

Exploratory Research on an Affective e-Learning Model

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Abstract:

This paper explores how emotion evolves during the learning process with the longer term aim of developing learning systems that are able to recognize and respond appropriately to emotions exhibited by learners. We undertook this research by designing and building an experimental prototype of an emotion aware learning system conducting experiments and studying the relationship between emotion and learning. We report on our initial results which not only indicate there is a usable relationship between affect and learning, but by using the emotion states in Russell's affective model, we have been able to make some significant progress towards experimental validation of Kort's learning spiral model, which has not been empirically validated to-date.

Keywords: e-Learning, affective computing, emotion-aware

1. INTRODUCTION

Background

Technology is changing our lives at a breathtaking rate, no more so than in the world of education and e-Learning. The evolution of e-Learning can be traced from its roots in Computer Aided Instruction, through Intelligent Tutor System and Web-based Learning, to the Smart Classroom, Mobile Learning, Pervasive Learning and Personalized Learning technologies of today. To date, in these developments, there has been a bias towards the cognitive and relative neglect of the affective. Of course nobody denies the role of 'affect' or emotion in learning. Certainly teachers know that it

plays a crucial role in motivation, interest, and attention. Research has demonstrated, for example, that a slight positive mood does not just make you feel a little better but also induces a different kind of thinking, characterized by a tendency towards greater creativity and flexibility in problem solving, as well as more efficiency and thoroughness in decision making[7]. These findings suggest emotion may be an important factor in learning and point to new advances in understanding the human brain not just as a purely cognitive information processing system, but as a system in which both affective functions and cognitive functions are inextricably integrated with one another.

Related Work

The extension of cognitive theory to explain and exploit the role of affect in learning is, at best, in its infancy [12]. Kort [9] has proposed a four quadrant learning spiral model in which emotions change while the learner moves through quadrants and up the spiral, yet it has not been empirically validated.. He also proposed 5 sets of emotion that may be relevant to learning, but, no follow-on studies into these basic emotion sets for learning was reported. The Affective Computing Group at MIT's Media Lab is investigating the interplay of emotion, cognition, and learning as part of its "Learning Companion" project. This project is developing an 'affective companion' prototype that will provide emotional support to students in the learning process, assisting them by helping to alleviate frustration and self-doubt [1]. Studies carried out by the AutoTutor Group have provided evidence for a link between learning and the affective states of confusion, flow and boredom [4]. For user emotion modeling, Russell's two-dimension 'circumplex model of affect' [14], where emotions are seen as combinations of *arousal* and *valence*, is widely referenced. The OCC [11] model has established itself as the standard appraisal model.

This model specifies 22 emotion categories based on valenced reactions to situations constructed either as being goals of relevant events, as actions of an accountable agent, or as attitudes of attractive or unattractive objects. Conati and Zhou are using the OCC theory explicitly for recognizing user emotions in their educational game Prime Climb [3]. Katsionis and Virvou have adapted OCC theory to model students' emotions while they learn in an educational game [8]. Beyond education applications, there is also relevant work underway such as that by Hanjalic and Xu who represent and model video content (in their case, movies) with emotion tags to support personalization that can be used for applications such as the automatic generation of 'video highlights' or personalized recommendations for video films [6].

2. TECHNOLOGY PLATFORMS

The work reported in this paper is based on the integration of an emotion detection system used to augment the operation of a cutting-edge intelligent environment test-bed in Colchester known as the iDorm

IPTV and mobile phones. It also includes a number of what are called, "smart classrooms". The lecture material can be accessed by students both in real-time (i.e. live) or from an archive (within minutes of the lecture finishing). There are more than 15000 Students in Network Education College, most being part-time students. They have different backgrounds with dynamic knowledge structures. Given such diversity, it is important to provide personalized learning services and to create learner profiles for students the system has harnessed data mining technologies [16].

The intelligent Dormitory (iDorm) [2] is a cutting edge test-bed, based at Essex University, for pervasive computing taking the form of a digital home. The operation of the iDorm is orchestrated by intelligent agents and the occupants of the iDorm utilize a variety of networked services, including e-Learning (the iDorm is University based, and occupants are frequently learners). Thus iDorm and the Smart Classroom share much in common. As part of the iDorm work, Leon et al. have developed a real-time emotion detection system, which achieved an 85.2% correct recognition rate in

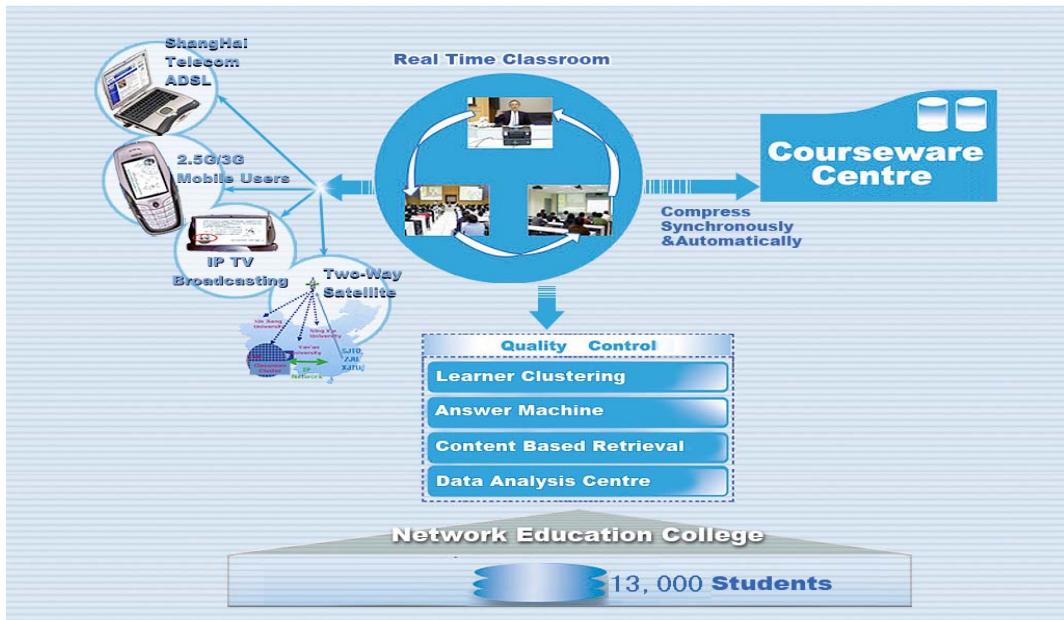


Figure 1. Pervasive eLearning Platform in Shanghai

(intelligent Dormitory), with a massive e-Learning test bed in Shanghai. The pervasive e-Learning platform (Fig 1) was developed by the School of Network Education of Shanghai Jiao Tong University [17]. It delivers fully interactive lectures to PCs, laptops, PDA,

experiments involving three emotional categories, (neutral, positive, and negative), on 8 subjects [10]. This approach comprises an eXperimental Vital-sign-based Emotional State Transmitter (X-Vest, Fig 2), a finger clip with built-in sensors providing

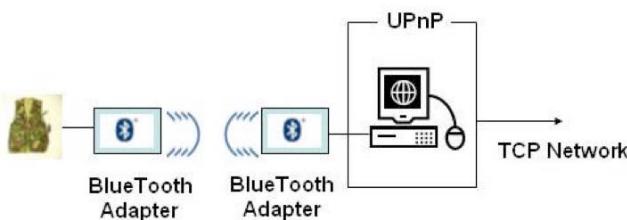


Figure 2. The X -Vest Architecture

physiological signals (heart rate - HR, skin resistance -SR, blood volume pressure -BVP, gradient of skin resistance -GSR, and speed of the changes in the data -CS). It recognizes affective changes using a combination of Auto Associative Neural Networks (AANNs) and sequential analysis (UK Patent 0611762.6).

3. AFFECTIVE LEARNING MODEL

3.1 Rational & R&D Strategy

Russell and Kort's models share a common axis: the emotional state. If, during learning, emotion is found to change in a consistent manner then this would provide a means to study how learning behaviors relate to emotion (and vice-versa). At a simple level this might be employed to provide teachers with feedback on a learner's emotional state (useful for remote learning where there are no visual cues). Moreover if, during learning, the transition between emotional states on Kort's model displays some kinds of loops then this would indicate a tighter coupling between Russel and Kort's models, opening the possibility for the theory associated with these well established models (e.g. Kort's affective learning spiral) to be applied to emotion-aware e-Learning systems.

Thus our experimentation focused on gathering data to explore the affective evolution during learning and the relationship between Russell and Korts Models.

3.2 Affective Learning Models

As Picard [13] stated, “*Theories of affect in learning need to be tested and evolved. However, there is still very little understanding as to which emotions are most important in learning, and how they influence learning. To date there is no comprehensive, empirically validated, theory of emotion that addresses learning*”, so as a first step, we will use our prototype to fix the

user emotion space using Russell's ‘circumplex model’. We will then use the emotion states (personalized to the user) detected during learning process to empirically validate Kort's ‘Learning Spiral Model’. The following is the description of these models and our rationale for exploring the relationship between these two models.

3.3 Russell's Circumplex Model of Affect

In Russell's circumplex model of affect (Fig. 3), emotions are distributed in a system of coordinates where the y-axis is the degree of arousal and the x-axis measures the valence, from negative to positive emotions [13]. This model focuses on subjective experience which means emotions within these dimensions might not be placed exactly the same for all people. In fact, Figure 3 is the author Russell's own dimensional model of emotion.

Whilst Russel provides a comprehensive set of emotions, these are not well matched to our more focused application of learning, and are too numerous for self-assessment tests; therefore we have chosen a carefully selected subset and additions to explore a basic emotions for learning, namely, interest/curiosity, engagement, confusion/comprehension, frustration, boredom and hopefulness/optimism. At this stage it is not clear that we have the optimum set for our needs, rather this is a starting point and undoubtedly this may evolve or take many investigations before it is well

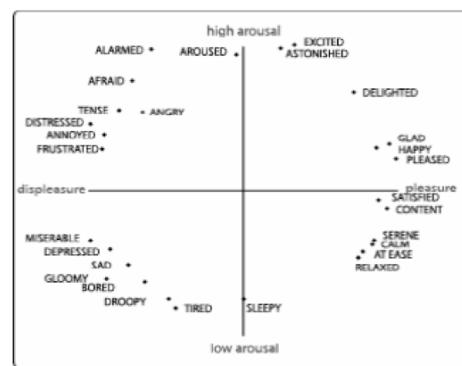


Figure 3. Russell's circumplex model of established.

3.4 Kort's Learning Spiral Model

Kort [9] has proposed a four quadrant learning spiral model in which emotions change while the learner moves through quadrants and up the spiral (Fig. 4). In

quadrant I the learner is experiencing positive affect and constructing knowledge. At this point, the learner is working through the material with ease and has not experienced anything overly puzzling. Once discrepancies start to arise between the information and the learner's knowledge structure, they move to quadrant II, which consists of constructive learning and negative affect. Here they experience affective states such as confusion. As the learner try to sort out the puzzle but fails, he might move into quadrant III. This is the quadrant of unlearning and negative affect, when the learner is experiencing states such as frustration. After the misconceptions are discarded, the learner moves into quadrant IV, marked by unlearning and positive affect. While in this quadrant the learner is still not sure exactly how to go forward. However, they do acquire new insights and search for new ideas. Once they develop new ideas, they are propelled back into quadrant I; thus, concluding one cycle around the learning spiral of Kort et al. As learners move up the spiral, they become more competent and acquire more domain knowledge.

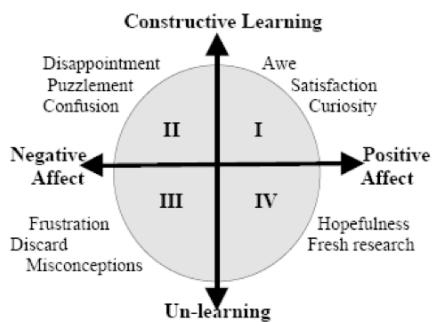


Figure 4. Kort's Learning Spiral

3.5 Rationale for Exploring Relationship between Russell and Korts Models

Russell and Kort's models share a common axis: the emotional state. If, during learning, emotion is found to change in a consistent manner then this would provide a means to study how learning behaviors relate to emotion (and vice-versa). At a simple level this might be employed to provide teachers with feedback on a learner's emotional state (especially useful for remote learning where there are no visual cues). Moreover if, during learning, the transition between emotional states

on Kort's model displays some kinds of loops, then this would indicate a tighter coupling between Russel and Kort's models, opening the possibility for the theory associated with these well established models (e.g. the affective learning spiral) to be applied to emotion-aware e-Learning systems.

Thus our initial experimentation has been focused on gathering data to explore the affective evolution during learning and the relationship between Russell and Korts Models.

4. PRELIMINARY EXPERIMENTS AND RESULTS

The preliminary experiment was carried out in the intelligent inhabited environment, iDorm2.

4.1 Methods

The participant was a female visiting scholar who lived and worked in the iDorm2. During the experiment, she wore the X-Vest which provided the valence value and raw data from 5 biosensors. Data from the X-Vest was collected every 2 seconds. As Skin Resistance (SR) is a very good indicator of arousal [12], we used the raw SR data to linearly evaluate and track, in real-time, the arousal value. A low level of SR denotes high arousal and vice versa. We observed that the subject's skin resistance can vary by as much as a factor of ten between morning and evening. To settle this diurnal SR variation problem, we introduced a dynamic normalization (averaged over the previous 5 minutes). The participant was asked to conduct the experiment twice a day for 5 days, wearing the X-Vest and collecting arousal and valence data while she was learning. In this preliminary experiment, the learning process and learning materials are not pre-designed, i.e. the subject and learning materials are selected by the participant herself. Each learning session lasted at least 30 minutes. The arousal-valence data was displayed, in real time on a colored four quadrant diagram. Each time the system detected a change of emotion, a multi-choice dialog was triggered, listing six basic emotions, from which the participant had to select the nearest match to her current emotion.

All the raw data, arousal, valence, and self reports were recorded together with time tag in a data file for further

study and analysis.

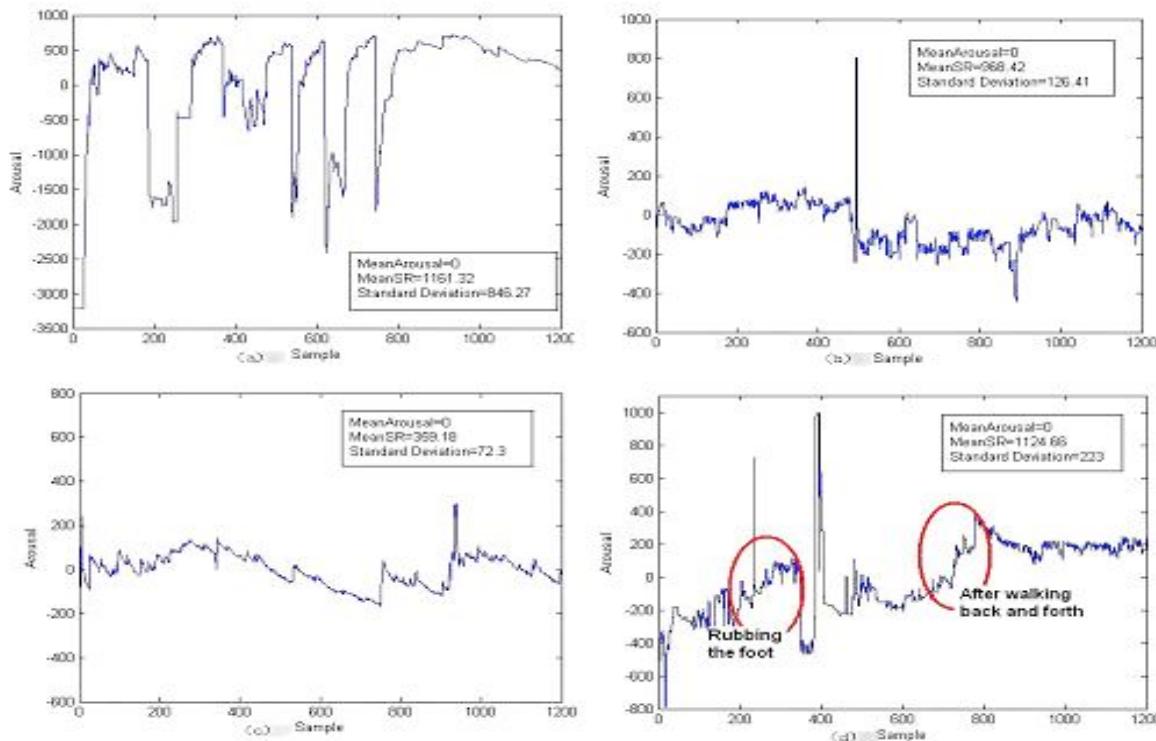


Figure 5. Skin Resistances Experimental Data

4.2 Results

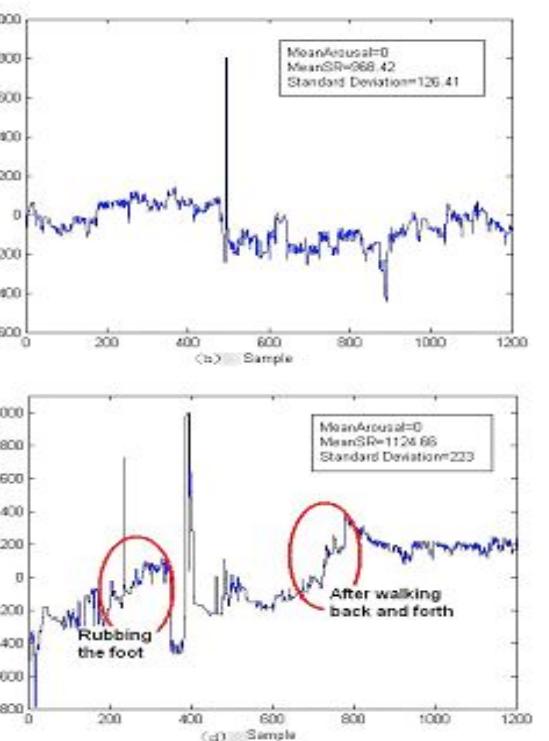
Experimental data was gathered from 9 learning sessions and 1 TV session (unstructured entertainment). Each session lasted at least 40 minutes with 4 sessions including a self-reporting function.

Arousal Results

From the data, we observed the following interesting characteristics about how arousal evolved during learning process:

1. During a single learning session, the arousal remains relatively stable. The standard deviation was found to be around 100 K-Ohms (Fig 5b, c).
2. During the TV session, the arousal varied greatly and the standard deviation was as large as 846 K-Ohms (Fig 5a). This is consistent with the unstructured nature of the material.
3. Arousal was not only the result of learning, but was influenced by other factors such as physical exertion. For example, the participant reported that she was more aroused to learn when she walked to and fro around the room (which she usually does when she feels tired or sleepy). The recorded SR data revealed this phenomenon (Fig 5d).

4. From Figure 5b, c, d, it can be seen that when the



participant was learning, the arousal was usually moderate, i.e. not too high or low.

Self-reporting Results

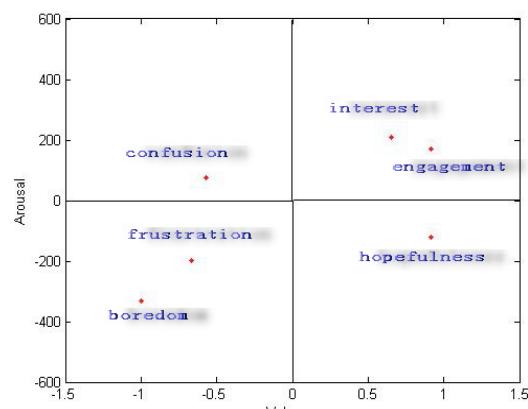


Figure 6. Participant's Emotional Space

Russell's two-dimension model of affect focuses on subjective experience; as such, emotions within these dimensions might not be placed in exactly the same for all people as it relies on personalities and the diversities of language (i.e. understanding and expression of words differs greatly on culture and self-experience) and what's more, one emotion does not have a single fixed value in the Russell's space [15]. Thus, to work on

Table 1. The means, standard deviation and confidence intervals of 6 basic emotions

Russell's model, we need to locate the experimenter

three loops across the 4 quadrants (the red, green and

Emotion		Mean	Standard deviation	80% Confidence intervals	Probability of occurrence (%)
Interest	valence	0.6552	0.4837	(0.5373, 0.7731)	19.1
	arousal	208.2759	252.4283	(146.7515, 269.8002)	
Engagement	valence	0.9184	0.2766	(0.8670, 0.9697)	32.2
	arousal	171.2653	216.6808	(131.0420, 211.4887)	
Confusion	valence	-0.5690	0.4995	(-0.6540, -0.4839)	38.1
	arousal	74.8448	334.8836	(17.8311, 131.8586)	
Frustration	valence	-0.6667	0.5774	(-1, -0.0381)	2.0
	arousal	-199.6667	70.0024	(-275.8756, -123.4577)	
Boredom	valence	-1	0	-1	0.7
	arousal	-333	76	(-409, -333)	
Hopefulness	valence	0.9167	0.2887	(0.8030, 1)	7.9
	arousal	-122.2500	208.7217	(-204.4004, -40.0996)	

emotions within this space. As explained earlier, we adopted a set of 6 basic learning emotions to locate the participant within the Russell's space. From the self-report data (Table 1), for this participant, we observed confusion and engagement were the two most frequent emotions her learning, whereas the frustration and boredom rarely occur. The standard deviations are all very large, so we have chosen to use an 80% confidence interval for each emotion. Figure 6 gives the emotional valence-arousal space of the participant.

Affective Loop Results

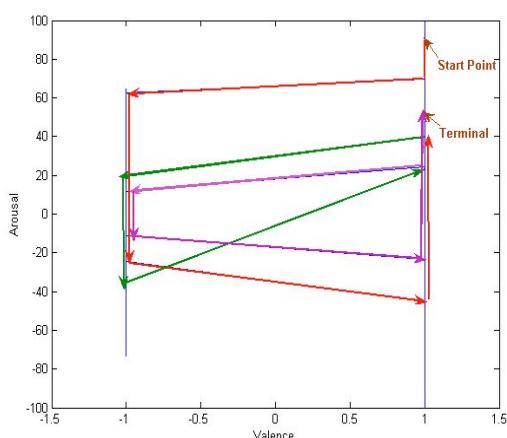


Figure 7. Affective Loop during Learning

Kort has suggested that learning behavior would manifest itself in a spiral-like form i.e. a series of linked cycles separated in time. From our data we observed

purple loops) during a 15 minutes learning process (Fig 7). In addition, like all real-life processes, they are not idealized forms, rather a noisier (e.g. our recognition rate is around 85%) and less smoothly formed geometry. Even at this early stage of our work, these results suggest that there is an approximately spiral nature to this data, although clearly we need more data and better visualization to confirm this. We believe that learning loop depends on the learning material and learning activity but, again, these need further study to validate. However, we hope these initial results will prove encouraging to others who have speculated on this relationship and hopefully will motivate more detailed work on this aspect.

5. DISCUSSION

Whilst our research is still 'work in progress', even at this early stage we have uncovered some interesting results, such as:

- During a single learning session (up to 40 minutes), the arousal is relatively stable
- People usually learn best in a state of moderate arousal.
- Arousal is not only the result of learning, but is effected by other factors.
- The participant's emotional space was compatible to that of Russell's model.

- Our experimental data reveals some kinds of learning loops which, to some extent, validates Kort's model (although more experiments and analysis are needed)

The results we have reported in this paper are of preliminary experiments that, whilst very encouraging, are still very coarse and need further refinement. In particular we flag the following issues for additional research:

- How knowledge accumulates as the affective learning loop evolves, in relation to the higher level learning goals needs to be studied.
- Kort's learning spiral model is restricted to a constructive approach and it needs to be broadened out to include other 'types' of learning process, for example, conceptualization and identification [5].
- The learning material used to evaluate this model needs to be more formally designed to reveal learning behaviours, be more diverse and representative.
- There are factors, other than learning, that could influence emotion; for example, who people are learning with; what they are learning; how they are learning; where they are learning; why they are learning and so on. It may be that combining these variables at the right degree is the key to a better affective learning model.
- To simply use skin conductivity as the sole indication of arousal is too crude. There needs to be some investigation as to how more reliable arousal can be obtained from physiological signals. Likewise, ideally valence would be continuous than discrete.
- Our current experiments are based only on one participant; clearly, to make the results more reliable, we would need to have a bigger and more controlled sample.

As should be clear from our discussion, this paper is work-in-progress and we are reporting results from the first phase of a much longer term research program. Our immediate aims are to refine the arousal analysis, design structured learning material, and gather data from more participants. After that we plan to develop the affective learning model combining affective

information with wider learner profiles and the existing Shanghai architecture. Finally we aim to deploy it in the Shanghai e-Learning platform and evaluate it with real learners. We will look forward to report on this work as it moves from research to real deployment over the coming years.

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