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The effects of perceived risk and technology type on users' acceptance of technologies[☆]

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Abstract

Previous studies on technology adoption disagree regarding the relative magnitude of the effects of perceived usefulness and perceived ease of use. However these studies did not consider moderating variables. We investigated four potential moderating variables – perceived risk, technology type, user experience, and gender – in users' technology adoption. Their moderating effects were tested in an empirical study of 161 subjects. Results showed that perceived risk, technology type, and gender were significant moderating variables. However the effects of user experience were marginal after the variance of errors was removed.

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Keywords: Technology acceptance; Perceived risk; Technology type; User experience; Gender; UTAUT; Moderating variable

1. Introduction

Venkatesh et al. [26] compared and tested the variables in eight different models about users' technology acceptance including the technology acceptance model (TAM) [6] and diffusion of innovation (DOI) [22]. Subsequently, they proposed a unified theory of acceptance and use of technology (UTAUT), which consisted of four core determinants of acceptance/use and four moderating factors.

Although such models explain much of the variance, there seem to be two critical factors that are overlooked or have received inadequate attention—perceived risk (PR) and technology type. PR has been recognized as an important factor and was modeled as an antecedent of perceived usefulness (PU), and a sub-construct of others, such as trust (or as its antecedent [21]). However, PR was not considered in UTAUT.

When people decide whether or not to use a technology, the technology type affects their decision. In marketing, for example, it is widely acknowledged that consumers' decision-making criteria vary across different types of products [20,23]. It is not reasonable to assume that the effects of PU and perceived ease of use (PEU) on behavioral intention (BI) would be similar for different technologies.

The main object of our study was therefore to refine UTAUT, by considering the effect of PR and technology type on it. We also re-evaluated the effect of two moderating variables: gender and experience.

2. Prior research and theoretical background

Davis' original TAM had three key constructs—PU, PEU, and system usage (SU). Hong et al. [12] added two categories of external variables – individual differences and system characteristics – and Chau [4] modified it by using only four constructs—PEU, perceived long-term usefulness,

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perceived short-term usefulness, and behavioral intention to use. Gefen et al. [11] combined ‘trust’ in explaining users’ acceptance of online shopping.

The UTAUT had four core constructs – performance expectancy, effort expectancy, social influence, and facilitating conditions – and four moderating variables – gender, age, experience, and voluntariness of use. It integrated eight major theories and has been tested using real world data.

2.1. Perceived risk (PR)

PR or uncertainty affects people’s confidence in their decisions. Risky situations can be those where the probabilities of outcomes are not known and the outcome is known or unknown. In previous studies on consumer research, PR was defined as the perceived uncertainty in a purchase situation. PEU was defined as people’s subjective appraisal of performance and effort; usually discrepancies exist between people’s judgments and actual performance. This entails a ‘risk’ because users do not know the significance of this discrepancy. If a technology fails to deliver its expected outcome, it will result in a loss to the user (financial, psychological, physical, or social).

UTAUT examined a construct similar to PR: anxiety. However, it differed from PR, because it was mainly about the concerns or fears in trying a new technology rather than a long term effect. In practical terms, anxiety can be mitigated whereas PR will remain unchanged for some time.

An important issue about PR in technology acceptance is thus whether PR directly affects PU/PEU or BI (as an antecedent) or whether it moderates the effects of PU/PEU on BI (as a moderator). These different roles are depicted in Fig. 1.

Understanding whether PR is a moderating variable or an antecedent is obviously important. In TAM studies, PR was mostly considered an antecedent of PU, trust, or BI. However, when PR is modeled as an antecedent of PU, it is assumed that PU and PR are related, whereas they are independent of one another.

Therefore, we expected that PR would modify the effects of PU and PEU on BI. The relationships between PU/PEU and BI would be attenuated as users perceived higher risk.

Hypothesis 1. With higher PR

- (a) The effect of PU on BI will be attenuated.
- (b) The effect of PEU on BI will be attenuated.

2.2. Technology type

Most TAM studies have not considered the effect of different technologies. UTAUT was no exception. Adams et al. [1] did look at several technologies—e-mail, voice mail, word processor, spreadsheet, and graphics software. They found that the effects of PU and PEU on BI for those

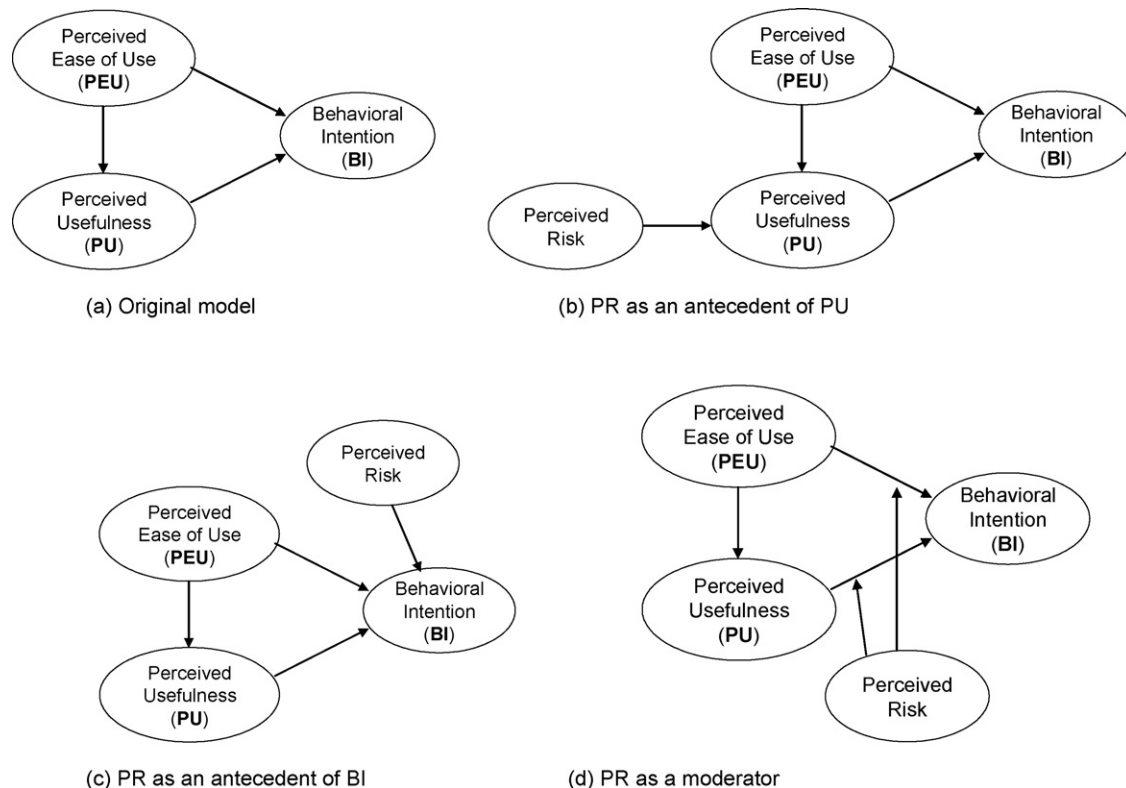


Fig. 1. Alternative conceptualizations of PR.

technologies differed substantially. They argued that it may have been because the importance of PEU diminished as users gained experience with the technology.

Gefen and Straub [9] theorized that the effect of PEU on BI would be affected by the nature of the task. Their study showed that PEU affected BI when users searched product information at an online bookstore, while it did not when users purchased books from a traditional store. Another way to categorize technologies is into hedonic and utilitarian types. This has been used in past marketing literature to categorize different types of products. Hedonic systems aim at providing self-fulfilling value to the user, rather than just being utilitarian. A recent study demonstrated that PEU had greater effects on BI than PU for a hedonic technology [24]. Conversely, PU would be more important when the technology was more job-related or utilitarian. When a technology is job related, the user considers usefulness more important than ease of use. Lin et al. [17] investigated the adoption of a technology in law enforcement, and found that PU correlated closely with BI. Other studies [19,29] also found similar results: strong effects of PU on BI when the technology is job-related. The categorization of hedonic and utilitarian technology thus seemed relevant.

Hypothesis 2. When the technology is hedonic

- (a) The effect of PU on BI will be attenuated.
- (b) The effect of PEU on BI will be strengthened.

2.3. Experience with the technology

There is great variety in past studies in terms of the subjects' familiarity with the technology. Apparently there is a significant difference in PU and PEU before and after the use of technology [7]. The effect of PU on BI was more significant after use of the technology, while PEU lost its effect on BI after users used the technology. Karahanna et al. [16] examined the decision to adopt technology (pre-adoption) versus the actual use (post-adoption). They found that potential users' intentions were based on a richer set of behavioral variables while actual users' intentions were continuously determined by PU and image. In their longitudinal study, Venkatesh et al. [25] emphasized the importance of training and developed an integrated model of longitudinal perspective, examining the influence of pre- and post-training environments over time.

The effect of experience was also examined in UTAUT. The researchers examined the changes of the constructs in the model as users gained experience. It was found that the effect of PU became stronger while the effect of PEU became weaker as users gained experience. Thus, we formulated hypotheses to confirm such results.

Hypothesis 3. When users' experience with the technology increases (or after users gain experience with the technology)

- (a) The effect of PU on BI will become strengthened.
- (b) The effect of PEU on BI will become attenuated.

2.4. Gender

In UTAUT, it was found that gender and age moderate the effects of PU and PEU on BI. Most studies have indicated that males perceive less risk than females in a similarly framed situation. In UTAUT, gender was found to be a significant moderating variable—the effect of PU on BI was stronger for males while the effect of PEU was stronger for females. We therefore examined the effects of gender postulating the following hypotheses:

Hypothesis 4. For male users

- (a) The effect of PU on BI will be strengthened.
- (b) The effect of PEU on BI will be attenuated.

3. Empirical study

We tested our hypotheses using data collected from subjects who participated in a group task experiment. For each subject, two identical questionnaires were used to measure the variables of interest before and after the experiment.

3.1. Experiment procedure

The authors recruited students who were taking undergraduate and graduate courses in a university in the northeastern US. Subjects were asked to work on a group decision-making task for a period of 2 weeks. The task was to develop specifications for web-based applications for the Exchange Student Service Center at the university, including its functionality and services, user interface design, definition of business values, and making decisions on priorities for the developing of each function. There were three different treatments:

- (1) Those using only asynchronous communication technology (a bulletin board called "Webboard").
- (2) Those using both asynchronous (Webboard) and synchronous (MSN Messenger) communication technologies.
- (3) Those with mobile devices (wireless PDA) using both asynchronous and synchronous communication technologies.

Prior to this study, the majority of the recruited students had experience with Webboard since it had been used in courses at the university. MSN messenger, although it had sometimes been used in courses (e.g., for online office hours), had been used mostly for personal communication among students. Wireless PDA use had been somewhat

mixed, because students could use it for personal use or for courses.

The decision-making task in this experiment required the subjects to use a technology in an utilitarian way, no matter whether it could be classified as hedonic or utilitarian. It was reasonable to assume that a subject's intention to use the technology (which was a question he or she answered in the post-experiment survey) reflected an overall evaluation of the technology.

The questionnaire was uploaded to Webboard and the subjects were asked to download, fill out, and return it via email. Of the 197 participants, 195 pre-task and 170 post-task questionnaires were collected. The number of subjects who completed all the relevant survey forms was 161; these provided the data used for analysis.

3.2. Measurement instruments

The questionnaires asked students their opinions about BI, PU, PEU, and PR. For PU, PEU, and BI, the standard TAM and UTAUT measurement instruments were used. Data for user experience and gender were collected from the background questionnaire. For PR, the measurement instruments were developed by the authors from the literature on risk. There are five commonly used categories in marketing literature [3,14,23]; all were included: financial (worth the cost), performance (effectiveness), social (changes in work), psychological (frustration), and physical (comparison to other products). The instruments were refined through a pilot session after three graduate students filled out the questionnaire, checking if there were any unclear or misleading questions.

3.3. Analysis of results

The hypotheses were tested using Structural Equation Modeling (SEM). SPSS/PC Version 11.5 and AMOS Version 4 were used. Table 1 shows the demographics of the subjects.

3.3.1. Confirmatory factor analysis and construct validity

Although the validity of the three constructs – PU, PEU, and BI – had been tested in previous studies, their validity was retested in our study. The data from the pre- and post-task results were pooled to check the overall construct

validity. A confirmatory factor analysis (CFA) was conducted for all constructs—PU, PEU, BI, and PR. Similarly, the measurement model was revised by dropping items with low (<0.50) factor loading. As a result, all items, except one from PR, were retained in our analysis. The final list of retained items is given in Table 2. The final CFA results are acceptable ($\chi^2 = 292.3$, d.f. = 113, GFI = 0.903, AGFI = 0.868, CFI = 0.951, NFI = 0.924, RMR = 0.055, RMSE = 0.07). In order to check discriminant validity, every pair of the four constructs was united (setting covariance = 1) and tested if the change in χ^2 was statistically significant. The χ^2 of the original model was significantly ($p < 0.01$) smaller than any possible union of any two constructs, which indicated the discriminant validity of the constructs. Next, the reliability of the constructs was examined with Cronbach's α , composite reliability, and average variance extracted (AVE) shown in Table 2. All Cronbach's α s and composite reliabilities were over 0.7, the cut-off for confirmatory research [10]. The AVE of each construct was over 0.5 and, as shown in Appendix A, the square root of AVE of each construct was larger than the construct's correlations with other constructs, which also indicated good convergent and discriminant validity.

As summarized in Tables 3 and 4 (marked as 'whole sample'), the model showed a very good fit as most fit indices were in the desirable range.

3.3.2. Test of moderating variables

The common way of testing moderating effects in SEM is to divide the data set into two groups (high and low value of the candidate moderating variable) and to compare the model fitting across groups. For example, for gender the dataset is divided into two sub-sets, and SEM applied to one of the two groups (male group, for example). Once the model is identified for the male group, the statistics are used to conduct tests for the female group. Two models for the female group are then compared—one without any constraints and one with the coefficients set to that for the male group. If the model without any constraints is significantly better (smaller χ^2) than the constrained one, the female group's coefficients differ from those of the male. If the changes of χ^2 are significant, a moderating effect exists.

Although this method is straightforward, it does not test whether (or how much) the differences are determined by the error variance (direct effect) or factor loadings and coefficients (moderating effect) of the dependent variables. A more rigorous method based on Jöreskog and Sörbom [13] was proposed by Dabholkar and Bagozzi [5]. Their methodology is similar to the above method: the dataset is divided into groups and the statistics from one are used to constrain models off the other. It also tests to find whether the change of χ^2 is statistically significant given the change in the degree of freedom ($\Delta\chi^2/\Delta\text{d.f.}$). In order to test if the changes of χ^2 were caused by the moderating variable,

Table 1
Demographic background of subjects ($N = 161$)

Gender	Class	Age
Male: 109 (67.7%)	Undergraduate: 81 (50.3%)	Under 23: 60 (37.3%)
Female: 52 (32.3%)	Graduate: 80 (49.7%)	23–30: 82 (40.9%)
		Over 30: 19 (11.8%)

Table 2
Factor loadings and reliability

Construct	Operational variable (item in the questionnaire)	Factor loading	Cronbach's α	Composite reliability	AVE
Intention to use (BI)	I predict I would use it	0.830	0.894	0.757	0.711
	It would be one of my favorite technologies for my work	0.818			
	I intend to use it	0.593			
Perceived usefulness (PU)	... would enhance my effectiveness in my job	0.903	0.951	0.952	0.798
	... would make it easier to do my job	0.881			
	... would increase my productivity	0.879			
	... would improve my performance in my job	0.856			
	... to be useful in my job	0.855			
Perceived ease of use (PEU)	Learning to operate ... would be easy for me	0.825	0.838	0.849	0.531
	My interaction with ... would be clear and understandable	0.811			
	It would be easy for me to become skillful at using ...	0.782			
	I would find it easy to get ... to do what I want to do	0.732			
	Interacting with ... would not require a lot of my mental effort	0.723			
Perceived risk (PR)	It is probable that ... would not be worth its cost	0.791	0.749	0.906	0.510
	It is probable that ... would frustrate me because of its poor performance	0.781			
	Comparing with other technologies, using ... has more uncertainties	0.714			
	It is uncertain whether ... would be as effective as I think	0.705			

however, this method compares four models for each moderating variable:

- Model A has all factor loadings constrained across groups, and error variances of the items for endogenous variables are constrained.
- Model B has the factor loadings free but error variances are constrained.
- Model C has both factor loadings and error variances are free.

- Model D has factor loadings constrained but error variances are free.

If models A and D (or models B and C) are different, it is caused by error variances in dependent variables. If models A and B are significantly different from each other (or if models C and D are different from each other), this is caused by the different factor loadings and path coefficients, which implies that there is a significant moderating effect. Thus by comparing these models, the difference due to error variance

Table 3
Test result of moderating effects

Variables	Model	χ^2	d.f.	GFI	AGFI	NFI	CFI	RMR	RMSEA	$\Delta\chi^2/\Delta d.f.$
Whole sample		195.8	62	0.914	0.875	0.942	0.959	0.055	0.082	N/A
Perceived risk	A	235.0	80	0.820	0.795	0.858	0.902	0.061	0.113	N/A
	B	206.0	70	0.837	0.788	0.876	0.914	0.045	0.113	2.9 ^a ,a
	C	153.8	62	0.870	0.810	0.907	0.942	0.046	0.098	6.5 ^{**} ,b
Technology type (Webboard and MSN) ^c	A	346.7	80	0.750	0.715	0.791	0.831	0.120	0.154	N/A
	B	277.0	70	0.785	0.720	0.833	0.869	0.074	0.145	6.9 ^{***} ,a
	C	191.1	62	0.832	0.753	0.885	0.918	0.065	0.122	10.7 ^{***} ,b
Gender	A	473.4	80	0.716	0.677	0.789	0.819	0.087	0.151	N/A
	B	443.9	70	0.723	0.639	0.802	0.828	0.067	0.157	2.9 ^a ,a
	C	179.9	62	0.885	0.831	0.920	0.946	0.062	0.094	33.0 ^{***} ,b
Experience (pre- and post)	A	167.2	80	0.873	0.855	0.920	0.957	0.074	0.083	N/A
	B	150.1	70	0.882	0.847	0.928	0.960	0.059	0.085	1.7 ^a
	C	110.8	62	0.905	0.861	0.947	0.976	0.059	0.070	4.9 ^{**} ,b

^a Difference between model A and model B.

^b Difference between model B and model C.

^c Due to the small sample size of PDA ($n = 40$), only Webboard and MSN were compared.

* Significant at $\alpha = 0.1$ level.

** Significant at $\alpha = 0.05$ level.

*** Significant at $\alpha = 0.01$ level.

Table 4
Changes in standardized β coefficients

Standardized β	Whole sample	Perceived risk		Technology type		Gender	
		Low	High	MSN	Webboard	Male	Female
PEU \rightarrow PU	0.306**	0.168*	0.291**	0.396**	0.260**	0.262**	0.395**
PU \rightarrow BI	0.686**	0.771**	0.486**	0.522**	0.780**	0.694**	0.636**
PEU \rightarrow BI	0.224**	0.163**	0.395**	0.294**	0.193**	0.228**	0.251**

* Significant at $\alpha = 0.1$ level.

** Significant at $\alpha = 0.01$ level.

can be separated from the difference from factor loadings and path coefficients.

The effects of the four variables – PR, technology type, user experience, and gender – were tested following this procedure. Because PR was not a categorical variable, the groups were divided into high and low groups using the median [2,5]. PR was divided by the median of the sum of the two items displayed in Table 2.

Table 3 illustrates the comparisons of models A, B, and C with fitting indices and $\Delta\chi^2/\Delta d.f.$ Model D did not need to be compared, because the comparison was redundant. The test results of moderating effects and significant coefficients of the paths were determined.

3.3.3. Perceived risk (PR)

PR moderates the effects of PU and PEU in the model (2.9 in the $\Delta\chi^2/\Delta d.f.$ column in Table 3). For users perceiving a higher risk in using the technology, PU has smaller effects on BI (PU \rightarrow BI coefficients, 0.486 and 0.771 in Table 4) than those perceiving a lower risk, which supports Hypothesis 1(a). However, PEU has a bigger effect on BI (PEU \rightarrow BI coefficients, 0.168 and 0.291 in Table 4) for the high perceived risk group than the low perceived risk group; this did not support Hypothesis 1(b).

PR has often been modeled as an antecedent of PU or BI in many previous studies [8,11,15,18,28]. The three models in Fig. 1 were tested by running different SEM models as shown in Table 5.

The five models were:

- Model I: original model (Fig. 1(a)).
- Model II: PR was modeled as an antecedent of PU (Fig. 1(b)).
- Model III: PR was modeled as an antecedent of BI (Fig. 1(c)).

- Models IV and V: PR was modeled as a moderating variable. The sample was divided into a high-risk group (model IV) and a low-risk group (model V) and the original model, the same as model I, was run for each group (Fig. 1(d)).

For more accurate comparisons, $\Delta\chi^2/\Delta d.f.$ values were computed. The $\Delta\chi^2/\Delta d.f.$ value for model III was statistically significant, which indicated that the increase in χ^2 when PR was added to the model exceeded the increase in d.f.. The $\Delta\chi^2/\Delta d.f.$ value for model II was also large, although statistically insignificant. Therefore, it could be concluded that model I (without PR) was a better fit than models II and III (with PR as an antecedent).

Models IV and V had the same constructs as the original model (model I), but they had different sample sizes. Therefore, they could not be compared head-to-head with the original model (the value of Chi-square likelihood ratio statistics was directly dependent on the sample size). A Normed Fit Index (NFI), the percentage of observed-measure covariance explained by a given measurement or a structural model, was used. In the table, the NFI for models IV and V were slightly lower than those for model I. Since the value of χ^2 dropped significantly, without sacrificing other statistics, when PR was modeled as a moderating variable, it could be concluded that users' acceptance behavior was better explained when PR was modeled as a moderating variable.

3.3.4. Technology type

The type of technology affected the coefficients (see 6.9 in the $\Delta\chi^2/\Delta d.f.$ column of Table 3) – PU was more important in using Webboard than in using MSN messenger (the coefficients were 0.780 versus 0.522) and PEU was more important for MSN messenger than Webboard (with coefficients of 0.193 versus 0.294). MSN messenger was

Table 5
Test result of different conceptualizations of PR

Modeling of PR	χ^2	d.f.	GFI	AGFI	NFI	CFI	RMR	RMSEA	$\Delta\chi^2/\Delta d.f.$
I. Without PR (original model)	195.8	62	0.914	0.875	0.942	0.959	0.055	0.082	N/A
II. An antecedent of PU	325.0	115	0.895	0.860	0.915	0.943	0.096	0.075	2.44
III. An antecedent of BI	357.1	115	0.883	0.844	0.907	0.934	0.142	0.081	3.04*
IV. A moderating variable (high PR)	153.8	62	0.870	0.810	0.907	0.942	0.046	0.098	N/A
V. A moderating variable (low PR)	145.9	62	0.880	0.824	0.914	0.948	0.069	0.090	N/A

* Significant at $\alpha = 0.1$ level.

believed to be more hedonic than Webboard, as has been stated in several media reports which have identified instant messenger programs as the preferred medium (over email or Webboard-like applications) for private communications between employees in the workplace. The larger effect of PEU on MSN messenger and the greater coefficient of PU on Webboard support [Hypothesis 2](#).

3.3.5. Experience and gender

Whereas gender moderated the effects of PU and PEU in the model, experience did not (see 2.9 and 1.7 in the $\Delta\chi^2/\Delta d.f.$ column of [Table 3](#)). Thus [Hypothesis 3](#) were not supported.

Gender is a significant moderating variable. The effect of PU on BI was slightly stronger for male (coefficients of 0.694 versus 0.634) and the effect of PEU on BI was slightly stronger for women (0.251 versus 0.228).

3.3.6. Interactions between perceived risk and other variables

Since it was not practical to test several moderating effects together using SEM, the moderating variables were not tested together. However, it is possible that PR and experience are correlated—users perceive a higher risk before they use the technology than after they use it. This was examined by testing the difference in PR between pre- and post-use (see [Table 6](#)). There was no significant difference (all $p > 0.05$) in PR between pre- and post-use of technology.

Another pair of variables that might have been correlated were PR and technology type. A t -test on PR across the two technologies (Webboard and MSN) showed that there was a significant difference in PR across these technologies for both pre-use and post-use ($p < 0.01$).

The difference of PR across gender was also tested. It is interesting that female subjects perceived lower risks before they used the technology than males; this is contrary to many past studies. However, a study also showed that the gender difference in PR varied across different problem domains [[27](#)].

4. Discussions

4.1. Limitations

Our study had several limitations due to the sampling methods and measurement instruments. First, the sample was a student group in a university; the sample was relatively homogeneous and does not represent the real world population. However, the subjects were diverse in terms of ethnic background, job experience, and age. Also, though the sample size of 161 was not too small for a model with 3 or 4 constructs, a bigger sample size would have been better. Second, the technologies examined in our study were of one type—technology for communications. Studies with other technologies may have resulted in different results and thus they cannot be generalized. Third, the subjects' familiarity with the technology was not controlled. Subjects were more familiar with MSN messenger than Webboard or wireless PDA. Therefore, it is possible that the different level of familiarity might have affected the results. Finally, this study examined only a limited set of constructs, which is small considering the variety of those studied in other research.

4.2. Implications

PR changes the effects of PU and PEU on BI. Users who perceive a higher risk about adopting the technology will be affected by how easy it can be used. This has several implications for managers. When they deploy a technology perceived risky, they need to emphasize 'ease of use'. However, when users perceive a low risk, managers have to focus on communicating 'usefulness' of the technology.

Technology type is a significant moderator variable of use. Managers need to emphasize 'ease of use' when they market a technology that is hedonic or for personal use. On the other hand, if the technology is utilitarian, managers should try to convince users that it is of value in their jobs.

Table 6
PR before and after use of the technology

	Webboard		MS messenger		Wireless PDA	
	Pre-use	Post-use	Pre-use	Post-use	Pre-use	Post-use
PR*	15.8	16.0	18.5	18.8	14.6	12.6
	Perceived risk* (pre-use)			Perceived risk* (post-use)		
Technology						
Webboard		15.8	$p < 0.01$		16.0	$p < 0.01$
MS messenger		18.5			18.8	
Gender						
Male		18.0	$p < 0.01$		16.8	Not sig.
Female		16.0			16.5	

* Sum of four items used in the main analysis (1 = high risk, 7 = low risk, for each item).

5. Conclusions

In a practical sense, managers may introduce a new technology successfully by emphasizing different factors based on the degree of perceived risk and technology type. We considered two moderating variables, PR and technology type, in addition to the moderating variables in UTAUT. We tested how they moderate the effects of PU and PEU on users' intention to use a technology. It was shown the PR and technology type were moderating variables.

While analyzing the effects of the variables, this study also demonstrated a systematic manner of testing moderating effects using SEM.

Appendix A. Square root of AVE and construct correlations

PU	0.893			
PEU	0.307	0.728		
BI	0.756	0.436	0.843	
PR	-0.457	-0.333	-0.497	0.714
	PU	PEU	BI	PR

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