LEARNING TO DO FROM THE TEACHING METHOD- A TECHNOLOGY INTEGRATED CLASSROOM TO ENGAGE PRESERVICE TEACHERS

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ABSTRACT

Teachers' belief and attitude towards educational technology in relation to social psychology prevent them from integrating technology into their classrooms. This paper introduces a social incentive constructivist environment (SICE) for training preservice teachers (PT) to persuade them through experience. SICE has a social incentive model as an attempt to bring social psychology closer to educational technology, and a PT-to-PT pairing algorithm to do pairing among PT, Instructor and external tutor to improve collaboration. An experiment shows that SICE influences better knowledge outcome when compared with a constructivist situation where the social incentive and pairing do not applied.

KEYWORDS

Preservice Teachers, Social Incentive Constructivist, P2P Collaboration, Learner Centered, Learner Pairing

1. INTRODUCTION

To encourage teachers to integrate technology into teaching, studies suggest that, today's preservice teachers (PT) should be trained in such environments (Delfino & Persico 2007, Hua & Peggy 2008). However, there is no agreement on the type of content and methodology to support their classroom because changing their attitude is more than simply integrating technology to educate them (Delfino & Persico 2007). This attitude is not due to only extrinsic factors, but intrinsic factors that relates to belief about education and familiar teaching practice (Hua & Peggy 2008); such as using their social psychological skill to observe and encourage students (Cuban 1993). This has created a lag between real-world learning and educational uses of technology which continues to plague educators (Barbara & Donna 2005). Secondly, studies show that online learners (or PT) can easily dropout unless they get system and human assistance. However, how to improve online collaboration by enabling easy identification and pairing of PT in difficulty or with low efficacy (i.e. challenged PT) with their resourceful PT, Instructor and any external tutor (i.e. any hired, or volunteered person who joins online) inside and outside the classroom for support and consultation is also an issue (Farouck & Watanabe 2007). Ravenscroft (2003) suggested that there is a need to reconcile behaviouristic and social constructivist, through considering the stimulation, motivation and reward for online behaviour and the need for educational discourse along Vygotskian lines. Thus this paper introduces a social incentive constructivist environment (SICE) that enables content and human assistance for PT training. It proposes a social incentive model as an attempt to bring social psychology closer to educational technology, and a PT-to-PT pairing algorithm that pairs PT and Instructors for P2P collaboration to improve participation.

2. SICE DESIGN

The SICE is a blended environment where PT access contents through terminals and gain assistance inside and outside the classroom synchronously and asynchronously (Farouck & Watanabe 2007), with focus on learner-centered to enable PT to take control of their learning (Barbara & Donna 2005). It gives novice PT opportunity to gain assistance on computer learning from peers and Instructor in the classroom to learn with

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fewer problems inside and outside the classroom. To encourage learning and aid PT, Instructor and external tutor(s) to know the right person to give or consult for support, an *online social incentive* that rewards with social status and assigns roles to PT, and a *pairing algorithm* that pairs challenged PT with a resourceful peer, Instructor or external tutor(s) for P2P collaboration, by utilizing online actions are proposed (Figure 1).

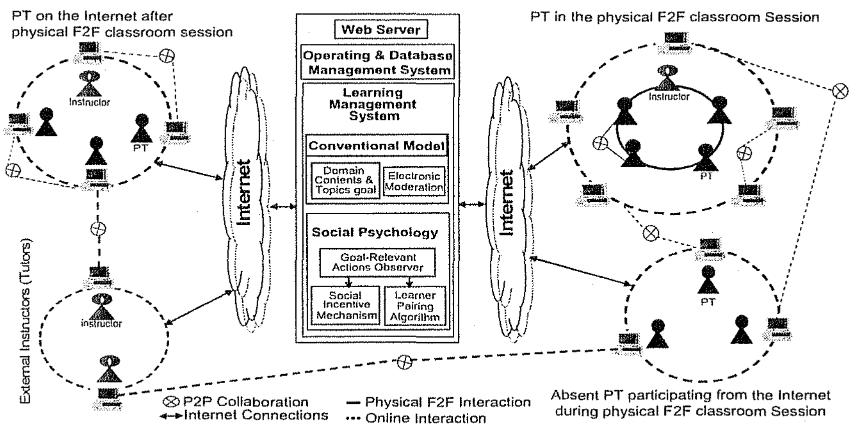

Figure 1. Social incentive constructivist environment

2.1 Social Incentive Model

2.1.1 PT Actions Evaluation

PT's actions are the goal-relevant activities. The main goal activities implemented in SICE for any PT, *ID*, on a topic, *p*, are knowledge comprehension (i.e. function $A_{ID,p}$), knowledge confidence (i.e. function $B_{ID,p}$), and teaching peers (i.e. function $C_{ID,p}$), and these functions are broken into sub activities for reward points arranged in order of importance as shown in the following activity-reward functions (ARF).

$$A_{ID,p} = \begin{cases} a_{1,p}, & \text{if (knowledge comprehension 1)} \\ a_{2,p}, & \text{if (knowledge comprehension 2)} \\ \vdots & \\ a_{e,p}, & \text{if (knowledge comprehension e)} \end{cases}, \quad B_{ID,p} = \begin{cases} b_{1,p}, & \text{if (Confidence Choice 1)} \\ b_{2,p}, & \text{if (Confidence Choice 2)} \\ \vdots & \\ b_{f,p}, & \text{if (Confidence Choice f)} \end{cases}, \quad C_{ID,p} = \begin{cases} c_{1,p}, & \text{if (support 1)} \\ c_{2,p}, & \text{if (support 2)} \\ \vdots & \\ c_{g,p}, & \text{if (support g)} \end{cases}$$

Where e, f and g are integers for number of sub activities respectively.

Function $A_{ID,p}$ is linked to an online multiple-choice assessment (OMA) that takes the first two levels of Bloom's taxonomy. Function $B_{ID,p}$ is linked to knowledge confidence checks that includes Skip, Understood, Not understood and not Clear. Learning is from topic *1* to topic *n*, where n is number of topics, and every PT must choose a confidence check after studying any topic, and the system confirms the choice as follow:

If a PT selects U or C or S, then PT will take OMA to confirm the choice.
If the PT passed the OMA, points are awarded, through $A_{ID,p}$ *and* $B_{ID,p}$, *and PT continues to next topic.*
If the PT failed the OMA then PT will be considered as selecting N, and has to learn topic again, or request support from BBS, or contact or be contacted by a resourceful peer or instructor or external tutor with the aid of learning system.

Any PT who supported synchronously or asynchronously gets rewarded through $C_{ID,p}$ automatically after the supported challenged PT passed OMA. The confidence check confirmation enables diagnostic, formative and summative assessments (Niall et al 2007), and reduces knowledge confidence discrepancies (Davies2002).

2.1.2 PT Promotion

The first stage is to make hierarchical social status (position) structure, $\Phi_1, \Phi_2, \ldots, \Phi_{\beta \in I}$, ($\beta$ = number of positions). The positions can take any motivational social titles, e.g. Beginner, Assistant, Master etc. All PT start from the lowest position, Φ_1, and a PT will be promoted if the PT's total reward score hits some limits determined dynamically online. From the ARF, the minimum and maximum total reward scores per topic will be, $MnS_p = a_{1,p} + b_{1,p}$ and $MxS_p = a_{e,p} + b_{f,p} + c_{g,p}$ respectively if reward points are in ascending order. It can be seen that $MnS_p < MnS_{p+1} < MxS_p$. This enables the online dynamic positioning as PT can complete learning without necessarily on position Φ_β, and resourceful PT can be on position Φ_β without necessarily completing all topics. Let a maximum scale point (MxSP) = Ω and a minimum scale point (MnSP) = 0 on a promotion scale at any learning stage. Ω is a real number that holds the total reward score of the PT with the maximum reward score (TRS). Before learning starts, $\Omega = \sum_{p=1}^{n} MnS_p$. This is because any PT, *ID*, must get minimum $A_{ID,p}$ and $B_{ID,p}$ scores on topic, *p*, before proceeding to the next topic, unlike $C_{ID,p}$, which is not a precondition. The Ω value is divided by β to get a range, say r, for a position. The ranges are then distributed

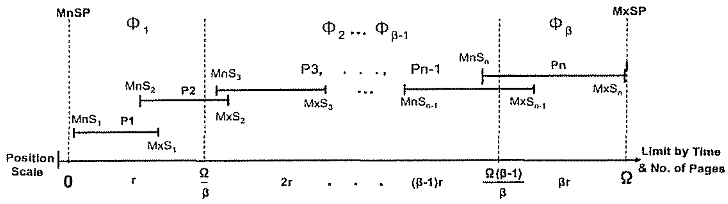

Figure 2. Dynamic Positions and Promotion Scale

to the positions as follows, $\Phi_1 = r$, $\Phi_2 = 2r$, ..., $\Phi_\beta = \beta r$ (figure 2). The ranges dynamically change anytime Ω holds a greater TRS. Anytime a PT completes any topic, PT's activity log data will be checked automatically and the current positions are computed and displayed, which may promote or demote a PT. If a PT reaches the highest position, Φ_β, a facilitating role of searching and supporting challenged PT will be assigned automatically. Any PT, *ID*, can upgrade or maintain position by going through the learning process again on topics, *p*, already studied, and select a better knowledge confidence check, if necessary, and/or support any challenged PT to better $A_{ID,p}$, $B_{ID,p}$ and $C_{ID,p}$ scores.

2.2 PT-to-PT (or P2P) Pairing Model

2.2.1 Challenged PT (CPT) to Resourceful PT (RPT) Pairing

Suppose a CPT, X, on a position, Φ_X, has a difficulty on topic P_X. The algorithm picks a closer RPT, Y, on a position, Φ_Y, and topic, $P_Y >= P_X$, to collaborate with X. Where X, Y$\in${PTIDs}, P_X, $P_Y \in${TopicsIDs} and Φ_X, $\Phi_Y \in${Positions}. Let **D** be difficulty familiarity level. The following pairing algorithm lists RPT in a window according to the selection priority with focus on value of **D** (Table 1).

Essential Data Objects
{PTIDs}
{DifficultyIDs}
{TopicIDs}
{Positions}
{PT Familiarity of Difficulty,
D<<: 2 = Offered support on the current difficulty before.
1 = Received support on the current difficulty before.
0 = No difficulty familiarity.}

Programming Logic
1) *Pick all PTIDs(Y's), Current Positions and Current TopicIDs from the Database.*
2) *Compute Content Distances, K, between P_X and P_Y's as follow: $K = P_Y - P_X$. Where $K \in I$ and K is the smallest topic distance for all $K >= 0$.*
3) *Perform the knowledge distance function in* (table 1):

Table 1. Knowledge Distance Function for Pairing PT

Selection Priority		Determinant	Cognitive Reasons (According to Priority)
1	1	$\Phi_X = \Phi_Y$, D= 1&2, min(K)	X and Y are co-equal, and Y is familiar with the same difficulty.
	2	$\Phi_X = \Phi_Y$, D= 1, min(K)	
	3	$\Phi_X = \Phi_Y$, D= 2, min(K)	
2	4	$\Phi_X < \Phi_Y$, D= 1&2, min(K)	Y is a senior to X and familiar with the same difficulty.
	5	$\Phi_X < \Phi_Y$, D= 1, min(K)	
	6	$\Phi_X < \Phi_Y$, D= 2, min(K)	
3	7	$\Phi_X > \Phi_Y$, D= 1&2, min(K)	Y is a junior to X and familiar with the same difficulty.
	8	$\Phi_X > \Phi_Y$, D= 1, min(K)	
	9	$\Phi_X > \Phi_Y$, D= 2, min(K)	
4	10	$\Phi_X < \Phi_Y$, D= 0, min(K)	Y is just a senior PT to X.
5	11	$\Phi_X = \Phi_Y$, D= 0, min(K)	Y is just a co-equal to X.
6	12	$\Phi_X => \Phi_Y$, D= 0	Y is any PT to share difficulty with

PT with D=1&2 is given higher priority because such PT knows the difficulty and its solution. Next is PT with D=1 because PT knows the difficulty and would have solved it before proceeding to the next topic. The next is PT with D=2, then PT with D=0. PT with D=2 and D=0 may have better solutions but the system can not know without prior knowledge. Such RPT can be contacted directly by CPT if CPT know them.

2.2.2 Resourceful PT to Challenged PT Pairing

A facilitating model was designed whose functions pick *CPT'ID*, *DifficultyID*, *TopicID*, *DocumentID*, *Start Time*, *Comprehension score*, *Confidence score* and *Current Position* from a database to feed a facilitating interface of a LMS. This is to enable the RPT, Instructor and external tutor, to easily identify CPT and their difficulties, in addition to the classroom F2F problems, to give them support to achieve their learning goal.

3. EXPERIMENT

An experiment was conducted with 33 college students (not actual PT) enrolled for Beginners Java programming course were randomly grouped into Group A and Group B. Due to difficulty in getting students for experiment Group A had 23 students, 10 students in year 2008 and 13 students in year 2009, and Group B had 10 students in year 2008 only. Group A (both years) was placed in the SICE which has P2P chatting and BBS for online interaction, and position titles as "Master", "Assistant" and "Beginner". Group B was placed in a similar environment with the online action recognition, social incentive and pairing algorithm disabled, but chatroom and BBS were available. Both groups started learning in their technology supported classroom for two hours after which they continued on the internet conveniently for one week. At the end of the week both groups took a test. The goal of the experiment was to find out if the online social incentive and pairing algorithm enables better knowledge outcome when test result of Group A is compared with that of Group B.

3.1 Experiment Result

At the end of the one week course's test, a statistical analysis of test scores (score mark: 0-100%) between Group A and B (table 2) shows that, Group A's knowledge outcome outperformed that of Group B. Additionally, at the end of learning 56.5% of the students in Group A attained "Master" status, and the rest attained "Assistant" status. Authors think the 56.5% of the students who were given facilitating roles and the pairing algorithm that enabled challenged students to know these students, and other resourceful peers, improved participation which accounted for the better test scores.

Table 2. Group Knowledge Performances

Group	Year	N	Mean	Variance	P-Value (2 Tailed)	Group A Year 2008 + Year 2009	P-Value (2 Tailed)
A	2008	10	89	54.4	**0.44** (year 2008 Group A & year 2009 Group A)	N = 23, Mean = 90.4	0.001
	2009	13	91.5	64.1	**4.8E-03** (year 2008 Group A & Group B)	Variance = 58.9	
B	2008	10	78	62.2	**6.4E-04** (year 2009 Group A & Group B)	**Group B** (only 2008)	

4. CONCLUSION AND FUTURE WORK

This paper proposed a social incentive constructivist environment (SICE) to suggest a technological supported classroom for training preservice teachers (PT) to convince them through experience to integrate technology into their future classrooms. The SICE has a social incentive model as an attempt to bring social psychology closer to educational technology, and a PT-to-PT pairing algorithm to do pairing among PT, Instructor and external tutor to improve collaboration. Experiment results, though not adequately shown, show that when social constructivist is embedded with online social incentives and pairing algorithm, it can improve knowledge outcome and narrow the social-technical gap. Therefore SICE can be improved to enable an environment for training PT to gain experience on how to integrate technology into their future classrooms.

REFERENCES

Cuban L., 1993. *How Teachers Taught: Constancy and Change In American Classrooms-1890-1990.* Teachers College Press, New York USA, pp. 25-45.

Niall S., et al., 2007. *Contemporary Perspectives in E-Learning Research.* Routledge, New York USA, pp. 147-159.

Delfino M. and Persico, D., 2007. Online or face-to-face? Experimenting with different techniques in teacher training. *Journal of Computer Assisted Learning*. Vol. 23, pp. 351–365.

Hua B. and Peggy A. E., 2008. Teacher Educators' Beliefs and Technology Uses as Predictors of Preservice Teachers' Beliefs and Technology Attitudes. *Journal of Technology and Teacher Education*, Vol. 16, No. 1, pp 93-112.

Ravenscroft A., 2003. From conditioning to learning communities: Implications of fifty years of research in e-learning interaction design. *Journal of Association for Learning Technology,* Vol. 11, No. 3, pp. 4-18.

Barbara M. and Donna V., 2005. Learner-Centered Framework for E-learning. *Teachers College record*, Vol. 107, No. 8, pp. 1582-1600.

Davies P., 2002. There's no confidence in multiple-choice testing. *proceedings of the 6th international computer-assisted assessment conference*, Loughborough University, UK, pp. 61-71.

Farouck I. and Watanabe S., 2007. Amalgamated Learning Framework: A Communication Solution for College Students in Beginners Programming Class. *Poster Proceedings of ICCE 2007*, Hiroshima, Japan, pp. 35–36.