Emotion Based LMS: An Investigation of User Perceptions and Attitudes

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***Abstract*—This study offers a comprehensive review of various methodologies for emotion based emotion Learning Management Systems (LMS) and examines the use of Technology Acceptance Model (TAM) to investigate how learner beliefs and attitudes influence emotion based LMS use among higher education learners by evaluating the relationships between perceived usefulness, perceived ease of use, attitude and behavioural intentions. In the study, 40 potential users were presented with an introductory demonstration of emotion based LMS for an IT course. Following the demonstration, data on user perceptions and attitudes about emotion based LMS were gathered based on this initial exposure. Hierarchical multiple regressions were used to assess the overall model and influence of each variable of interest in determining behavioural intentions to use emotion based LMS. The analysis showed that both the user perceptions and attitudes have significant positive effects on behavioural intention to use emotion based LMS. Implications of these findings for practice and research are examined and discussed.**

***Index Terms*—emotion recognition, emotion-based e-learning, e-learning, learning management systems, technology acceptance model**

I. Introduction

Computer and Internet technologies, in particular the World Wide Web, provide educators and learners with an innovative learning environment to stimulate and enhance the teaching and learning process. Classroom learning and teaching differs significantly from online learning and teaching due to many factors. For example, researchers have concluded that the learning styles of online learners differ significantly from traditional classroom learners [1]. Another key difference is that a classroom teacher can actively evaluate his or her students' reaction to lessons and respond accordingly. The teacher can choose to repeat his lessons or use simpler explanation if students appear confused, or continue at the current pace if students appear to understand the lesson, or teach at a faster pace or move to more complex content if students feel that the lesson is dull or too easy. In other words, face-to-face classroom teaching adopts the basic tenets of natural communication in which feedback plays a crucial role (Fig. 1) while current LMS lacks this essential factor.

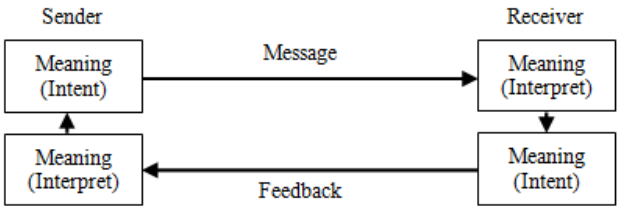

Figure 1. Communication model (adapted from [2])

One of the key successes for communication is the recognition of emotion, often evident through non-verbal communication.

Studies on student emotion and information systems often use terms such as emotion, affect, feeling and mood to describe the way a person feels during learning. Feidakis, Daradoumis and Rosmalen [3] distinguished the four terms by defining emotion as "an intense experience of short duration", affect as "a synthesis of all likely effects of emotion", feeling as similar to emotion but with varying lengths of time, and mood as "subtler, longer-lasting, less intensive, more in the background". In terms of an actual classroom scenario, Feidakis *et al.*'s 'mood' best describes the general overall class emotion [3]. However, when describing how an individual student feels, for example when learning online, 'emotion' is best used.

In addition, researchers such as [4] argue that current LMS are not adaptive in nature. In other words, most LMS are not capable of providing customized learning or adapt to individual learner's abilities and pace of learning. They assume that all learners learn at the same level and understand the online learning contents in the exact same way. As such, most learning multimedia contents have only three controls: stop, forward or rewind. These learning objects also assume that students who replay an online learning content will be able to understand what has been taught once the process is repeated. In short,

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typical LMS assumes that it is the student's responsibility to decide if re-learning needs to occur, putting the onus of a reaction to poor learning on the student, rather than the system.

Boticario, Santos and Rosmalen [4] identified three related areas deemed important towards adaptive learning management systems: "intelligent tutoring systems, adaptive hypermedia systems, and computer-supported collaborative learning systems". This study examines user acceptance of two of the three elements – intelligent tutoring systems and adaptive hypermedia systems.

The increased use of new educational technologies in higher education institutions [5]-[7] has made user acceptance an increasingly critical issue, as the end users are crucial for the effective use of the information technologies [8]. The measurement of the user perception [9] and an understanding the factors that promote the effective use of systems [10] become increasingly important to enhance our understanding and prediction of the acceptance and utilization of educational technologies. This study used the Technology Acceptance Model (TAM) as the baseline model to predict the likely usage of emotion based LMS to enhance learning experiences in a higher-education context.

II. Background

A. Emotion and Learning

Early academics believe that emotions have no place in learning and teaching, contending that learning and teaching should be based solely on logic and common sense. Some think of emotion as non-scientific [3] and should deliberately be ignored. The behaviorists found later that motivation is a major contributor of learning. In real class environments, a good teacher scans students regularly and assesses students' faces for feedback. The general students' mood tells the teacher if they understand the lesson and if any actions should be taken to rectify confusion, boredom or distress. In addition to verbal feedback, mood can be assessed by looking at body language or based on the emotions expressed on student's faces. Being able to judge quickly students' sentiments is important to improve classroom engagement. Researchers such as [11] acknowledge this "lack of immediate feedback in asynchronous e-learning" as a weakness of e-learning systems. In the long term, negative moods and emotions of online students may result in students dropping out [12].

The expression of human emotions has long been deemed important for effective communication. Writers use various means to communicate emotions such as the use of exclamation marks, dialogues, and sentence structures. Online communication introduced emoticons and stickers to further express emotions in online chats. A review of emotion based studies in face-to-face communication and computer-mediated-communication by [13] found minimal or little difference in the emotions expressed in both mediums. On the contrary, the study found that emotions are expressed slightly more frequently in computer-mediated-communication.

It is clear that the learners' state of emotion is an essential factor for learning systems to adopt. It enables the system to respond accordingly and offer mediating corresponding actions, thus creating a more natural and effective learning environment.

B. Review of Emotion Based LMS

In this section, we provide a short summary of some of the work on emotion or affective learning systems.

One of the simplest methods for affective systems is the use of texts. Such inputs can be in the form of words or lately, emoticons. The obvious advantages of this method are that they are precise and require minimal emotion recognition processing. In addition, many users are already familiar with the use of emoticons, used popularly in online chat-rooms and during texting. It is not surprising therefore that many educators have long recognized and experimented with the use of emoticons in learning systems [14], [15].

The use of texts and emoticons, however, are largely dependent on user input, which may be distracting during an online lesson. In other words, students may opt not to provide emotion text input to the system. In short, they do not represent how humans communicate naturally and require conscious effort to express.

Agent-based systems are one of the early methods to address immediate asynchronous feedback for learning systems. Such systems are often based on embodied characters in the form of still or animated avatars and also known as tutor based systems [16]-[18]. The reason for the popularity of agents is that they are believed to be able to artificially replace teachers in online learning environments. For example [16] introduced an intelligent tutor system that analyses voice or text input from medical students, deduces the emotive states and generates voice or text output that also incorporates emotion. Such systems met various degrees of success and some researchers report that they are able to assess emotions to help learning. The success of these early studies using artificial agents and emotions emphasizes the importance of emotion in learning systems.

While the use of intelligent agents has found popular support with educators who want to provide natural immediate feedback to students, some researchers express caution with its adoption. Many researchers found that when the novelty of the virtual agents fades, users often found them rather annoying [19], [20], an oft-quoted example being the Microsoft Assistant, which Microsoft opted to drop from its later operating systems.

Some learning systems employ biosensors to recognize emotions. These sensors detect bio-signals of users' physiological states. Popular bio-signals used are electroencephalography (EEG) produced by the brain, Skin Conductance (SC) of the hand, blood volume pulse (BVP) from blood pressure and respiration rate [3]. The advantage of such methods is that they are very precise and do not require user's manual input. Bio-signals can be used quite accurately to deduce a user's emotional states. For example, Arroyo *et al*. [21] report that their bio-signal based learning system predicts more than 60%

of the variance of emotions (confident, frustrated, excited and interested) expressed by their respondents accurately.

A drawback of bio-sensor based affective learning systems is that they require users to use sensors. These sensors can be obtrusive and may require learners to learn how to wear them properly. They can also be expensive to purchase and an additional cost that students may be unwilling to bear. In addition, they are often not comfortable to wear for prolong use.

Alternative means to detect emotions accurately which do not require the use of wearable sensors include voice and facial based emotion recognition.

Voice analyses parameters such as pitch, rhythm, loudness, etc. can be harnessed to identify emotional states [22], [23] from a student's voice. Voice is a natural method of communication and displays consistent array of emotions. Emotion recognition through voice analyses is particularly useful when students provide voice input to a system, often through the use of a microphone. The advantage of voice input is that it is relatively easy, and only requires a microphone, which is often built into modern computers and laptops.

However, voice recognition is rather difficult to implement in real life, especially in a situation where noise pollution exists and interferes with the analyses, resulting in poor accuracy of results. Voice input is also difficult for students who need to access online learning content at public places such as libraries and buses due to the lack of privacy and ambient interference.

Facial recognition is fast gaining popularity in affective learning systems research. Humans display emotions by expressing them on our faces due to involuntary movements of facial muscles as we react to events and information. Typically, images of the face are captured and features such as eye brows, lips, and eyes, etc. extracted for analysis. As the facial muscles contract and expand when displaying emotions, we can compare facial image patterns to match similar patterns for sets of emotions. As early as 1969, a set of facial features for emotion called Facial Action Coding System (FACS) have been introduced by Carl-Herman Hjortsjo for this purpose [24]. Facial recognition detection offers the practicalities of convenience and ease. As many modern computers and laptops have cameras built-in, they are readily available to be integrated into learning systems.

In general, while modern facial recognition methods have proved quite efficient, some also suffer from noise (when the lighting condition is poor) or when multiple users appear on images. A few solutions have been proposed to overcome these conditions such as infrared [25] and colour images [26]. As emotions change quickly in tandem with sections of a lesson, it is also important to assess the changes in emotion dynamically in video streams [27] and not mere static images.

Due to the existing weaknesses in almost all types of methodologies to identify emotion, many researchers [23], [28] have adopted multimodal approaches. A multimodal approach generally combines two or more existing methods, for example voice and facial recognition. The benefit of multimodal approaches is that the dual (or more) systems confirm the result of each other, much in the same way as a patient seeking alternative prognosis from another doctor. Thus, the results can be re-verified, and accuracy improved significantly.

C. Review of Adaptable LMS

According to Ho [29], adaptable e-learning "allow[s] instruction to be tailored to the needs of the individual learner". Various methodologies have been proposed for the design of adaptive learning. A study using two methodologies: eye tracking and content tracking technologies stand out due to its success.

Both eye and content tracking adaptive learning have been studied by Doll *et al.* [33] using a system called AdeLE. AdeLE tracks the eye movements of users by using cameras and complex algorithms. Eye movements (and non-movement) are associated with cognitive processes during learning and can show if students are experiencing difficulties or are comfortable with what they are reading.

Content tracking, on the other hand, tracks the content students use in learning systems by working hand in hand with profiles generated by eye tracking. For example, if the systems determine that a student's eyes have gleaned too quickly through certain modules, it may deduce that the student did not read the materials in detail and may suggest that the student re-read the modules.

Seddon [34] proposed converting existing learning objects to adaptable learning objects by mapping possible outcomes to three: relearning same information, using simpler explanation of the information in a different layout chosen by user, or using simpler information in a layout chosen by device.

D. Intention Based Models

Information technology has been widely implemented in education to augment traditional face-to-face teaching and learning [29], [30]. As with other trends involving information systems, this has made user acceptance an increasingly critical issue, as the success of the information systems largely depends on user satisfaction and acceptance [31]-[34]. Stokes [35] indicated that the issue of learner satisfaction and acceptance in the digital environment is essential. A high level of learner satisfaction and acceptance reflects that the users are more willing to continue to use the technology [36], [37].

Several intention-based theories and models have been proposed and empirically tested in the last decade in understanding user adoption and use of information technology innovations. For example, the Theory of Reasoned Action (TRA) [38], Technology Acceptance Model (TAM) [39], the Theory of Planned Behavior [40], Innovation Diffusion Theory [41], and the Information Systems (IS) Success Model [32]. Those frameworks have been applied to a variety of information technologies in different contexts and populations [42-46]. Among them, TAM [47] is one of the most influential and frequently tested models, and is widely applied to explain general IT adoption in the information system literature [48]-[50].

TAM is a specific model developed to explain and predict users' computer usage behavior. Derived from the TRA [38], [51], it predicts user acceptance based on the influence of two user beliefs: perceived usefulness (PU) and Perceived Ease of Use (PEU). Both PU and PEU are posited as having significant impact on a user's attitude (AT) towards using the system. Behavioral Intentions (BI) to use is jointly determined by a person's attitude towards using the system and its perceived usefulness. BI then determines the Actual Use (AU) of the system. Using different methodologies, numerous studies have found that PU and PEU correlate well with IT acceptance across a wide range of information systems [42]-[46]. Likewise, empirical research has also shown that BI is the strongest predictor of AU [39], [52].

III. Research Model and Hypotheses

In this study, TAM was used as the baseline model to verify the following hypothesized relationships in the context of emotion based LMS usage among higher educational learners. Fig. 2 shows the studied model which posits that perceived usefulness and perceived ease of use have direct effects on attitude toward emotion based LMS use and intention to use. Attitude toward emotion based LMS use has a direct effect on behavioural intention to use emotion based LMS.

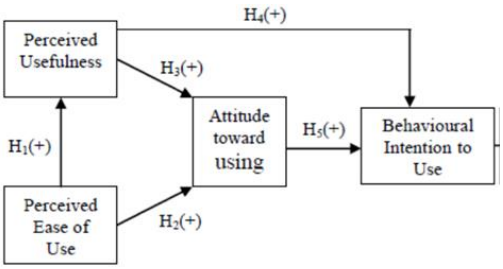

Figure 2. Research model and hypotheses

IV. Methodology

A. Instruments

Data for this study was collected via a questionnaire by the instructors. A review of the Information System (IS) literature was used to identify existing measures for constructs, which had been used in previous IS research. The scales for PU, PEU, AT, BI and AU were adapted from literature [53]-[58]. Items were rewritten as necessary to fit the context of this study. A five-point Likert scale from strongly disagree to strongly agree was used to measure the items. The instrument in this study was divided into two sections in the questionnaire. The first section contains items used to measure all the independent variables assumed to affect emotion based LMS acceptance and adoption. Multi-items were used to measure each. The second section contains five questions relating to demographic data about the respondent. The questionnaire is enclosed in the appendix.

B. Participants

The sample was conveniently selected resulting in a sample of 40 potential users of emotion based LMS. Among them, there were 23 males and 17 females. Participants were familiar with the Internet and computers, but without previous emotion based LMS learning experience.

C. Prototype

Based on the experiences of previous researchers, we built a prototype of an emotion based LMS which uses face recognition and emoticons for input due to the obvious advantages of multimodal approaches. The emotions recognised by the system are neutral, happy, sad, disgust, anger, surprise and fear. These form the six basic emotions advocated by [53]'s seminal work. We also developed materials and content for a university subject, Digital Systems, and incorporated the adaptable contents approach. While the system was still in prototype stage, it was sufficient for us to gauge user acceptance.

D. Procedure

Subjects were told the purpose of the study and after providing consent, the instructors provided a brief in-class introduction on the capabilities of emotion based LMS in general for learning. Immediately after the introduction session, each subject had a chance to familiarize himself/herself with the emotion based LMS. At the end of the session, all subjects received and completed the questionnaire designed to capture the emotion based LMS's perceived usefulness, perceived ease of use, students' attitude toward using emotion based LMS, and their intentions to use emotion based LMS.

E. Analysis Methods

The respondents' scores for each construct were obtained by summing across all the item scores of the individual variables. The hypothesized relationships among the study variables depicted in the model were tested using multiple regressions and path analyses with SPSS.

V. Data Analysis and Results

A. Sample Demographics

The goal of the study was to apply and evaluate TAM in emotion based LMS for learning purpose. There were 22 male and 18 female students. Most subjects has 2 to 4 years of computer experiences and spent about 2 to 4 hours each day on the Internet. Overall, the sample group could be considered potential users to use emotion based LMS for online learning, and thus met the necessary conditions for taking this survey.

B. Hypothesis Testing

Hypothesis testing is based on regression analysis using SPSS. H_1 – H_5 test the causal relationships demonstrated in TAM.

Hypothesis 1 (H_1) states that perceived ease of use of emotion based LMS would have significant positive influence on perceived usefulness of emotion based LMS. It was tested by regressing perceived ease of use on

perceived usefulness. As indicated in Table I, the results of the regression indicated the predictor explained 27.6% of the variance (R2 = .276, F(1,39) = 14.45, p<.05). It was found that perceived ease of use significantly predicted perceived usefulness (β = .52, p<.05). Thus, hypothesis 1 receives strong support.

TABLE I. REGRESSION TEST FOR HYPOTHESIS 1 (H_1)

	Unstandardized Coefficients		Standardized Coefficients					
	β	Std. Error	β	t	Sig	F	Sig	R^2
PEU	.645	.170	.525	3.802	.001	14.45	.001	
								.276

TABLE II. REGRESSION TEST FOR HYPOTHESIS 2 (H_2) AND HYPOTHESIS 3 (H_3)

	Unstandardized Coefficients		Standardized Coefficients					
	β	Std. Error	β	t	Sig	F	Sig	R^2
PEU	.401	.144	.332	2.775	.009	29.82	.000	
PU	.550	.118	.559	4.678	.000			
								.617

Hypotheses 2 and 3 state that perceived usefulness and ease of use would have significant positive influences on attitude toward using, respectively. These hypotheses were tested by regressing both perceived usefulness (H_3) and perceived ease of use (H_2) on attitude toward using. Table II provides results from the regression analysis for both Hypotheses 2 and 3. The results of the regression indicated that the two predictors explained 61.7% of the variance (R2 = .617, F(2,37) = 29.82, p<.001). It was found that perceived ease of use (β = .33, p<.05) and perceived usefulness (β = .56, p<.001) significantly predicted attitude toward using. Thus Hypotheses 2 and 3 are supported.

Hypotheses 4 and 5 stated that perceived usefulness and attitude toward using would each have a significant positive influence on behavioral intentions to use. Results for Hypotheses 4 and 5 are presented in Table III. The results of the regression indicated the two predictors explained 53.8% of the variance (R2 = .538, F(2,37) = 21.51, p<.001). It was found that perceived usefulness (β = .36, p<.05) and attitude toward using (β = .42, p<.05) significantly predicted behavioral intention to use. Thus Hypotheses 4 and 5 are supported.

TABLE III. REGRESSION TEST FOR HYPOTHESIS 4 (H_4) AND HYPOTHESIS 5 (H_5)

	Unstandardized Coefficients		Standardized Coefficients					
	β	Std. Error	β	t	Sig	F	Sig	R^2
PU	.357	.160	.366	2.228	.032	21.51	.000	
AT	.418	.163	.421	2.562	.015			
								.538

VI. DISCUSSION

In summary, the results show that behavioural intention to use emotion based LMS for learning is largely influenced by users' perceived usefulness and attitude towards the emotion based LMS.

Students' attitude towards the use of the emotion based LMS are influence by the perceived usefulness and perceived ease of use of the emotion based LMS with perceived usefulness having a greater impact than perceived ease of use.

The study proves that the technology acceptance model provides researchers and practitioners a theoretically sound and parsimonious model suitable to predict users' intention to use emotion based LMS.

As perceived usefulness is found to have a direct impact on attitude and behavioural intention to use, it is deemed the most significant factor affecting user's acceptance of emotion based LMS. The significance of perceived usefulness suggests that initial exposure i.e. the introduction and demonstration of the emotion based LMS is an important factor to allow students to form initial beliefs.

There are generally two implications from this study. First, the proposed model can be used as a predictive tool for researchers, instructional designers, and proponents of emotion based LMS. The results of this study can be used during the conceptual design of emotion based LMS. The proposed model is also useful as a practical tool to test user acceptance, which would provide early clues to risks of user rejection of the emotion based LMS. The knowledge of risks at this stage would enable designers to take preventive measures to ensure user acceptance of the emotion based LMS.

The results of this study also show that emotion based LMS should be perceived as easy to use and useful for learning process to occur. Hence, introductions to the benefits of using emotion based LMS and demonstration of its relevance to emotion based LMS could ease students into accepting the emotion based LMS system. A training session is recommended to allow students to

be competent in the use of the emotion based LMS prior to the exposure to the emotion based LMS system.

VII. Conclusion

This study has validated that TAM can be employed to explain and predict the acceptance of emotion based LMS. In predicting emotion based LMS acceptability among higher education learners, it suggests that early user perceptions and attitudes have a very powerful influence on whether users will actually use emotion based LMS in the future. Perceived ease of use and perceived usefulness were shown to be important to users' perceptions of the emotion based LMS. Therefore, educators and practitioners must consider not only the ease of use of emotion based LMS, but also their usefulness in order to promote and encourage end user acceptance of emotion based LMS. In future work, a longitudinal study to investigate the extended TAM in emotion based LMS context will be conducted to gain more insight about how learners' beliefs and attitudes toward emotion based LMS usage change over time. The emotional states identified by the system will also be improved to include more emotions in order for the system to be more precise.

Appendix Questionnaire

Perceived Ease of Use (PEU)

- PEU1 Learning to use emotion based LMS would be easy for me.
- PEU2 I would find it easy to get an emotion based LMS to do what I want it to do.
- PEU3 My interaction with emotion based LMS would be clear and understandable.
- PEU4 I would find emotion based LMS to be flexible to interact with.
- PEU5 It would be easy for me to become skillful at using emotion based LMS.
- PEU6 I would find emotion based LMS easy to use.

Perceived Usefulness (PU):

- PU1 Using emotion based LMS would make me easier to learn.
- PU2 Using emotion based LMS would improve my learning performance.
- PU3 Using emotion based LMS would enhance my effectiveness of learning.
- PU4 Using emotion based LMS would improve my efficiency of learning.
- PU5 Using emotion based LMS would give me greater control in learning process.
- PU6 I would find emotion based LMS useful for online learning.

Attitude toward use (AT):

- AT1 Using the emotion based LMS for learning would be a very good/very bad idea.
- AT2 In my opinion it would be very desirable/very undesirable for me to use emotion based LMS.
- AT3 It would be much better/much worse for me to use emotion based LMS.
- AT4 I like/dislike the idea of using emotion based LMS for learning.

Behavioural Intention to use (BI):

- BI1 I intend to use the emotion based LMS whenever possible.
- BI2 I intend to increase my use of the emotion based LMS in the future for learning.
- BI3 I would adopt the emotion based LMS in the future.

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