *unfamiliar* and unexpected.
4	.5001 .6666	To increase attention, use analogies to make the strange familiar and the familiar strange.
5	.6667 .8333	To increase attention, guide students into a process of question generation and *inquiry*.
6	.8334 1	Optimal level of attention, no reaction needed.

Because students' attention can be at an optimal level (reaction 6) such state would not require any attention reinforcing strategy. Since there are 6 types of reactions in the attention model, the specific reaction (column 3, Table II) that will be selected for an attention level in any given episode depends on the values of attention associated to that episode (column 2, Table II).

Experimental setting

A multiple choice questionnaire (MCQ) with ten questions in the area of Algorithms was defined in Second Life. An AI-driven avatar asked nine theoretical questions to the avatar being controlled by individual participants. The AI-driven avatar also presented three possible answers. For example, the AI-driven avatar would ask 'How do you call a finite and ordered number of steps to solve a computational problem?' while offering 'a) Program, b) Algorithm, c) Programming language' as possible answers. Depending on the value of student's attention during the resolution of individual questions, the AI-driven avatar selected varying reactions, see Table II. For example, suppose that Question 1 was correctly answered by the learner in 43 seconds. During this time the ThinkGear detected an average attention value (calculated considering 43 attention inputs) of 56 which divided by 100 equals .56. The values for this episode are (following Table I): EEG reading = high (EEG readings average .56), quality = high (correct answer), time = high (time < 1 minute), and give up = high (the user did not give up). The specific value of attention for this episode will then be calculated as (.56+1+1+1)/4 = 0.89. There will be no reaction for this particular example since the level of attention falls in the range of values associated to strategy 6, Table II. The interaction consisted of limited, text-based conversations in Second Life where the participants answered the questions using the keyboard. Individual participants were asked to wear the ThinkGear during the resolution of the ten questions; the readings provided by the ThinkGear were transmitted to the computer via a USB interface. In this way, the model of attention was dynamically built and was able to reason about the reactions of the AI-driven avatar, thus responding to varying levels of attention.

Materials

An adaptation of the Attention Deficit and Hyperactivity disorder (ADHD) were used to self-asses attention levels. An adaptation of Harter's motivation test (Harter 1981) was employed to self-report motivation. The self-reported attention tests consisted of seven items based on the DSV-IV (Diagnostic and Statistical Manual of Mental Disorders) criteria (American Psychiatric Association 1994). The items chosen for the attention test were: 1. Difficulty to stay in one position, 2. Difficulty in sustaining attention, 3. Difficulty to keep quiet often interrupting others, 4. Difficulty to follow through on instructions, 5. Difficulty to organize tasks and activities, 6. Difficulty or avoidance of tasks that require sustained mental effort and 7. Difficulty to listen to what is being said by others. Each item was adapted to self-report attention both in the Algorithms class (pre-test) and during the interaction (post-test). Each item in the test used a Likert-type scale with five options. For example, question one asked the participant: 'How often is it difficult for me to remain seated in one position whilst working with algorithms in class/during the interaction?' with the answers 1) all the time, 2) most of the time, 3) some times, 4) occasionally and 5) never. Note that for both pre- and post-test attention questionnaires, the same seven questions were asked but rephrased considering different contexts: the class for the pre-test and the interaction for the post-test. To assess motivation in the Algorithms class, a self-reported motivation questionnaire was adapted from Harter's motivation test (Harter 1981). In this adaptation, the five subscales were considered: 1) Preference for challenge vs. preference for easy work, 2) Curiosity/interest vs. pleasing teacher/getting grades, 3) Independent mastery vs. dependence on teacher, 4) Independent judgment vs. reliance on teachers' judgement and 5) Internal criteria vs. external criteria. In sub-scale one of the motivation questionnaire questions included aspects such as preference for easy work to solve algorithms, or preference for only learning what is needed to pass. In sub-scale two of the questionnaire, learners are prompted to answer whether they prefer to do extra projects or find out things they are interested in. Sub-scale three includes aspects such as independence to find solutions when facing problems or dependence on teacher to find solutions. Sub-scale four presents questions related to whether students believe their teachers should decide on the work to do or whether students' stick to their own opinions. Finally, sub-scale five questions include aspects related to dependency on marks or teachers' reassurance to know they are doing well in the Algorithms class. These sub-scales were used as an indication of the motivational state of the learner and resulted in a 29-item questionnaire. There were six questions for sub-scales one, two, three and four, and four questions for sub-scale five. Questions from each sub-scale were alternated and students answered individual questions in a scale from one to four; an answer of four indicates more motivation. The questions were adapted to reflect student's motivation in the Algorithms class.

Participants and methodology

The evaluation was conducted among first-year undergraduate students (N=40, 12 females) in the Informatics Department at the University of Veracruz, Mexico; 65% (26 students) of the population were 18 years old, 30% (12 students) were 19 years old and 5% (2 students) were 20 years old. The participants interacted with the AI-avatar for an average of 9.48 minutes (SD = .0018). The procedure was as follows:

1) Students were asked to read the consent form, specifying the objectives of the study and prompted to either agree or disagree,

2) Students were asked to solve a pre-test consisting of the adaptation of the attention deficit and hyperactivity disorder (ADHD) questionnaire and the motivation questionnaire,

3) Students were asked to wear the ThinkGear device 5 minutes before the experiment started. Special care was given to wearing the device properly to avoid data loss. The ThinkGear takes approximately 10 seconds to calibrate itself to a new user.

4) Students were instructed on how to use Second Life and then asked to solve the MCQ,

5) Students were asked to answer a post-test consisting of the adaptation of the ADHD questionnaire to assess their attention levels during the interaction with the assessment exercise. All students agreed to participate in the experiment. Cases with missing data were not considered for analysis.

Results

Data collected consisted of three measurements of attention: 1) Pre-test to assess students' self-perceived attention in the topic (*A1*), 2) Discrete measurements in a scale 0-100 related to attention during the interaction provided by the ThinkGear (*A2*) and 3) post-test to assess students' self-perception of attention during the interaction (*A3*). The data also consisted of six measurements of motivation: 1) data related to sub-scales one to five (see materials section) and 2) a composite measurement of motivation (M) consisting of averaging out the data from the five sub-scales. Table III presents descriptive statistics of all the variables.

TABLE III. DESCRIPTIVE STATISTICS

	N	Min	Max	M	SD
A1	40.00	2.43	4.57	3.55	0.49
A2	34.00	14.99	88.00	53.40	16.69
A3	40.00	3.00	5.00	4.26	0.46
SS1	40.00	1.50	3.83	2.91	0.67
SS2	40.00	2.00	3.67	3.03	0.45
SS3	40.00	1.33	3.67	2.47	0.61
SS4	40.00	1.67	3.50	2.54	0.46
SS5	40.00	1.60	4.00	2.75	0.64
M	40.00	1.86	3.45	2.74	0.37

To shed some light onto the relationship between attention and motivation, a series of correlations and between-subjects analyses were defined. The first set of hypotheses (1-4) considers the relationship between various attention measurements and motivation. Results are presented as a series of correlations for each hypothesis to test the degree to which these variables are associated. A Pearson's correlation test showed there is not a correlation between self-reported attention in the class (A1) and the readings of attention provided by the portable EEG device (A2) (hypothesis 1 Pearson's = -.158, p = .372). For hypothesis 2) dealing with the relationship between self-reported attention in the class (A1) and self-reported attention during interaction (A3), the results indicate a significant positive correlation (Pearson's = .451, $p < .01$) between these two variables, see Table IV.

TABLE IV. CORRELATION BETWEEN A1 AND A3

		A1	A3
A1	Pearson Correlation	1	.451
	Sig. (2 tailed)	.	.004**
	N	40	40
A3	Pearson Correlation	.451	1
	Sig. (2 tailed)	.004**	.
	N	40	40

** Correlation is significant at the 0.01 level (2 tailed).

Hypothesis 3) assessed the readings of attention provided by the portable EEG device (A2) in relation to self-reported attention levels during the interaction (A3). Pearson's tests showed that there is a negative correlation between these two variables (Pearson's = -.389, $p < .05$) which suggests students' perception of attention during the interaction do not coincide with the readings provided by the EEG device, see Table V.

TABLE V. CORRELATIONS BETWEEN A2 AND A3

		A2	A3
A2	Pearson Correlation	1	.389
	Sig. (2 tailed)	.	.023*
	N	34	34
A3	Pearson Correlation	.389	1
	Sig. (2 tailed)	.023*	.
	N	34	40

* Correlation is significant at the 0.05 level (2 tailed).

TABLE VI. CORRELATION BETWEEN A1 AND M

		A1	M
A1	Pearson Correlation	1	.544
	Sig. (2 tailed)	.	.000**
	N	40	40
M	Pearson Correlation	.544	1
	Sig. (2 tailed)	.000**	.
	N	40	40

** Correlation is significant at the 0.01 level (2 tailed).

Hypothesis 4) looked at whether there is a relationship between motivation (M) and attention before the interaction (A1). The results indicate that there is a significant correlation between these variables (Pearson's =

.544, p < .01), see Table VI. Hypothesis 5) asked if there is a relationship between motivation (M) and attention as assessed by the portable EEG device (A2), the results of a Pearson's correlation showed there is no correlation between these two variables (Pearson's = -.262, p = .134). However, hypothesis 6) dealt with the relationship between motivation (M) and attention as self-reported by students after the interaction (A3). The results of a Pearson's correlation showed there is a weak positive correlation between the two variables (Pearson's = .381, p <.05), see Table VII.

TABLE VII. CORRELATIONS M AND A3

		M	A3
M	Pearson Correlation	1	.381
	Sig. (2 tailed)	.	.015*
	N	40	40
A3	Pearson Correlation	.381	1
	Sig. (2 tailed)	.015*	.
	N	40	40

* Correlation is significant at the 0.05 level (2 tailed).

Hypothesis 7) asked whether there is a relationship between the five sub-scales of Harter's motivation test and attention as assessed by the portable EEG device (A2), but the results showed no relationships between them. Hypotheses 8), 9) and 10) dealt with finding difference in the readings of attention (A2) distinguishing between low and high motivation students. To that end, the mean for the motivation values (row 9, Table III) was used as cut point.

TABLE VIII. GROUP STATISTICS

	M	N	M	SD	SE Mean
Correct answers	Low	19	5.47	1.611	.370
	High	19	6.84	1.167	.268

The results of a between-subjects test showed that there is a significant difference in the number of correct answers t(36) = -2.998, p =.005, which suggests motivation in the class is a strong factor influencing answering correctly in this assessment exercise (Hypothesis 8).

TABLE IX. GROUP STATISTICS

	A1	N	M	SD	SE Mean
Correct answers	Low	16	5.38	1.746	.437
	High	22	6.73	1.120	.239

However, no significant correlations were found between low- or high- motivation students and their relation to A2 (Hypotheses 9 and 10). Hypothesis 11) dealt with the number of correct answers considering attention in the class (A1). As was the case with motivation, the average number of attention values (row 1, Table III) was used as cut point. Table IX presents the average numbers of correct answers for high and low A1 values.

The results of a between-subjects tests showed that there is a significant difference in the number of correct answers when A1 values are considered t(36)=-2.908, p = .006, which suggests self-reported attention in the class is also an influential factor in answering correctly in the assessment exercise. Hypothesis 12) asked whether students with higher levels of attention as assessed by the portable EEG device (A2) had significantly more correct answers, however, a between-subjects tests showed non-significant results. Finally, hypothesis 13) dealt with whether students with higher levels of self-reported attention during the interaction (A3) answered significantly more correct questions but a between-subjects tests showed non-significant results.

Discussion and future work

The intention of developing an attention model was to aid learners to increase or sustain higher attention levels to influence their motivation and, in turn, the number of correct answers in the assessment exercise. The results of this experiment, however, provide interesting results. Firstly, it was expected that overall attention levels as read by the portable EEG device (A2) would lead to more correct answers but it was not the case (hypothesis 12). The same is true for self-reported levels of attention during the exercise (A3, hypothesis 13) as a between-subjects test showed non-significant results. Interestingly, students with self-reported higher attention levels at pre-test (A1), hypothesis 11, attained more correct answers than students' self-reporting low levels. This result suggests *perceived* attention plays an important role in answering correctly. Similarly, significant but weak correlations were found between motivation (M) and self-reported attention during the interaction (A3) (hypothesis 6) and between motivation (M) and self-reported attention in the topic (A1) (hypothesis 4). Similarly, as expected, there exists a positive and significant correlation between self-reported attention in the class (A1) and during the interaction (A3), hypothesis 2. In contrast, when considering attention as assessed by the portable EEG reader (A2), it was found that there is no difference in A2 values when low- and high- values of motivation are considered (hypotheses 9 and 10). In a similar line, no correlation was found between M and A2 (hypothesis 5). The discrepancy between the portable EEG readings (A2) and self-reported attention levels during the interaction (A3) indicates that real-time physiological measurements of attention do not coincide with self-reported values of attention in the exercise. However, it appears self-reported attention before the exercise (A1) (t(36) =-2.908, p = .006) and self-reported motivation (M) (t(36) = -2.998, p =.005) are better predictors of answering correctly. This result is important as it suggests self-perceptions of motivation and attention account for better performance.

The results of this experiment suggest that base-line variables such as self-reported attention and motivation might have a greater influence over the learner's performance. The results also suggest the attention model needs further refinement. In particular, the new model needs to include self-reported attention and self-reported motivation as baseline variables to model student's attention. Since attention measurements with the ThinkGear (A2) did not correlate with self-reported levels of attention during the same interaction (A3), motivation (M) or self-reported attention levels in class (A1) we hypothesize Beta waves reflect only one aspect of cognitive attention as understood in educational settings (i.e. Keller 1983). Future work will consist on refining the model of attention presented in this paper. In particular, new ways of measuring attention will be devised. An example of a new approach could use Beta waves and students' gaze. In this way, it will be possible to model Beta wave patterns that significantly relate to learners' gaze. Twelfth

Acknowledgements

The help of teachers and students at the Faculty of Statistics and Informatics from the University of Veracruz is greatly appreciated. The researchers of the Computational and Educational Technology group at the University of Veracruz and PROMEP are acknowledged. NeuroSky Corporation is also acknowledged for allowing the use of their prototype to be tested for research purposes.

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