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A TECHNOLOGY DIFFUSION APPROACH TO SOFT TECHNOLOGY: ITS DESIGN AND EFFECTS

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In light of the current state in which existing studies on the technology acceptance model are examined predominately in the context of hard technology, this study set out to examine the applicability of these results to soft technology. Also, in response to a call for more intervention-type studies in TAM, a technology diffusion approach to one specific soft-technology (student question-generation learning strategy) was devised. Its impacts on learners' perceived task value, learning approaches and their relationships were the focuses of this study. Results of t-tests and regression analyses indicated that learners in the diffusion group perceived the introduced learning strategy as having significantly higher value than did the non-diffusion group. Additionally, learners in the non-diffusion group were inclined to adopt the surface learning approach more frequently than the diffusion group. Last, the prediction effect of task value on learning approaches was supported for the deep learning approach for both groups but was not supported for the surface learning approach for either group. Empirical significance of the study as well as suggestions for instructional implementation and future studies are provided.

Keywords: Technology acceptance and diffusion; task value; learning approaches; student question-generation.

1. Introduction

Factors affecting technology acceptance and adoption have been extensively investigated in past decades. As suggested by the Technology Acceptance Model (hereinafter named TAM), users' behavior intention (BI) to use a technology is the dominating factor influencing their later actual technology use behavior (Davis, 1989). Such an intention is found to be influenced by users' perceived usefulness of technology (PU) and perceived ease of use (PEU) (Davis *et al.*, 1989; King & He, 2006; Legris *et al.*, 2003).

Existing studies on technology adoption have been conducted in different contexts with different technologies as the focus, for instance, web-technology, tablet PC,

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decision-support systems and wireless internet in industrial and business sectors (Djamasbi *et al.*, 2010; Moran *et al.*, 2010; Shin & Kim, 2008; Wang *et al.*, 2008) and computers, e-portfolio systems, video-game, wiki and web-based systems in educational settings (Bourgonjon *et al.*, 2010; Gong *et al.*, 2004; Holden & Rada, 2011; Liu, 2010; Ramayah, 2010; Tzeng, 2011). While studies have highlighted factors affecting technology designs (such as technology infrastructure, technical support, teachers' technology beliefs, and so on) and substantiated the robustness of TAM in explaining users' adoption of various technologies (Oncu *et al.*, 2008; Ozel *et al.*, 2008; Rogers, 1999; Surry *et al.*, 2005), most have been focused on "hard technology" (i.e. media and delivery systems for instruction). Few, if any, have examined the applicability of TAM for "soft technology" in education.

Soft technology in education refers to techniques, methods and strategies that form the psychological and social frameworks for learning (Smaldino *et al.*, 2011). As relevant as hard technology, nevertheless, its integration and adoption process is less examined. Whether the results of TAM applied to hard technology can hold true for soft technology is not known. Specifically, the issue regarding whether learner PU of soft technology affects their intention to adopt is one focus of this study.

Later, adding the perspectives of diffusion theory leads to extensions to TAM. This line of research directs attention to factors that might influence users' decisions regarding adoption and different levels of adoption and emphasizes the notion that how users view usefulness and ease of use depends on their awareness or knowledge of the attributes of an innovation (Burton-Jones & Hubona, 2005; Davis, 1993; Rogers, 2003; Venkatesh & Davis, 2000; Venkatesh *et al.*, 2003). Despite the fact that some work has been done to validate the relationships among the proposed constructs, again, all existing work has dealt with hard technology (Al-Gahtani *et al.*, 2007; Chang & Chung, 2001; Chau, 1996; Demir, 2006; Geri & Naor-Elaiza, 2008; Liao, 1999; Lee, 2010; Park, 2009; Richardson, 2009; Venkatesh, 2000; Yeow & Loo, 2009). Therefore, the validity of proposed constructs for soft-technology remains un-examined. Thus, whether diffusion theory applies to soft technology is another focus of this study.

Finally, while TAM validation studies have shed some light on the technology adoption process, work examining the effect of intervention on users' PU and BI has been suggested as the next fruitful direction (Chau & Hu, 2002; Venkatesh, 2000; Venkatesh & Bala, 2008). To address this, an attempt was made in this study to apply a technology diffusion approach to soft technology. Issues regarding if and how the designed approach affects learners' PU and BI, respectively, and also if it influences the causal-effect relationships between PU and BI are examined.

In the following sections, literature on the technology acceptance model and diffusion theory within the context of soft technology is briefly described.

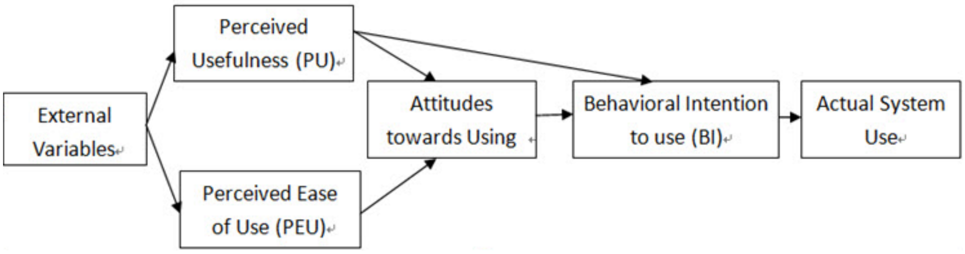

Figure 1. Technology acceptance model (Davis *et al.*, 1989, p. 985).

1.1. *TAM in the context of soft technology*

TAM, originally proposed by Davis (1989), has been extensively studied and validated in information technology industrial and business domains to explain users' adoption of innovative technologies. As shown in Figure 1 (Davis *et al.*, 1989), a user's actual use of an innovative technology is determined by his/her behavioral intention to use (BI). Both a user's perception of the usefulness (PU) and ease of use of the technology (PEU) collectively affect attitude formation toward the incorporated technology, which impacts BI. Individual PU and PEU perceptions are influenced by external variables, such as system technical design characteristics (Davis *et al.*, 1989).

To apply the model to soft technology (i.e. educational strategies, methods, techniques), BI, a major determinant of actual use behavior, can be interpreted as the amount of cognitive effort one is inclined to devote to attaining a learning goal regarding the soft technology concerned. This concept, in essence, reflects the core construct of learning approaches proposed by the Student Approaches to Learning (SAL) theory.

The SAL views learning processes as strategies that dynamically change with students' perceptions of the learning context and requirements (Biggs, 1987). It consists of two dimensions—deep and surface approaches (Laurillard, 1979; Marton & Säljö, 1976; Ramsden, 1979). Learners with a surface approach tend to learn content by rote and subsequently reproduce it in order to avoid academic failure. Learners adopting a deep approach to learning, on the other hand, seek meaning in order to understand (Bigg, 1987; Kember *et al.*, 2004). Considering that surface and deep dimensions are both valid forms of learning approaches, both are included as indicators of BI in this study.

Furthermore, PU and PEU are two other central concepts in TAM. PU is defined as the degree to which individuals believe using a technology will improve their performance in near and long terms, and PEU is defined as the degree to which individuals believe using a particular technology will be effortless (Davis, 1989). Both PU and PEU help to explain how and when users form attitudes toward an incorporated innovation and their intention to use the technology, which in turn leads to different levels of actual adoption and acceptance (Davis *et al.*, 1989). Nonetheless, in light of recent findings indicating its insignificant contribution to the actual use of technology

(Teo, 2009; Thompson *et al.*, 1991), the element of attitude was removed and therefore not examined in this study.

Finally, in light of the fact that perceived task value, defined by Pintrich (1989) as learners' perceived value of the learning tasks for their current learning and future job, has been widely used in motivation research (Wigfield, 1994) and is analogous to PU in the context of soft technology, perceived task value is used in this study.

1.2. *Diffusion theory and related theories within the context of soft technology*

The diffusion theory proposed by Rogers (2003) suggested that users' adoption behavior about an innovation is a process occurring over time. It is based on an innovation-decision process and consists of a series of actions and decisions contingent on several predictors. An innovation's rate of adoption is not simply determined by its technical design characteristics. A more important set of predictors is how the attributes of an innovation are perceived. Users' perceived attributes of an innovation can determine the value of the innovation, the effort or resources needed and the worthiness of the devoted effort and costs, thus influencing the initial decision to adopt (BI) and to continually use an innovation. Five perceived attributes of the innovation identified by Rogers (2003) as essential adoption predictors to be considered in the diffusion process are briefly explained and discussed in the context of soft-technology adoption – relative advantages, compatibility, complexity, trialability and observability.

First, the relative advantage of an innovation is defined as a ratio of expected benefits and the costs or effort demanded as a result of adopting an innovation. During the innovation-decision process, potential users look for information regarding an innovation (such as economic benefits, a decrease in discomfort, a saving of time and effort, and so on) in order to minimize their uncertainty about an innovation. The identified advantages are further subjectively evaluated as the degree to which an innovation is perceived as being better than the current idea or practice being used (Rogers, 2003). Users' awareness of relative advantages has been reported as the strongest predictor of adoption, and it has been suggested that more attention be devoted to this aspect of the technology-diffusion process (Rogers, 2003). As for this idea applied to soft technology in education, learners should, in theory, be more likely to adopt an innovative strategy for which they see relative advantages for their current or future learning as compared to available known learning strategies. In other words, learners' subjective estimation of the short and long term learning benefits that might be brought about by the introduced strategy should influence their perceived usefulness of the technology and the BI afterwards.

Secondly, compatibility is defined as the consistency of an innovation with regard to potential user needs, existing values and experiences. An innovation's incompatibility with user needs or values can de-motivate users' intention to take any further action to approach it. On the other hand, users' interest in knowing more about an innovation may be initiated by a higher possibility that an innovation may satisfy perceived needs. Moreover, previous experiences provide a basis against which an innovation can be interpreted, thus decreasing user uncertainty about the compatibility of the innovation. To put this idea to work in the context of soft technology, information and opportunities that allow learners to analyze the consistency of the introduced soft technology with their current and future learning needs, values or experiences will be essential so as to enable learners to gauge fairly the compatibility of the introduced strategy and their further intention to engage with the technology.

Thirdly, complexity refers to the perceived or actual difficulty of adopting an innovation. Either the novelty of the innovative ideas or complex procedures involved in operation may discourage users from initial adoption and continuous use (Rogers, 2003). In other words, users might abort their intention to adopt if the costs, effort or time needed to successfully figure out the innovative ideas or operation procedures exceed those that they anticipate or are willing to devote. As for soft technology, learners will need time and information about the introduced soft technology and any associated operational procedures so as to decrease anxiety, uncertainty and any actual and perceived difficulty related to the use of the introduced strategy.

Fourthly, trialability is defined as how easily an innovation may be experimented with as it is being adopted. Trialability helps potential users to clarify questions raised prior to or during the process of approaching an innovation. Moreover, the trial process enables learners to estimate the worthiness of devoted costs, time or effort required before adoption. On one hand, if it takes potential users more effort or expense to try an innovation, they will be less likely to adopt. On the other hand, the perceived complexity of the technology might be reduced with a gradual accumulation of understanding and confirmed expectations regarding the soft technology during the trial process. Giving learners opportunities to try out any introduced soft technologies is one way for learners to give meaning to this technology and to find out how it may work for the benefit of their own learning.

Lastly, observability refers to the extent to which the results of an innovation are visible to others. A technology that has more visibility will drive communication among peers and personal networks and will result in sharing and exchanging their use experience (regarding confirmed benefits or encountered difficulties). Observation of other peoples' adoption results can be used to confirm one's initial expectations toward a technology before one initiates actions leading toward approaching the observed technology. Positive changes that can be readily observed from others' experiences will lead to more positive perceptions toward the innovation on the part of potential users. On the other hand, it may take longer for potential users to decide whether to approach an innovation or not if the results of adopting the innovation are less visible (Rogers 2003). As, comparatively speaking, the results of adopting a soft technology cannot be easily detected and shown within a short period of time (i.e. its observability is relatively low as compared to hard technology), mechanisms to enable the outcomes of adopting a soft technology to be known and shared among potential users/adopters becomes an important design issue with regard to its diffusion.

In addition to the five predictors proposed by Rogers (2003), another predictor inferred from the Expectation-Confirmation Model (ECM) (Bhattacherjee, 2001) was included in this study as part of the technology diffusion approach. ECM postulates that despite the fact that users' perceived value influences their initial intention toward soft technology, only with constant interaction with the technology will users be granted opportunities to confirm their expectancy toward performance and effort. That is, only through continuous experience and prolonged engagement with the technology can perceived value be either confirmed (which leads to continuance of use), or disqualified or modified (which may lead to abortion of the technology).

In light of the fact that learners may not readily and willingly take in the pedagogical advantages and ease of use associated with an introduced soft technology that is novel to them, in reference to Rogers' diffusion theory (2003) and ECM (Bhattacherjee, 2001), this study set out to adopt a technology diffusion approach to a learning strategy and to examine its effects on perceived task value, learning approaches and their relationships.

1.3. *Research questions*

An intervention to diffuse a soft technology was designed on the basis of diffusion theory and the expectancy confirmation model. Three research questions to explore the impacts of the designed intervention are proposed (see Figure 2):

(1) Does the perceived task value of learners vary with different approaches to soft technology (i.e. the diffusion approach vs. the non-diffusion approach), and if so, how?
(2) Do learning approaches (surface and deep learning approaches) vary with different approaches to soft technology (i.e. the diffusion approach vs. the non-diffusion approach), and if so, how?
(3) Will there be any predictive effects of task value on learning approaches (surface and deep learning approaches) for the two examined groups (the diffusion and the non-diffusion approach groups)?

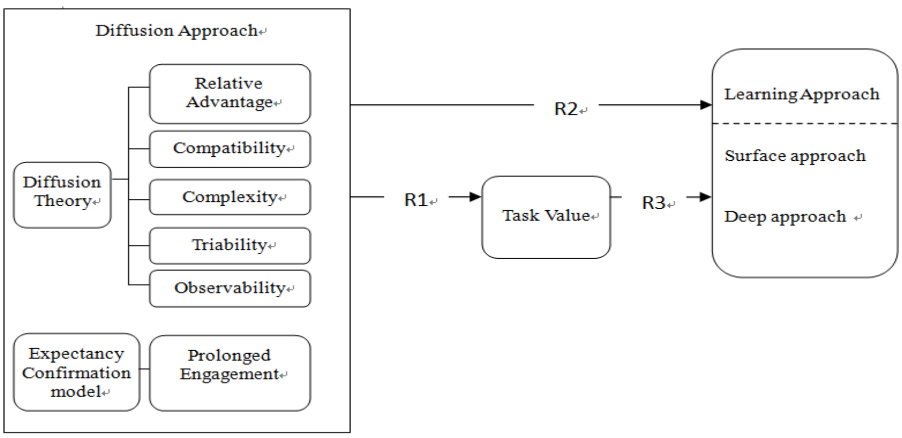

Figure 2. Proposed research model.

2. Method

2.1. *Soft technology in focus—student question-generation strategy*

Student question-generation strategy has brought much potential to enhance learning and cognitive enhancement among learners (Yu, 2011). This strategy suggests that learners are engaged in constructing and modifying their internal knowledge representations and structures through the process of composing questions (Yu *et al.*, 2005). The impact of student question-generation technology on enhancing students' comprehension of studied content and developing cognitive and metacognitive strategies has been evidenced in numerous empirical studies (Brown & Walter, 2005; Rosenshine *et al.*, 1996; Yu & Liu, 2005). In light of the increasing attention given recently to student question-generation strategy, it was chosen as the focus of this study.

2.2. *Design of the technology diffusion approach to the student question-generation strategy*

Diffusion theory (Rogers, 2003) and ECM (Bhattacherjee, 2001), described in section 1.2, were used as the framework for structuring the chosen soft technology—student question-generation. How each of the predictors was designed and implemented in this study is briefly explained below (see Table 1).

Relative advantages design: As noted, providing learners with needed information regarding the value of question-generation for their current learning process and future use should enable relative advantage judgment. In this study, in light of the fact that participants are students enrolled in secondary teacher education programs, they were advised in the first session that the student question-generation strategy will help them: to be active learners during the process, to master the covered content and also to be proficient at constructing questions, which is one essential skill expected of teachers.

Table 1. Technology diffusion approach to the student question-generation strategy.

Theory foundations	Predictors	Designs in action
Diffusion Theory	Relative advantages	● Help users to be active learners during the process; ● Help users to master the covered content; ● Help users to be proficient at constructing questions
	Compatibility	● Stress how needs are satisfied and goals are attained via this arrangement
	Complexity	● Select an approach at an appropriate difficulty level; ● Delineate procedures in a step-by-step fashion; ● Model question-generation in accordance with studied content
	Trialability	● Training sessions
	Observability	● Whole-class feedback session
ECM[a]	Prolonged engagement	● Routine practice sessions with the introduced strategy in class for 16 weeks

[a] ECM refers to Expectancy Confirmation Model

Compatibility design: Mainly, the focus was on how the introduced strategy can help students to satisfy their current needs (enhancing learning outcomes and mastering the covered content) and to actualize their future goals of being teachers (to be proficient at constructing questions). This design was intended to increase the consistency of student question-generation and students' felt needs and held values.

Complexity design: In light of the fact that most students do not have experience in generating questions in formal learning contexts, several measures were put in place to account for the issue of complexity. First, an easy to follow approach proposed by Dreher and Gambrel (1985) and Ritchie (1985) was selected and introduced—main ideas. The procedural steps were then delineated as consisting of two steps: identifying the main idea of the studied content together with significant details and forming questions that asked for new examples of the identified idea or writing a question about a concept in a paraphrased form if finding new examples for the identified idea proved to be difficult. Third, generating questions via the two-step procedure was demonstrated by the instructor. These designs were intended to decrease the perceived or experienced complexity level of the introduced strategy.

Trialability design: A training session on the operational procedures of student question-generation was arranged right after the instructor's demonstration phase. Learners were able to practice using the two-step procedure to generate questions and to assess usability and efficacy.

Observability design: Observing the consequences of peers' use of the introduced strategy was implemented in this study by arranging a feedback session. Specifically, a teaching assistant purposely selected three to five pieces of students' work from the previous question-generation session to accentuate important question-generation practices for whole-class observation.

Prolonged engagement design: To enable learners to confirm or disregard their expectations (e.g. pre-calculated needed mental effort and expected learning benefits), in this study, learners not only got to practice the introduced strategy in a training session, but they were also given opportunities to generate questions on each of the covered chapters as a routine for the whole implementation period.

2.3. *Experimental conditions*

In total, 211 students participated in the study. Among these, fifty students taking an "Instructional Principles" course were assigned to the diffusion condition. The rest of the 161 students enrolling in five other teacher education programs national-wide were designated as the non-diffusion condition. These subjects have similar academic backgrounds to those subjects in the diffusion condition. To examine the effects of different diffusion approaches to learning strategies, two conditions were set up: diffusion versus non-diffusion groups.

For the diffusion group, principles suggested by innovation diffusion theorists, as described in sections 1.2 and 2.2, were used as the framework for structuring the student question-generation activity. A training session on the basic concepts of question-generation was delivered to the students at the beginning of the semester. For the following 16 weeks, students were required to generate at least two multiple-choice questions on the covered chapters in twenty minutes in class. They were then requested to respond to four randomly assigned questions after class. Not only did they routinely practice the activity of question-composing and assessment, but also received feedback on the questions from their peers and the teaching assistant.

On the other hand, for the non-diffusion group, similarly to how most instructional or learning strategies are typically introduced in teacher preparation programs, students were introduced to the features, values and procedures of the student question-generation strategy with reference to related theoretical and empirical literature. However, elaborated-upon explanations and first-hand experience in the introduced strategy were not arranged for use in specific contexts, nor were learners able to observe the consequences of the use of the strategy (i.e. lack of compatibility, complexity, trialability, observability and prolonged engagement).

2.4. *Variables and measures*

Students' perceived task value and learning approaches to the introduced soft technology were measured by a self-reported questionnaire. Based on a literature review on existing validated instruments, relevant items were adopted and adapted to make them better fit the task at hand (i.e. the student-generated questions activity) and the applied context (a secondary teacher education program). Each of the scales is briefly introduced in the following sections.

2.4.1. *Task value*

Task value in this study was defined as learners perceiving the introduced student question-generation strategy as useful for their learning and future job. It was measured by the "Task Value of Online Student-Generated Questions Scale" modified from Lai's "Utility Strategy Subscale" of the "Motivational Regulation Strategies Inventory" (Lai, 2007). In each item, learners rated themselves on a six-point Likert scale from "not at all true of me" to "very true of me." The sum of the scores of items that make up the scale was used for data analysis. The higher the score, the more positively the subject was believed to value the learning task.

Factor loading matrix produced in the exploratory factor analysis process indicated that each item had high factor loading (between 0.62 and 0.87) on one single factor. The total variance explained by the factor was 59.72%, and the Cronbach's α was 0.91. As evidenced, the task value scale had excellent consistency across the items that form this scale. Sample items included: *"I could apply the learned knowledge and skills on student question-generation to other courses offered in the teacher education program;" "Compared to other methods, the learned knowledge and skills gained from student question-generation should be useful for my future teaching jobs."*

2.4.2. *Learning approaches*

Both deep and surface approaches of learning approaches stress the interplay of strategies with motives. The "Study Process Questionnaire," developed by Biggs *et al.* (2001), was adopted. In this questionnaire, each approach has ten items. In each item, learners rate themselves on a five-point Likert scale from "never or only rarely true of me" to "always or almost true of me." Scales were constructed by taking the sum of the scores of items that make up the composite construct of the scale.

Exploratory factor analysis using principal components extraction with oblique rotation was executed to ensure the construct validity of the scales. Factors with eigenvalues greater than 1.0 and items with factor loadings greater than 0.4 were used as the two criteria for item inclusion. Results on the exploratory factor analysis evidenced two dimensions (deep and surface approach). The factor loading matrix indicated that each item had a high factor loading (0.75~0.54, 0.74~0.46) on one factor and a very low factor loading on the other factor. The total variance explained by the two extracted factors was 46.45%. The Cronbach's α for the deep approach (10 items) and the surface approach (10 items) were 0.85 and 0.88, respectively. As evidenced, the "Learning Approaches" had excellent consistency across the items that form the subcomponents of the scale, and each dimension had a distinct construct of its own.

Sample items from the deep approach are: *"I found that I have to do enough work on a topic so that I can form my own conclusions before I am satisfied; I test myself on important topics until I understand them completely; I make a point of looking at most of the suggested readings that go with the lectures."* Sample items from the surface approach include: *"My aim is to pass the course while doing as little work as possible; I find I can get by in most assessments by memorizing key sections rather than trying to understand them."*

2.5. *Data analysis*

To examine the effects of the diffusion approach, t-tests and regression analysis were performed to compare the differences between the diffusion and non-diffusion groups in the scores of the outcome variables. As the subjects designated to the non-diffusion groups came from five sub-groups, the decision of combining all the subgroups into one for further analysis was based on the homogeneities of these five sub-groups on the variables, which include task value, the surface approach and the deep approach. The homogeneities of the sub-groups were evidenced in the results of ANOVAs ($p = 0.88$, $p = 0.02$, $p = 0.22$, respectively). The effect sizes using the indicator of Hedges adjustment on the sample size were also reported.

Table 2. Results of learning approaches for the two groups.

Variables / Treatment groups	Task value			Surface approach			Deep approach		
	Mean (SD)	*t*-value	Cohen's d [b]	Mean (SD)	*t*-value	Cohen's d [b]	Mean (SD)	*t*-value	Cohen's d [b]
Diffusion group (N=50)	43.12 (5.41)	-7.42**[a]	1.10	11.12 (6.44)	-6.46 **[a]	-1.07	21.78 (6.30)	0.2	0.03
Non-diffusion group (N=161)	35.99 (7.39)			18.48 (7.21)			21.57 (6.37)		

[a] ** denotes that the difference level is significant at 0.01 level

[b] Cohen's d based on sample size using Hedges adjustment

3. Results

3.1. *Descriptive statistics*

The means, standard deviations and *t*-tests statistics on learning approaches of the two conditions are presented in Table 2. For the diffusion group, the mean scores of perceived task value rested in the upper half of the possible score ranges while for the non-diffusion group, they rested in the middle. Explicitly, students in the diffusion approach generally expressed positive attitudes toward the value of student question-generation, with a mean score of 43.12. On the other hand, those in the non-diffusion approach were more conservative and not affirmative of its value for their present learning or future work.

Additionally, students in the diffusion group indicated that their inclination toward a deep learning approach happened "*almost half of the time*" (a mean score of 21.78) while their inclination toward a surface approach happened only "*sometimes*" (with a mean score of 11.12). As for the non-diffusion group, their inclination toward a deep learning approach presented as similar to the diffusion condition, that is, happening "*almost half of the time*" (with a mean score of 21.57); however, their inclination toward a surface approach, unlike the diffusion condition, happened "*almost half of the time*" (with a mean score of 18.48).

The results of *t*-tests supported the idea that different diffusion approaches differed statistically significantly in both task value and surface approach to learning ($p < 0.001$, $p < 0.001$, respectively). Students in the diffusion group perceived higher value toward student question-generation ($t = -7.42$, $p < 0.001$) and tended to adopt significantly less frequent surface approach to learning than was the case for the non-diffusion group ($t = 6.46$, $p < 0.001$). Differences in deep approach use, however, did not reach significant level between the two conditions ($t = -0.2$, $p > 0.05$).

3.2. *The relationships between task value and learning approaches*

As shown in Table 3, the correlations between task value and deep approach in both groups reached statistical significance, with the intensity of the correlations in the diffusion group reaching a high level, $r = 0.63$ and the non-diffusion group reaching a

Table 3. Correlations between task value and learning approaches.

	1. Surface approach	2. Deep approach
Task value		
Diffusion group	-0.13	0.63 (**)[a]
Non-diffusion group	0.12	0.32 (**)[a]

[a] ** denotes that the difference level is significant at 0.01 level

medium level, $r = 0.32$. Additionally, task value was not found to be significantly correlated with surface approach in either group. As a consequence, only regression analyses of the deep approach using task value as the predictor were conducted.

Table 4 indicates that task value significantly predicts inclination toward a deep approach for both the diffusion ($\beta = 0.63$, $p < 0.01$) and non-diffusion groups ($\beta = 0.32$, $p < 0.01$).

4. Discussion and Conclusions

4.1. *Discussion*

This study investigated if a technology diffusion approach to student question-generation strategies influenced students' perceived task value, learning approaches and their relationships. Three major findings are obtained and discussed as follows:

First, the diffusion approach designed in this study was found to affect learners' perceived task value with respect to student question-generation at a different level, as compared to the non-diffusion group. This finding substantiated the applicability and advantage of applying Rogers' (2003) technology diffusion theory and Expectancy Confirmation Model (Bhattacherjee, 2001) to soft technology in order to enhance perceived task value.

Table 4. Regression results of task-value predicting the deep approaches.

Treatment conditions	Models[a]	B	SEB	β
Diffusion group	Constant	-12.98	12.86	
	Task value	0.81	0.14	0.63** [b]
	R-square		0.40	
	F		31.36 ** [b]	
	Effect size (f^2)		0.67	
Non-diffusion group	Constant	11.64	2.38	
	Task value	0.28	0.07	0.32 ** [b]
	R-square		0.10	
	F		18.16 ** [b]	
	Effect size (f^2)		0.11	

[a] Predictor: (Constant), task value while dependent variable is the deep approach

[b] * $p < 0.05$, **$p < 0.01$

Secondly, learners in different groups (diffusion versus non-diffusion) were found to exhibit different learning approach patterns within the context of student question-generation. Specifically, students in the non-diffusion group reported adopting both surface and deep learning approaches at the same level (almost half of the time). On the other hand, with designs based on the diffusion theory and the expectancy confirmation model, students in the diffusion group reported adopting both surface and deep learning approaches at different levels (with a deep approach at "almost half of the time" and a surface approach "sometimes"). It seems that students with the diffusion approach could more adequately interpret the requirements and adjust their cognitive capacity in order to be devoted more to a deep approach and less to a surface approach.

Thirdly, the predictive effects of task value on learning approaches, as suggested by TAM, were partially supported in this study. Explicitly, the predictive power of task value on a deep learning approach was evidenced for both groups, but its effect on a surface learning approach was not evidenced for either group. Furthermore, the higher predictive power of task value in the diffusion group ($\beta = 0.63$), as compared to the non-diffusion group ($\beta = 0.32$), supported the superior effects brought about by the diffusion design. With a diffusion approach to student question-generation, students seemed to have a better appreciation of the associated task value and more accurate estimation and confirmation of the worthiness of the required efforts, which as a whole led to the adoption of a deep learning approach. In contrast, though task value was also found to predict a deep learning approach for learners in the non-diffusion group, without a diffusion approach, they might not comprehend or interpret the cognitive demands required at a substantial enough level to produce the high predicative power that was observed in the diffusion group.

4.2. *Significance and implication of the study*

The findings of the present study expanded the existing body of knowledge on TAM in several ways. First, this study validated the generalizability of TAM to soft technology. Second, the diffusion design based on Rogers' theory (2003) and Expectancy Confirmation Model (Bhattacherjee, 2001) proved to be an effective intervention for TAM. Finally, the designed diffusion substantiated the predictive effect of perceived usefulness (perceived task value in this study) on behavioral intention (specifically, inclination toward a deep learning approach).

On the basis of this substantiated predicative effect, instructors aiming to direct learners to adopt any specific soft technology are advised to refer to the diffusion theory for its inclusion or instruction. Such a diffusion approach, as found in this study, will influence the intensity of the relationship between perceived task values and a deep learning approach, which is intrinsically motivational in nature.

Finally, BI in TAM, to the best of the researchers' knowledge, has been generally viewed and measured as a one-dimensional construct. In fact, levels of technology adoption have been proposed; for instance, Hall and Hord (2006) proposed eight levels of technology integration (starting from nonuse, orientation, preparation, mechanical use, routine use, refinement, integration to renewal) and suggested that people in different levels exhibit different behavioral intention and concerns. Using a single dimension to measure users' behavioral intentions and adoption behavior might over-simplify the decision regarding the adoption process. With the current study finding that the predicative power between PU and BI are variant between different constructs of BI (with deep at the high level and surface at the medium level), researchers interested in TAM are encouraged to explore this area further.

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