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IMPACT OF COLLABORATIVE WORK ON TECHNOLOGY ACCEPTANCE: A CASE STUDY FROM VIRTUAL COMPUTING

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ABSTRACT

Aim/Purpose	This paper utilizes the Technology Acceptance Model (TAM) to examine the extent to which acceptance of Remote Virtual Computer Laboratories (RVCLs) is affected by students' technological backgrounds and the role of collaborative work.
Background	RVCLs are widely used in information technology and cyber security education to provide students with hands-on experimentation. However, students may not exploit their full benefits if they do not accept RVCLs as a viable educational technology.
Methodology	In order to study the impact of collaborative work on technology acceptance, an empirical study was conducted using collaborative and individual versions of an introductory level computer networking exercise in an RVCL. Trials for the empirical study included students from technology intensive and non-technology intensive programs.
Contribution	The relationship between the technological background of students and their acceptance of an RVCL and the effect of collaborative work on this relationship were explored for the first time in the literature.
Findings	The findings of the study supported that collaborative work could improve non-technology students' acceptance of RVCLs. However, no significant effect of collaborative work on technology acceptance was observed in the case of technology students.

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Recommendations for Practitioners	Educators should consider the benefits of collaborative work while introducing a new technology to students who may not have background in the technology introduced.
Recommendation for Researchers	In this study, student technological background was found to be a significant factor for technology acceptance; hence, it is recommended that technological background is included in TAM studies as an external factor.
Future Research	Repeating similar studies with multiple exercises with varying degrees of challenge is required for a better understanding of how collaborative work and student technological background affect technology acceptance.

Keywords collaborative learning, technology acceptance, virtual computer laboratories

INTRODUCTION

In the last decade, Remote Virtual Computer Laboratories (RVCLs) have increasingly changed the nature of how students learn real-life technical skills in the fields of computer science, information technology, and information security. RVCLs allow students to gain hands-on practice conducting what is considered risky operations that are not usually permissible in traditional computer laboratories on university campuses. In addition, RVCLs provide students with remote access to specialty software packages that are frequently used in many information technology classes. Furthermore, RCVLs facilitate distance learning in these fields by enabling students to perform self-paced activities remotely. Due to these reasons, RVCLs have been slowly replacing traditional computer laboratories in fields such as information security (Konak & Bartolacci, 2016).

Like many new educational technologies, in order to experience the full benefits of RVCLs, students should come to accept RVCLs as a useful learning tool. However, mastering the use of an RVCL can be intimidating for some students. Cognitive affective states such as frustration and confusion are mainly associated with students' negative experiences in computer-based learning environments (Baker, D'Mello, Rodrigo, & Graesser, 2010). Stress associated with technology use and dissatisfaction towards the technology itself are among the detrimental factors affecting students utilizing a virtual learning environment (Lee, Hong, & Ling, 2002). This paper hypothesizes that collaborative work can enhance students' acceptance of RVCLs by reducing such cognitive affective states. The paper investigates the impact of collaborative work on the acceptance and perception of an RVCL by students. In addition, the paper also examines the extent to which the effect of collaborative work depends on the technology background of students. The results of an empirical study based on the Technology Acceptance Model (TAM) (F. D. Davis, 1985) are reported to answer the following three main research questions:

1. What are the differences in acceptance of an RVCL between technology-savvy and technology-novice students?
2. Does collaborative work increase the acceptance of an RVCL?
3. Does the effect of collaborative work depend on the technology background of students?

As briefly explained in the background section below, TAM has been extensively tested and validated across a broad range of information technologies. TAM and its variants are frequently used to investigate factors affecting educational technology acceptance. However, the validity of TAM has never been studied in the context of an RVCL. Furthermore, the effects of collaboration on technology acceptance have not been sufficiently explored in the literature. These two points constitute the two main contributions of the paper.

BACKGROUND

The literature overwhelmingly agrees that collaborative learning has a positive impact on student attitudes toward the subject matter and learning (Johnson, Johnson, & Stanne, 2000). Many papers specially report the benefits of peer learning and collaborative work in learning information technology skills and related professional training. For example, based on a meta-analysis of 122 research papers, Lou, Abrami, and d'Apollonia (2001) reported that computer-based collaborative learning leads to higher knowledge gain than individual learning does. Harris, Peres, and Tamborello (2008) discussed that peer-to-peer learning could improve the efficacy and efficiency of software training in corporate settings. Similarly, Ellis (2002) contrasted the one-to-one and peer-to-peer instructional models for the technology training of teachers and reported that peer-to-peer training is an effective model for increasing the technological competency of teachers. In a survey conducted by Cornell University to investigate how students learn computer competency skills, students ranked peer support as a more effective learning strategy than many other methods including faculty support, help manuals, and workshops (P. Davis, 1999). In computer programming classes, Emurian (2007) integrated collaborative peer tutoring with hands-on learning and observed improvements in students' software self-efficacy. Hamada (2008) reported that a collaborative virtual environment also increased students' motivation for independent learning in the context of computational theory. Konak, Clark, and Nasereddin (2014) utilized peer-to-peer interactions in information security activities to promote a higher level of student reflection on the hands-on tasks that they performed. Their findings showed that a higher level of student interactions led to increased student learning.

Although the literature points out the positive role of collaborative learning in the acquisition of information technology skills, the effect of collaborative work on the acceptance of new educational technologies has not been addressed. The Technology Acceptance Model (TAM) is one of the keystone theories regarding technology acceptance in the business world. F. D. Davis (1985) first proposed TAM in 1985 to analyze the increasing important roles that technologies were playing in companies and organizations. TAM has also been utilized by many educational researchers over the years with respect to e-learning (Al-Mushasha, 2003; Cheung & Vogel, 2013), web-based collaborative learning systems (Liaw, Chen, & Huang, 2008), gamification (Torrente et al., 2014), e-textbooks (Ngafeeson & Sun, 2015), and computer technology education (Saleh, Prakash, & Manton, 2014). The application of TAM to study educational technologies follows from the argument that when examining the impact of a given technology on learning, one should also examine how students may accept the technology itself. It is clear that if the technology is not accepted, then learning stands little chance of being enhanced through its usage and application. TAM is used to predict an individual's use of technology as a response to motivation as shown in Figure 1. As part of the original theory, this motivation is believed to have been created by some stimulus external to the individual. The original TAM includes design characteristics of a given technology as the external stimulus that create three forms of internal user motivation: perceived usefulness (PU), perceived ease of use (PEOU), and attitude towards using (ATU) the technology. According to TAM, PU and ATU have a direct effect on a user's behavioral intention of future use (IFU) of a technology, and PEOU indirectly affects IFU through PU and ATU (F. D. Davis, 1989). In other words, PU mediates the effect of PEOU on behavioral intention. Together PU and PEOU form a basis for evaluating the attitudes toward using a given technology and ultimately generating IFU, which then leads to an actual end-user behavior of adopting the technology.

After its first introduction, several theoretical extensions of TAM, in particular TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008), were developed. These extensions of TAM mainly aim to explain TAM variables in terms of external factors. For example, in TAM3 constructs such as Computer Self-Efficacy, Perception of External Control, Computer Anxiety, and Computer Playfulness are proposed as the determinants of PEOU.

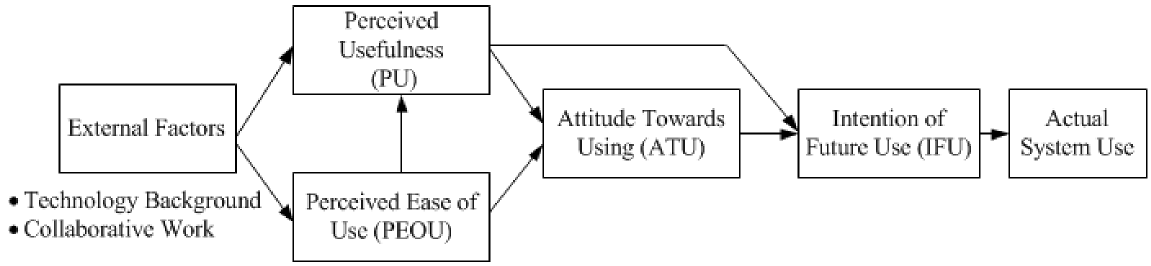

Figure 1. The version of TAM used to answer the research questions of the paper (F. D. Davis, Bagozzi, & Warshaw, 1989).

Although TAM has not been used previously to study RVCLs in the literature, earlier applications of TAM to other virtual learning environments are relevant to the research in this paper. Lee et al. (2002) conducted one of the first empirical studies that utilized TAM to examine students' acceptance of virtual learning environments. Their findings emphasized the importance of reducing anxiety and increasing preparedness of students in order to improve their acceptance of virtual learning environments. Raman, Achuthan, Nedungadi, Diwakar, and Bose (2014) investigated various attributes of virtual laboratories, including PEOU, and reported that PEOU significantly predicted the adoption of virtual laboratories by students. Konak, Bartolacci, and Huff (2012) reported that students perceived an RVCL as more useful for their learning when they performed activities in groups. Marn, Garca, Torres, Vzquez, and Moreno (2005) used a TAM-based model to redesign a web-based tool for teaching digital signal processing. The results of their study showed that interactive content and cooperative learning approach utilized improved the enjoyment and curiosity of students, which in turn increased the use of the web-based tool. Cheung and Vogel (2013) explored TAM in the context of collaborative technologies for e-learning. Their work confirmed that TAM was a useful model for examining the effectiveness of technologies utilized in e-learning. More importantly, they identified that peer influence is a determinant in the acceptance of e-learning technologies. Sun, Tsai, Finger, Chen, and Yeh (2008) explored e-learner satisfaction and the factors that influenced it. One of the key determinants identified in their work was flexibility. Hsieh and Cho (2011) used TAM to compare instructor-to-student interactive versus self-paced e-learning tools, and their findings indicated that instructor-to-student interactive e-learning tools led to higher perceived usefulness and learning outcomes.

RESEARCH METHODOLOGY

PARTICIPANTS AND DESCRIPTION OF THE EMPIRICAL STUDY

A total of 190 first-year students at Penn State Berks, a campus of the Pennsylvania State University, participated in the empirical study involving a computer networking exercise (n = 187 after data cleaning). The participants were recruited from two groups of students based on their information technology background. The first group is referred to as technology Novice (Group *N*) and second group as technology Savvy (Group *S*) herein after. Group *N* students were from non-technology majors (mainly business and social sciences), and they were recruited from an introductory level of Management Information Systems class. Group *S* were students from the Information Sciences and Technology program and aspired to work in information technology fields. Within these two groups, participants were divided into two sub-groups based on the nature of their interaction while carrying out the networking exercise. These groups were Collaborative (Group *C*) and Individual (Group *I*) respectively based on whether they conducted the exercise in teams of two or individually. Table 1 presents the number of participants in four Groups *NC*, *NI*, *SC*, and *SI*.

Table 1. The Number of Participants in Each Group

	Collaborative (*C*)	Individual (*I*)	Total
Novice (*N*)	47	46	93
Savvy (*S*)	59	35	94
Total	106	81	187

In order to validate the partitioning of students into these four groups, the participants were asked whether they consider themselves to be computer and system savvy on a five-point Likert scale (from Strongly agree (1) to Strongly disagree (5)). Group *N* rated themselves (mean=2.82, stdev=1.05) less computer savvy than Group *S* did (mean=2.19, stdev=0.895), and the difference was statically significant ($F = 21.374, p=0.000$). On the other hand, the mean ratings of Group *C* (mean=2.463, stdev=0.957) and Group *I* (mean=2.567, stdev=1.117) were virtually identical ($F = 0.483$, $p = 0.488$). The mean ratings of Group *NC* (mean=2.69, stdev=1.00) and Group *NI* (mean=2.97, stdev=1.101) were also not statically different ($F = 1.849$, $p = 0.177$).

The empirical study was conducted in the Collaborative Virtual Computer Laboratory (CVCLAB) that was specially designed to support hands-on learning in information technology and information security classes (Konak & Bartolacci, 2012, 2016; Richards, Konak, Bartolacci, & Nasereddin, 2015). In the CVCLAB, student participants performed an exercise involving several introductory computer networking concepts and skills such as the following: (*i*) discovering the TCP/IP setting of a computer; (*ii*) testing connections between computers (e.g., ping and route trace), (*iii*) remote messaging between computers, (*iv*) sharing files and directories over a network, and (*v*) configuring network file permissions. The exercise did not require any technical backgrounds in computer networking, and participants were provided with step-by-step instructions describing how to use the CVCLAB and perform the tasks of the exercise. Therefore, all participants were able to complete the exercise successfully.

In Group *C*, the students worked in groups of two to complete the required tasks and test one another's configuration settings. For this group, the exercise tasks were modified so that students had to depend on their partners to complete the exercise. To increase peer-to-peer interactions and encourage information exchange between students, the collaborative version of the exercise included several tasks in which students had to interact. For example, once a student completed the task of sharing a directory over the network. his/her teammate was also instructed to connect to this directory remotely and create a file in it. Such tasks aimed to initiate peer-to-peer learning by encouraging skilled students to help their teammates who are not as skilled as themselves. In Group *I*, students worked alone and used a target computer to perform most of the tasks and test their outcomes. It is important to note that the exercise was the first exposure to the CVCLAB for all participants, and both individual and collaborative versions of the exercise included the same tasks.

At the end of the activity, the participants completed a survey evaluating the CVCLAB. The survey questions for PEOU, PU, ATU, and IFU (five-point Likert scale ranging from Strongly Agree (1) to Strongly Disagree (5)) were adopted from (F. D. Davis, 1989) as follows:

Attitude towards using the technology (ATU):

Q1) Using the Virtual Computer Platform for this activity is a good idea.
Q2) I like using the Virtual Computer Platform for hands-on activities.
Q3) It is desirable to use the Virtual Computer Platform for hands-on activities.

Behavioral intention of future use (IFU):

Q4) I would like to use a Virtual Computing Platform in the future.
Q5) I will strongly recommend to others that they use Virtual Computing.
Q6) I would like to see more classes utilizing Virtual Computing.

Perceived ease of use (PEOU):

Q7) Learning to operate the Virtual Computer Platform is easy for me.
Q8) Overall, the Virtual Computer Platform is easy to use.
Q9) Interacting with the Virtual Computer Platform is clear and understandable.

Perceived usefulness (PU):

Q10) I believe that the Virtual Computing Platform increases the efficiency of my learning.
Q11) I find the Virtual Computing Platform useful.
Q12) I believe the Virtual Computing Platform is a useful learning tool.

The survey also included open-ended questions regarding the CVCLAB.

Model Validation

In this paper, the validity of TAM was tested not only for the whole data set, but also for the two sub-sets constituting only Group *S* and only Group *N* using Confirmatory Factor Analysis (CFA) in AMOS v22. Table 2 summarizes the calculated factor loadings (λ), Composite Reliability (*CR*), chi-squared (χ^2), degree of freedom (*df*), and Average Variance Extracted (*AVE*) for the three data sets. In addition, Cronbach's Alpha (a) values are provided only for the whole data set. All factor loadings exceeded 0.5 and were significant at $p < 0.001$ (p values of the individual factor loadings are not provided for the brevity of the presentation). In addition, all values of *CR* and a were greater than 0.80, indicating strong internal reliability. The squared roots of all *AVE* values were larger than the maximum correlation observed between any two survey questions of two different variables (0.652 between Q8 and Q12), which indicated good discriminant validity according to the Fornell-Larcker criterion. For the whole data set and the data sets of Groups *S* and *N*, the model had a good fit with respect to the Tucker-Lewis coefficient ($TLI > 0.90$), CFA Comparative Fit Index ($CFI > 0.90$), and $\chi^2/df < 2.5$ goodness of fit measures and had an acceptable fit with respect to the Root Mean Square Error of Approximation measure ($RMSEA \leq 0.08$).

Performing CFA individually on the data sets of Groups *S* and *N* allowed us to analyze how the relationships among the TAM variables changed based on the technological background of students. Table 3 shows the standardized path coefficients (β) with their t-statistics and p values of significance as well as the percentage of variance explained (R^2) of endogenous variables PU, ATU, and IFU for the models fitted to Groups *S* and *N*. For Group *N*, all path coefficients β values were significant, and the model was able to explain a large percent of the variance in endogenous variables IFU (R^2 = 0.821), PU ($R^2 = 0.697$), and ATU ($R^2 = 0.725$). As discussed in the following sections, these strong relationships observed among the endogenous variables can be attributed to the effect of collaborative work in the case of Group *N*.

For Group *S*, although the magnitudes of β values were similar to the ones for Group *N*, the relationships ATU←PEOU and ATU←PU were not significant ($p > 0.05$ for both relationships). Furthermore, ATU had a moderate level of variance explained ($R^2 = 0.366$). This observed difference between Groups *N* and *S* can be attributed to the fact that Group *S* found the CVCLAB easy to use and had overall very positive attitude toward using it regardless of whether they completed the exercise collaboratively or individually. Hence, collaborative work had no significant effect on ATU through PEOU. On the contrary, collaborative work had a significant effect on PEOU in the case of Group *NC* as the students working in teams found the CVCLAB much easier to operate, in turn increasing their PU ($\beta = 0.835$, $p < 0.05$) and ATU ($\beta = 0.397$, $p < 0.05$) compared to Group *NI*. In the following sections, these assertions are also studied using ANOVA and supported by a text analysis of the participants' responses to the open-ended questions.

Table 2. Confirmatory Factor Analysis Results for the All Data Set, Group *S*, and Group *N*

Question	TAM Variable	All Data Set				Group *S*			Group *N*		
		a	λ	*CR*	*AVE*	λ	*CR*	*AVE*	λ	*CR*	*AVE*
Q1	ATU	0.903	0.778	0.89	0.744	0.497	0.923	0.628	0.812	0.873	0.733
Q2	ATU		0.899			0.872			0.888		
Q3	ATU		0.905			0.936			0.867		
Q4	IFU	0.901	0.904	0.915	0.787	0.840	0.894	0.629	0.887	0.891	0.788
Q5	IFU		0.851			0.713			0.875		
Q6	IFU		0.906			0.820			0.901		
Q7	PEOU	0.884	0.841	0.883	0.713	0.758	0.916	0.632	0.829	0.843	0.684
Q8	PEOU		0.873			0.844			0.855		
Q9	PEOU		0.819			0.780			0.797		
Q10	PU	0.892	0.758	0.88	0.72	0.663	0.915	0.623	0.778	0.867	0.709
Q11	PU		0.903			0.792			0.892		
Q12	PU		0.877			0.895			0.852		
	χ^2		96.412			65.292			80.398		
	df		49			49			49		
	χ^2/df		1.968			1.968			1.641		
	TLI		0.968			0.965			0.965		
	CFI		0.976			0.974			0.974		
	RMSEA		0.072			0.06			0.06		

Table 3. The standardized path coefficients of TAM for Groups *N* and *S*.

Path	Group *S*				Group *N*			
	β	t	p	R^2	β	t	p	R^2
PU ←PEOU	0.803	5.382	0.000	0.645	0.835	6.987	0.000	0.697
ATU←PEOU	0.259	1.214	0.225	0.366	0.397	2.275	0.023	0.725
ATU← PU	0.378	1.711	0.087		0.492	2.786	0.005	
IFU←PU	0.553	4.282	0.000	0.700	0.533	3.698	0.000	0.821
IFU←ATU	0.383	2.973	0.003		0.415	2.976	0.003	

ANOVA to Identify Differences between the Groups

Table 4 summarizes the means and standard deviations of the TAM variables for sub-groups *NC*, *NI*, *SC*, and *SI* as well as the results of three ANOVAs to determine the effect of collaborative work and student technological background on the TAM variables. In addition, Cohen's *d* values were calculated to gauge the effect size of the factors, and their absolute values ($|d|$) are provided in the table. ANOVA-I included all participants (n=187) and two factors, type of exercise (two levels: *C* -Collaborative versus *I* -Individual) and technological background (two levels: *N* -Novice versus *S*-Savvy). The main objective of ANOVA-I was to compare Groups *N* and *S* (Research Question 1) while considering the effect of collaborative work. ANOVA-II and ANOVA-III were performed on the data sets of Groups *N* and *S*, respectively, and included the type of exercise as the only factor (Research Questions 2 and 3).

The results of ANOVA-I showed that technological background had the most significant effect on the TAM variables. As given in the table, technological background had a large main effect on all variables ($|d| > 0.8$ for all variables). Collaborative work also turned out to have a significant effect on all variables, excluding PU ($F = 2.396$, $p > 0.05$, $|d| = 0.323$). However, this result was due to the effect of collaborative work in Group *N* as shown in ANOVA-II.

The significant differences between the mean values of the variables across Groups *S* and *N* clearly indicate that the technology students in both Groups *SC* and *SI* found the CVCLAB much easier to use, considered it much more useful, showed more positive attitude towards it, and had a significantly higher acceptance of the CVCLAB than did non-technology students. These findings are somewhat anticipated. However, an unexpected finding was that collaborative work had no significant effect on the TAM variables in the case of technology students (Group *S*). In fact, the mean values of Group *SI* were slightly better than Group *SC*, albeit the differences were not statistically significant as shown in the results of ANOVA-III.

On the contrary, collaborative work had a significance effect on the TAM variables in the case of non-technology students as indicated in the results of ANOVA-II. The mean values for Group *NC* were consistently better than the ones for Group *NI*, in particular for PEOU ($F = 20.878$, $p < 0.05$, $|d| = 0.881$). These results suggested that collaborative work enhanced students' acceptance of the CVCLAB particularly for students with limited technological background.

Table 4. Results of ANOVA

					ANOVA-I			ANOVA-II (Group *N*)	ANOVA-III (Group *S*)
TAM Variable	Groups	Mean	Stdev		Background	Exercise Type	(Background)x (Exercise Type)	Exercise Type	Exercise Type
IFU	*NC*	2.510	0.929	$F =$	60.704	4.224	8.823	9.194	0.689
	NI	3.166	1.147	$p =$	0.000	0.041	0.003	0.03	0.409
	SC	1.881	0.671	$\|d\| =$	1.104	0.393		0.628	0.177
	SI	1.761	0.679						
PU	*NC*	2.212	0.678	$F =$	50.425	2.396	9.516	7.478	2.173
	NI	2.731	1.105	$p =$	0.000	0.123	0.02	0.008	0.144
	SC	1.762	0.57	$\|d\| =$	0.996	0.323		0.567	0.314
	SI	1.59	0.505						
ATU	*NC*	2.17	0.798	$F =$	44.03	4.879	9.242	9.715	0.616
	NI	2.789	1.098	$p =$	0.000	0.028	0.03	0.002	0.435
	SC	1.745	0.568	$\|d\| =$	0.936	0.408		0.646	0.167
	SI	1.647	0.615						
PEOU	*NC*	2.212	0.749	$F =$	45.265	9.472	19.331	20.878	1.349
	NI	3.058	1.016	$p =$	0.000	0.002	0.000	0.000	0.249
	SC	1.949	0.618	$\|d\| =$	0.904	0.512		0.881	0.254
	SI	1.8	0.572						

Discussion of the Results

With respect to Research Question 1, the findings showed that technology students had a significantly higher acceptance of the CVCLAB than non-technology students. This outcome should be expected according to TAM because technology students are expected to have higher levels of PU and PEOU in the context of virtual computer laboratories than non-technology students. Therefore, the empirical study in this paper verified TAM in the context of virtual computer laboratories.

The findings related to Research Questions 2 and 3 are more noteworthy. ANOVA-II showed that collaborative work could increase non-technology students' acceptance of the CVCLAB significantly. In particular, the difference in the mean values of PEOU between Groups *NC* and *NI* was quite no-table ($F = 20.878$, $p < 0.05$). Surprisingly, non-technology students found the CVCLAB much easier to use when they performed the activity in groups, and the effect of collaborative work on PEOU was large ($|d| = 0.881$). In addition, Group *NC* found the CVCLAB to be significantly more useful than Group *NI* did ($F = 7.478$, $p = 0.008$), and the effect size of collaborative work on PU could be considered medium ($|d| = 0.567$). According to TAM, higher levels of PEOU and PU should lead to higher levels of IFU, and this prediction was strongly held when the mean values of IFU for Groups *NC* and *NI* were compared ($F = 9.194$, $p = 0.03$, $|d| = 0.682$).

Earlier research on computer-based learning overwhelmingly reports the benefits of collaborative work as compared to individual work (Jackson & Kutnick, 1996; Johnson & Johnson, 1987). However, the effect of collaborative work on the acceptance of educational technology has not been studied before. Therefore, this finding of the paper is a unique contribution to the literature. The positive effect of collaborative work on the non-technology students might be justified by Vygotsky's Zone of Proximal Development (ZDP) Theory (Vygotsky, 1980), which explain the difference between what learners can achieve with and without help from instructors or more capable peers. A group's collective technology skill set is expected to be greater than that of each individual in the group. As a result, groups can achieve technical tasks that individuals may struggle to complete. Therefore, the better PEOU scores of Group *NC* when compared to Group *NI* could be explained by the fact that the students in Group *NC* were able to perform at a level beyond what they could do independently. This effect of collaborative work was not observed in Group *S* because this group of students already had the skill set and attitude to use the CVCLAB individually. In other words, collaborative work might not have made using the system any easier to use for technology students. This observation is similar to the empirical evidence given in the work of Szajna (1996) where PEOU is shown to become nonsignificant with increased experience.

In addition to the theoretical justification, the findings of the empirical study have practical implications. Firstly, RVCLs should be designed and utilized by considering the benefits of collaborative work to increase their acceptance by students. While introducing a new, complex educational technology to students, collaborative work may minimize problems due to individual differences in technical backgrounds and skill levels of students. Note that in Table 4, the standard deviations of the variables are always lower for Group *NC* compared to Group *NI*, and the differences in the standard deviations were statistically significant for PEOU ($F = 4.692$, $p = 0.033$), PU ($F = 9.428$, $p = 0.003$), ATU ($F = 5.652$, $p = 0.02$), but not for PEOU ($F = 2.354$, $p = 0.128$) in the Levene's Test for Equality of Variances between Groups *NC* and *NI*. The large variability observed in these variables for Group *NI* might be explained by the differences in students' individual information technology skills and knowledge. Note that the collaborative version of the exercise encouraged peer scaffolding in a structured manner by including task interdependency. In order to complete the collaborative version, students had to troubleshoot mistakes together and motivate one another to stay on the task. In Group *NC*, this structured-peer support could have smoothed out any differences in students' technical skills, leading to a smaller variability in their perceived experiences.

In order to better understand the differences in the experience and acceptance of the CVCLAB among the student groups, student comments for two open-ended questions (What did you like / dislike the most about the Virtual Computing Platform?) were analyzed systematically using grounded theory (Glaser & Strauss, 1967). Grounded theory is a social science research methodology to identify key themes in text data collected through interviews. The first phase of this research methodology involves conceptualizing all themes in the collected data and grouping them under broader categorizes. In this phase, two members of the research team independently analyzed all student comments to identify reoccurring themes in the comments. Later on, they created primary categories by combining similar themes into more general concept categories. These categories represented the common themes observed in the student comments. The final categories were determined by the consensus of the entire research team. After the categories were determined, each student comment was assigned to categories independently by each member of the research team. The comments including multiple categorical concepts could be assigned into a maximum of two categories. Finally, the four independent classifications of the comments were combined such that the assignment of a comment into a category was considered as valid if the same classification was suggested by at least two of the four raters. Fleiss' κ values of the inter-rater reliability were $\kappa = 0.747$ for the liked-most question and $\kappa = 0.631$ for the dislike-most question, indicating substantial agreement among the raters.

Figures 2 and 3 illustrate the identified categories from student comments and the percent of the comments in each category per Groups *NC NI, N, SI, SC* and *S* for the liked-most question and disliked-most question, respectively. In terms of the liked-most question (Figure 2), the major difference between Groups *S* and *N* was the perception of the CVCLAB. While Group *N* praised primarily technical skills that they learned (36.7% in Group *N* versus 19.4% in Group *S*), Group *S* emphasized the virtualization technology itself as the liked-most aspect of the exercise (3.8% in Group *N* versus 31.2% in Group *S*). In other words, Group *S* foresaw the potential of the CVCLAB as a learning tool to enhance their learning in information technology fields. This outcome is also in line with the findings of the statistical analysis of the TAM variables.

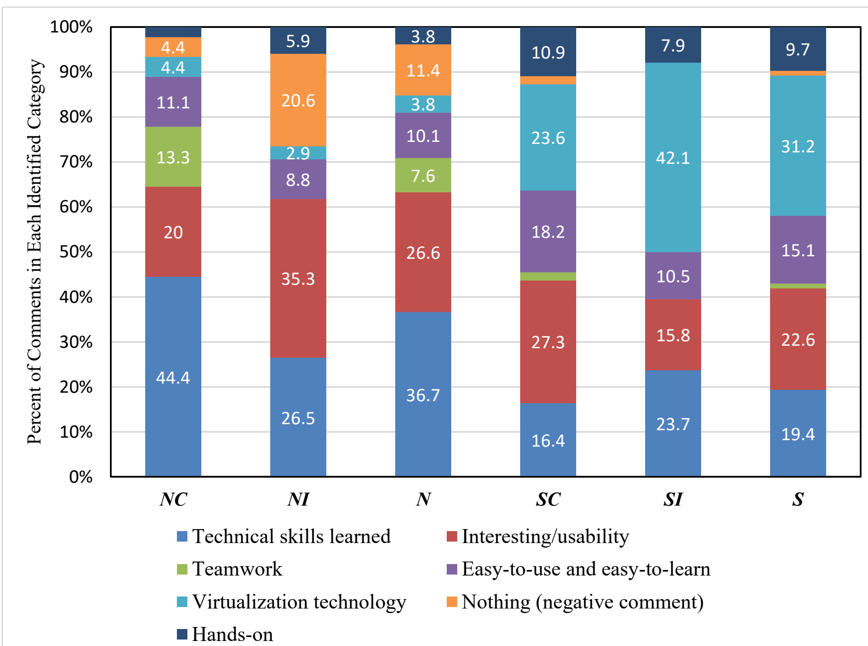

Figure 2. Identified categories for the liked-most question and the percent of comments assigned to each category over the participant groups (Small percentage values are not provided on the chart)

Even in the liked-most question, 20.6% of Group *NI's* comments explicitly included negative attitudes towards the CVCLAB and/or about the exercise whereas only 4.4% of Group *NC* did so. This might be attributed to the impact of collaborative work in the case of non-technology students. In addition, the impact of collaborative work was also observed in the responses to the disliked-most question for this group as shown in Figure 3. Fifty percent of Group *NI* found the CVCLAB and exercise instructions to be confusing and difficult to follow whereas only 35% of Group *NC* so stated. In addition, 12.5% of Group *NI* explicitly stated that they were frustrated during the exercise whereas none of Group *NC* so stated. Note that 24.3% of Group *NC* responded to the disliked-most question with a positive answer, indicating that they enjoyed all parts of the exercise and had no negative experience with the CVCLAB. It is also noteworthy that 13.3% of Group *NC* explicitly indicated teamwork as the liked-most part of the exercise.

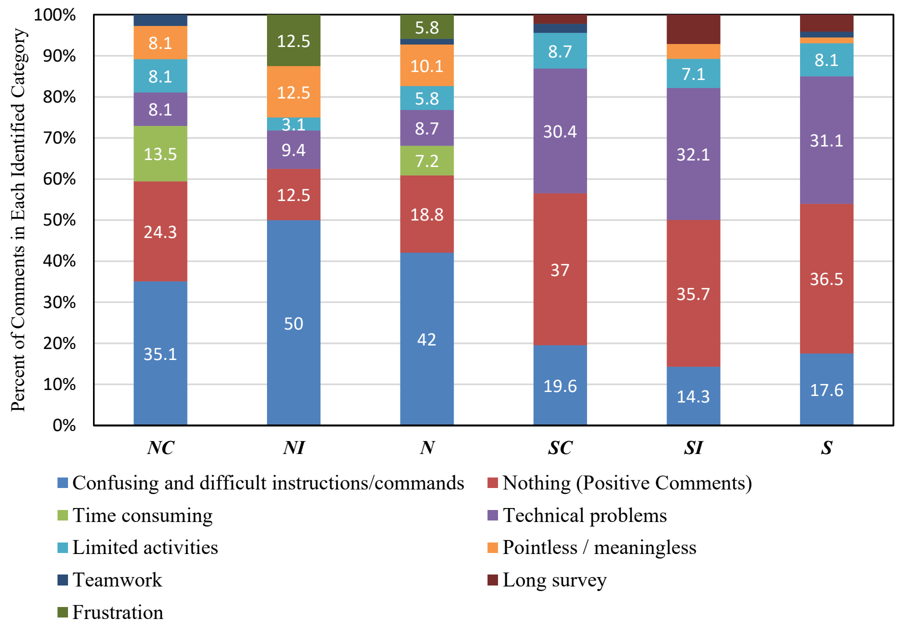

Figure 3. Identified categories for the disliked-most question and the percent of comments assigned to each category over the participant groups (Small percentage values are not provided on the chart)

These results may suggest that Group *NI* had difficulty with using the CVCLAB and performing the exercise, and collaborative work helped Group *NC* navigate the system and compete the exercise successfully. It can be claimed that the reflections of Group *NC* included less frustration and were clearly more positive than the reflections of Group *NI*. Therefore, these results support the earlier assertions about the benefits of collaborative work while introducing a new technology to students who do not have background in the technology introduced. Clearly, collaborative work seemed to help reduce frustration and confusion related to using the CVCLAB for non-technology students.

A limitation of the research is that the analysis is based on a single exercise that represents the snapshot of students' perception of the CVCLAB. Repeating the study with multiple exercises, possibility with varying degrees of challenge, would lead to a better understanding of how collaborative work and student technological background affect technology acceptance. In such more comprehensive empirical studies, the theoretical extensions of TAM, in particular TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008), could be used to study the relationship between collaborative work and technology acceptance. To the best of our knowledge, however, the main research questions of the paper have not been previously investigated in the literature. Due to the lack of related previous work, the findings of the paper contribute to the literature by raising an important research question that can be further investigated.

Another limitation of the research is the grouping of students as technology and non-technology solely based on their major. This assumption may not hold for all students. It should be noted that an attempt was made to group student participants based on their technology self-efficacy. However, self-efficacy turned out to be an unreliable construct to form the groups; therefore, it was not used to determine the groups in this work.

Conclusion

The research in this paper studied the relationship between the technological background of students and their acceptance of a remote virtual computer laboratory (RVCL) and the effect of collaborative work on this relationship. The findings of the empirical study support previous work that collaborative work can improve non-technology students' acceptance of RVCLs. However, no significant effect of collaborative work on technology acceptance is observed in the case of technology students, who already had very high level of acceptance of the technology. Overall, students' intrinsic motivation seemed to be the most important factor for determining the level of technology acceptance in the context of RVCLs. As a result, using collaborative work as a strategy to get students to accept a new technology is recommended.

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