User Acceptance of Emergency Alert Technology: A Case Study

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ABSTRACT

The purpose of the study is to investigate the factors affecting the user acceptance of emergency alert systems. By studying the adoption of a SMS-based alert system at a large public university in the United States, this paper explores the research question: How are different motivational factors related to the intention and behavior of using emergency alert technology? Through a mixed-methods approach, the study demonstrates a "deepening" effort in applying the technology acceptance model (TAM) to emergency response system, drawing attention to the holistic nature of motivation-behavior in technology acceptance. Results of this research show that: the concept of usefulness has multiple levels of meanings to its intended users; the ease of use is more about the users' ability to control the system behavior; and subjective norm need to be examined with relation to its originating source.

Keywords

Technology acceptance, TAM, motivation, emergency alert systems

INTRODUCTION

Despite the fact that more and more emergency alert technologies have been employed in residential communities and schools, much remains to be learned about the acceptance of such systems in these communities. We have learned from many past experiences that 'build it and they will come' is a false assumption. A concrete example illustrating the acceptance issue is the adoption of Campus Alerts (pseudonym) at Eastcoast University (pseudonym) in the United States. In April 2007, the University purchased a SMS (Short Message Service) alert software and deployed the system shortly after the Virginia Tech shooting occurred. ABC Alerts sends important alert messages to students' cell phones in the event of a major emergency. Since the subscription to Campus Alert is voluntary, the University has put considerable effort into promoting the system to the university community using various marketing strategies (for example, displaying ads on university shuttles, repeatedly sending promotional emails to all students, setting up information desks in public places on campus, etc.). By July 2008, student subscriptions were still rather low after all the advertising and promoting endeavors – only about 7,500 students signed up, or about 21% of the student population.

In fact, the Eastcoast University is by no means a special case. A 2008 *USA Today* article reported that college students are generally "slow to embrace text alerts" (Zagier, 2008). *The Chronicle of Higher Education* also reported that at many of the schools with the text alert services, fewer than half the students have signed up (cited in Williams, 2008). Matt Wagner, the Student Body President at Kansas State University expressed his frustration, which is perhaps shared by many school administrators: "I thought this would be a very simple thing that students would jump on…. The only cost to students is the 10 cents or so… It could be a matter of life or death" (Williams, 2008). Low cost plus "life or death" seem to be a sufficient driving force for adopting a very simple technology, but why are most students not motivated to do so?

SCOPE & RELATED WORK

Scope of the Study

The issue of user acceptance of technology has been tackled in many related fields such as information systems (IS), human-computer interaction (HCI), and communication studies. The present study adopts Dillon & Morris's (1996) definition of user acceptance as "the demonstrable willingness within a user group to employ information technology for the tasks it is designed to support" (p.5). This definition emphasizes the actual acceptance *behavior* ("demonstrable") rather than the self-reported *intention* of use. However, from the standpoint of system implementation and diffusion, behavioral intention is still the central subject in acceptance research, as researchers are mainly interested in understanding the social and psychological determinants of intention so as to model and predict future acceptance. Hence, following Ajzen's (1991) belief that intentions "capture the motivational factors that influence a behavior" (p.181), this study pays attention to both the non-user's intention of adopting Campus Alerts and the determinants of the behavior for those existing adopters.

Another clarification to make here is about the difference between initial adoption and subsequent continued usage. Research studies have found that the determinants of continued usage of a technology system are often different from that of initial adoption (e.g.,Hsu & Chiu, 2004). Certainly, the usage experiences during post-adoption period will impact the user's perception and attitude toward the system, which in turn might impact continued usage. Most emergency alert systems (like Campus Alerts), however, are designed in such a way that they are "set-and-forget" in nature. That is, once a person subscribed to the service, the actual usage will only occur when there is an emergency. Since most users are unlikely to have many usage experiences with this kind of alert systems, the post-adoption evaluation is difficult to do for both users and researchers. For this reason, this study concentrates only on the initial adoption of the technology.

Technology Acceptance

The two predominant perspectives in the acceptance research are the innovation diffusion theory and the Technology Acceptance Model (TAM).

Everett Rogers' (2003) innovation diffusion theory defines technology acceptance as a process by which the new technology is communicated through certain channels over time among members of a social systems. While diffusion theory provides a context in which one may examine the uptake and impact of information technology over time, it provides little explicit treatment of user acceptance itself (Dillon & Morris, 1996).

Modeling user acceptance at an individual level is better tackled within the theoretical framework of TAM. Based on the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975) and the theory of planned behavior (TPB) (Ajzen, 1985, 1991), Davis' (1989) Technology Acceptance Model (TAM) is probably the most widely cited framework for studying technology acceptance. The core idea of the TAM is that technology acceptance is determined by a person's behavioral intention, which in turn is determined jointly by the person's perceived usefulness (PU) and perceived ease of use (PEU) toward the technology. Interestingly, TAM purposefully dropped the subjective norm (SN) construct in the TRA and TPB. Subjective norms refer to perceived social pressure from significant others in performing a specific behavior. The issue of SN was later picked up by Taylor and Todd (1995) in their Decomposed TPB, which incorporates social influence and other social elements into TAM.

More recently, Venkatesh et al. (2003) proposed a Unified Theory of Acceptance and Use of Technology (UTAUT) model, attempting to combine all major theoretical constructs in previous IS literature into one definitive framework. The framework is based on three constructs that play a significant role as direct determinants of user's behavioral intention in technology acceptance: performance expectancy, effort expectancy, and social influence. Despite the terminology differences, UTAUT confirms once again the validity of the core constructs of TAM (PU, PEU, and SN) that have been constantly tested and validated in nearly two decades of acceptance research.

Motivation for Risk Prevention & Response

Within the general framework of cognitive theory of motivation, emergency response researchers draw heavily on a related area of research: health behavior. The health belief model (HBM) – the most widely utilized model in the study of health-related behaviors (Noar & Zimmerman, 2005) – posits that individuals assess health risks, costs, and likely benefits, before making a decision to take preventative actions or seek medical treatment. The HBM has been applied to a broad range of health behaviors and subject populations, explaining or predicting health-promoting (e.g. diet, exercise) and health-risk (e.g. smoking) behaviors as well as vaccination and contraceptive practices (Glanz, Rimer, & Lewis, 2002). In studies of emergency intervention and helping behavior, many scholars also believed that it is the balance of risk-reward calculations made by an individual that explains his or her motivation to help others (e.g., Penner et al., 2005). When it comes to individual's emergency preparedness, the ORC Macro report (2005) concluded that the perception of an imminent threat is probably the greatest factor in motivating people to get prepared. In the *Citizen Preparedness Review*, ORC Macro (2006) identified four main reasons to an individual's lack of motivation for emergency preparation and all of them are related to people's perception of threat and the value of action.

Clearly, there is a great deal of parallel between the constructs in HBM and the constructs identified in emergency response literature. In a nutshell, researchers in both fields tend to believe that the likelihood of taking preventative actions against potential risks (health, environmental, etc.) is largely determined by an individual person's cognitive analysis of risk and benefit of action.

RESEARCH QUESTION & METHODOLOGY

Using the TAM as the initial theoretical framework, this case study aims to answer the question: How are different motivational factors related to the intention and behavior of using an emergency alert system – Campus

Alerts? A two-phase, mixed-methods methodology was adopted in the empirical study. The first phase of the study consisted of qualitative interviews with the students, focusing on identifying potential motivational factors in the technology acceptance. The purpose of the qualitative phase is two-fold: 1) to obtain a holistic view the students' perceptions and motivations for using Campus Alerts; 2) to contextualize the TAM constructs and other constructs from the literature in order to design a context-specific survey instrument. Details about this part of the study have been reported in Wu, Qu, and Preece (2008). In brief, in the qualitative phase the researcher clarified what exactly constitute those broad theoretical concepts discussed in the literature (i.e., PU, PEU, and SN). Combing the findings from the literature review and the results of the interviews, a research framework is proposed to guide the second phase of the study (Figure 1).

The second phase of the empirical study, reported here in this paper, aims to examine the associations between some key factors and students' motivation for accepting Campus Alerts, as illustrated in Figure 1. In order to generalize the observations from the limited number of interviewees to the population, a quantitative survey method was used. The instrument consists of 35 (for Campus Alerts adopter) or 38 (for non-adopters) items. The survey items are centered on the constructs in the research framework. Some items about PU, PEU, and SN were adapted from technology acceptance literature in IS (e.g., Davis, 1989; Venkatesh et al., 2003). 29 items used 7-point Likert scale with 1 = "Strongly Disagree", 4 = "Neutral", and 7 = "Strongly Agree". The rest of the questionnaire are multiple choice items, some allowing open comments. The instrument was pilot-tested with 3 graduate students and 5 undergraduate students before releasing to the target population.

The survey was implemented in the environment of SurveyMonkey.com, a leading Web survey software application in the United States. The email invitations to survey were sent to the students through the university's daily FYI listservs. Three weeks after the first invitation, 288 responses were collected. Given approximately 35,000 student enrollments at the University, the response rate was very low. In order to increase the number of respondents (especially undergraduate student respondents) and to check non-response bias, a paper version of the questionnaire was distributed in 6 undergraduate classes during the Summer term of 2008. The paper questionnaire is identical to the online one, except for some minor modifications to resemble the conditional branching in the online survey (e.g., "If 'Yes', skip next page and proceed to question X."). 107 completed questionnaires were collected from the 6 classes, resulting in a total of 331 usable responses with online and paper surveys combined. The responses from the paper survey were manually entered into SPSS (version 15.0) and merged with the online survey data downloaded from SurveyMonkey.

DATA ANALYSIS & RESULTS

Sample Characteristics

The survey respondent sample was skewed in terms of gender. Female made up 64% of the sample, and male 36%. The much higher number of female respondents might be explained by previous research findings that women consistently showed more concern toward crimes and risks (Finucane et al., 2000; Weber, Blais, & Betz, 2002). In terms of academic year, the sample had solid representation from each group with reasonably larger proportions of Juniors and Seniors (Freshman 10%, Sophomore 13%, Junior 21%, Senior 21%, Graduate 35%), and the proportion of Graduate Student was also close to the proportion of the university population (39%). As for Campus Alerts adoption, the sample consisted 58% Campus Alert adopters and 41% non-adopters (1% missing).

Factor Analysis

The most important validity issue for this survey study is how well the questionnaire items measured the constructs as proposed in the research framework. A KMO and Bartlett test was performed to measure the sampling adequacy (see Table 1). The KMO overall (.784) is higher than the conventional cut-off point (.60) and the Bartlett has a significant value (p = .000). This indicates that the correlations observed in the variables are likely to contain common variance and the data are likely to factor well.

A Principal Component Analysis (PCA) was then conducted in SPSS to identify orthogonal factors that appear to represent the underlying latent variables. A Varimax rotation was used to simplify the interpretation of factors, and missing variables were excluded using a listwise deletion. The PCA performed in SPSS resulted in 7 factors using the default Guttman-Kaiser criterion (i.e., eigenvalue < 1.0). However, recent researchers often recommend Parallel Analysis (PA) as an additional method to further determine number of factors (Child, 2006; Lance, Butts, & Michels, 2006). Using a PA technique introduced by Child (2006), I found that only the first 6 factors are meaningful and the rest can be viewed as trivial error. Therefore, another PCA was performed in SPSS with the number of factors specified as 6. The resulting 6 factors combined explain more than 58% of the variance in the data.

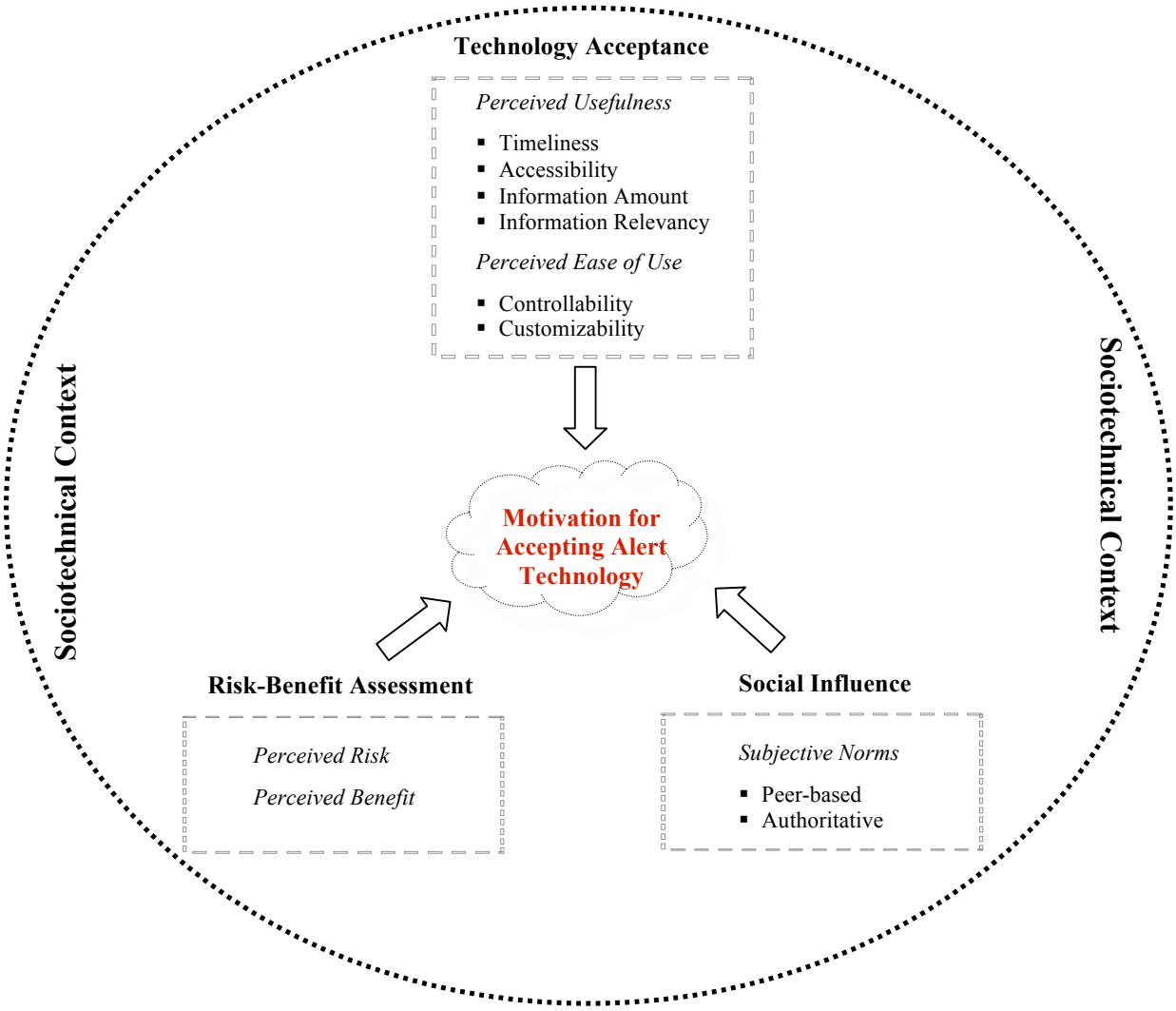

Figure 1: Research Framework

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.784
Bartlett's Test of Sphericity	Approx. Chi-Square	2989.124
	df	325
	Sig.	.000**

Table 1: KMO and Bartlett's Test

Two criteria were used to determine whether a variable was retained on a factor: 1) the rotated factor loading was greater or equal to .30; and 2) if a variable loaded on more than one factor, the variable was retained on the factor with the highest loading. The group of variables loading on each factor was examined against *a priori* constructs (from the literature and the qualitative study) to see if they confirmed the existence of those constructs. The resulting scale for each of the 6 factors was then examined for internal consistency using Cronbach's alpha, and factors 1, 2, and 3 were retained as their alpha values were greater than 0.7. To aid in further discussion of the factors, the researcher named each according to the variables that loaded together. Details about the factors are shown in Table 2 below:

Factor	**Factor Loading**	***A Priori* Construct**	**Questionnaire Item**
1 Perceived Utility	.762	Perceived Usefulness	I think the information that I receive from Campus Alerts will be relevant to my personal safety.
	.760	Perceived Benefit	Signing up makes me feel safer.
	.738	Perceived Benefit	Signing up is a good thing to do for myself.
	.730	Perceived Benefit	Signing up makes me more prepared for emergencies.
	.716	Perceived Usefulness	I believe I will receive timely information from Campus Alerts.
	.701	Perceived Usefulness	With Campus Alerts, I can get emergency information anywhere anytime.
2 Controllability Expectancy	.771	Perceived Ease of Use	I want to have control over the amount of text messages to be sent to me from Campus Alerts.
	.761	Perceived Ease of Use	I may get a lot of text messages from Campus Alerts.
	.739	Perceived Ease of Use	I want to have the option to choose what type of emergency messages to receive from Campus Alerts.
	.730	Perceived Usefulness	I may get some unwanted messages from Campus Alerts.
	.627	Perceived Cost	Receiving Campus Alerts messages can be costly.
3 Subjective Norm	.901	Subjective Norm	My friends think I should use Campus Alerts.
	.892	Subjective Norm	Other people who are important to me think that I should use Campus Alerts.
	.807	Subjective Norm	My parents think I should use Campus Alerts.

Table 2: Extracted Factors and the Associated Questionnaire Items

Test of Non-Response Bias

As mentioned earlier, one purpose of the paper-based survey was to check potential non-response bias given the low response rate of the online survey. That is, it is necessary to verify that the paper survey responses were not systematically different from the online responses on the three extracted factors. Hence, two sets of t-tests were conducted to compare: 1) Campus Alerts adopters' responses from the online survey and those from the paper survey, and 2) Campus Alerts non-adopters' responses from the online survey and those from the paper survey. The testing results generated by SPSS are shown in Table 3 below:

	Factor	T-test		
		t	df	Sig. (2-tailed)
Campus Alerts Adopters	Perceived Utility	-1.117	183	.266
	Controllability Expectancy	-1.658	183	.099
	Subjective Norm	-1.660	127	.099
Campus Alerts Non-Adopters	Perceived Utility	-.615	107	.540
	Controllability Expectancy	.640	107	.524
	Subjective Norm	-.085	80	.932

Table 3. T-Tests for Comparing Online Survey Responses and Paper Survey Responses

Table 3 shows that all sig values (*p*) are greater than .05, which indicates that on the three extracted factor scales the responses from the online survey and the paper survey are not significantly different for both Campus Alerts adopters and non-adopters. These t-tests results also increased the researcher's confidence on the representativeness of the sample and the external validity of any future analyses.

Hypothesis Testing

Guided by the research question, the first set of hypotheses focuses on whether the three factors were able to predict the acceptance *behavior*:

H1: Perceived utility is positively associated with the behavior of accepting Campus Alerts.

H2: Controllability expectancy is negatively associated with the behavior of accepting Campus Alerts.

H3: Subjective norm is positively associated with the behavior of accepting Campus Alerts.

The dependent variable was defined by the survey item: "*Have you signed up for Campus Alerts?*" The independent variables were the three factor scales which were found to have adequate internal consistency. The independent variables ranged in value from 1 to 7 as each was based on the mean of the respective scale items, with 1 being least favorable and 7 being most favorable. Since the value of the dependent variable is nominal (either signed up or not signed up), a logistical regression analysis was carried out. The categories of adopters and non-adopters were coded as 1 and 0, respectively.

Table 4 below shows that "controllability expectancy" ($p = .000$) and "subjective norm" ($p = .001$) were significant predictors of the acceptance behavior, while "perceived utility" ($p = .181$) was not. Hence, **H2** and **H3** were supported, but **H1** was not. "Controllability expectancy" also appeared to be a very strong predictor with a coefficient (*B*) value of –.804 and an odds ratio (*Exp(B)*) of 2.234.

Factor	B	S.E.	Sig.	Exp(B)
Perceived Utility	.260	.194	.181	.771
Controllability Expectancy	-.804	.168	.000**	2.234
Subjective Norm	.609	.186	.001**	.544
Constant	.587	1.200	.624	.556

Table 4. Logistical Regression Analysis of Factors Associated with Acceptance Behavior

After examining the associations between each of the three factors and the acceptance *behavior*, the researcher wanted to further explore how well the three factors predicted the *intention* of acceptance among the non-adopters. Therefore, another set of hypotheses were formulated:

H4: Perceived utility is positively associated with the Campus Alerts non-adopters' intention of accepting the system.

H5: Controllability expectancy is negatively associated with the Campus Alerts non-adopters' intention of accepting the system.

H6: Subjective norm is positively associated with the Campus Alerts non-adopters' intention of accepting the system.

The independent variables for this round of hypothesis testing were the same as the previous one, but the dependent variable was defined by the survey item: "*Overall, how likely are you going to sign up for Campus Alerts in the near future?*" The level of measurement for this item was a 7-point Likert scale with 1 = "very unlikely" and 7= "very likely". Since there were many missing values of "subjective norm" items for non-adopters, pair-wise exclusion was used in the regression analysis. The multiple regression analysis shows that the three independent variables altogether – perceived utility, controllability expectancy, subjective norm – explain approximately 40 percent of variance in the dependent variable (R^2 = .398); the analysis of variance suggests that the model can reliably predict the dependent variable (p = .000, F = 16.783). However, only the coefficient for "perceived utility" had a p value that is less than .05, whereas "controllability expectancy" and "subjective norm" did not appear to be significantly associated with the intention (Table 5). Therefore, in this round of hypothesis testing, only **H4** was supported.

Factor	**B**	**β**	**t**	**Sig.**
(Constant)	-.103		-.087	.931
Perceived Utility	.845	.534	4.989	.000**
Expected Controllability	-.160	-.087	-.965	.337
Subjective Norm	.184	.127	1.197	.235

Table 5. Multiple Regression Analysis of Factors Associated with Acceptance Intention

DISCUSSION

Although the survey respondents tended to agree that the Campus Alerts system is "beneficial", their perceptions of more concrete utilities of the system were less optimistic. The mean score of all survey respondents for the factor "perceived utility" was 4.79, and that of non-adopters was 4.32 – only slightly above the "neutral" point (4). Therefore, it is not surprising that **H1** was rejected, as both adopters and non-adopters had low ratings on the system utility. On the other hand, perceived utility was the only factor that had a significant correlation with non-user's intention of acceptance. This seemingly confusing result demonstrated students' mixed attitudes toward the usefulness of the alert technology: students generally believed that a technology like Campus Alerts might be able to improve the University's emergency preparedness, but the belief became rather weak when it comes to concrete utilities of the system such as information timeliness, information relevancy, and accessibility.

This might be in part due to the lack of "trialability" of Campus Alerts and many other emergency response technologies, as the benefits of using such systems in reality can only be assumed but not tried. As Rogers (2002) points out, preventive innovations generally diffuse slowly because the rewards "are often delayed in time, are relatively intangible, and the unwanted consequence may not occur anyway" (p. 991). For example, even though the university police send out test messages every month to ensure the system is operational, it is still unknown to students whether Campus Alerts will really help in a situation like campus shooting.

Controllability expectancy refers to the extent to which a user expects to control the behavior of a technology system. In this case, controllability encompasses the ability to control the type of alerts to be notified of and the amount of text messages to receive. Adopters and non-adopters of Campus Alerts had a significant difference in terms of how they expected the controllability. Non-adopters had a mean score of 5.38 on the scale (vs. 4.37 for adopters), indicating their strong inclination on being able to control the system behavior rather than to passively receive whatever information passed along by the police. A somewhat surprising finding was the lack of significant association between controllability expectancy and non-adopters' adoption intention. It might suggest that even though controllability is an important feature desired by the non-adopters, it is not a critical factor that affects their intention of use.

Subjective norm in this study refers to a student's perceived pressure from people important to him or her concerning their acceptance of Campus Alerts. The existing Campus Alerts users had a significant higher mean score (4.90) on the scale of subjective norm than the non-adopters (3.68), although the factor was not a strong predictor with an estimated odds ratio of .554. Subjective norm did not seem to associate with non-adopters' intention of acceptance (p=.235), either. A further investigation of the survey items grouped under the scale

revealed that for both adopters and non-adopters the social pressure from parents was the strongest, whereas that from friends was the weakest.

In assessing normative influences, researchers typically ask survey questions on whether "important others" think that one should perform a behavior. For example, Ajzen and Driver (1992) used these two items to assess subjective norm: "*Most people who are important to me approve/disapprove of …*" and "*Most people who are important to me think I should …*". However, the survey data suggested that the norms can have different degrees of effect on the adoption intention depending on where the social influence originated from. In this particular case, social pressure from parents seemed more salient than that from friends and from authorities.

IMPLICATIONS

Since its proposition in 1989 by Fred Davis, TAM has been the dominant paradigm in modeling user acceptance of information technology. Over the course of two decades, numerous studies have been done to validate, extend, and apply TAM in various research settings. Results from these studies generally confirms the power of TAM which consistently explain more than 50% of variance in acceptance (Dillon, 2001; Venkatesh et al., 2003). Indeed, it seems parsimonious that a user's acceptance behavior is determined by his intention of usage, which in turn is determined by perceived usefulness (PU) and perceived ease of use (PEU). Yet, these generic constructs in TAM often "seduced researchers into overlooking the fallacy of simplicity" (Bagozzi, 2007, p. 244) and steered them away from scrutinizing specific determinants in different usage contexts.

When it comes to refine TAM, most of the studies to date focused on extending the model by introducing more constructs so that high predicting power may be gained. This study, however, demonstrated an effort in deepening TAM through exploring local meanings of TAM constructs in a specific sociotechnical context. Thus, it is not my intention to extend TAM by adding yet another set of variables in order to better "predict" the emergency alert technology acceptance. As Bagozzi (2007) adequately put, such "broadenings" without explaining how the existing variables produce the effects they do are "unwieldy and conceptually impoverished." Hence, this study aims to provide a more holistic view of why the students refused to use such a simple technology that has obvious usefulness. Results of this research showed that: the concept of usefulness has multiple levels of meanings to its intended users; the ease of use is more about the users' ability to control the system behavior; and the subjective norm needs to be examined with relation to originating source (parents, friends, authorities, etc.).

The pervasiveness of mobile devices among young people certainly offers an opportunity to distribute critical information to this demographic group. A recent report from the Pew Internet Project showed that college students are highly likely to use extra cell phone features for communication and entertainment (Rainie & Keeter, 2006). For many college students, cell phones are part of their cultural identity that is formed from the hyperconnectivity with friends. However, the popularity of mobile devices and mobile applications does not necessarily translate into a smooth diffusion of mobile alert systems. Combined with the findings from the qualitative phase of this research project (Wu, Qu, & Preece, 2008), there seem to exist a mismatch between the one-to-many, top-down information distribution model adopted by emergency professionals and the peer-to-peer, social-networking-oriented information exchange model prevailing among young people. In other words, even though SMS as a communication medium may carry any kind of messages, the sociocultural meaning embedded in the medium greatly shapes how the messages are interpreted. The limited length of a SMS message and the private nature of SMS service make it ideal for instant social interactions but perhaps not for formal communications. This observation echoes Thurlow and Brown's (2003) finding in that most text messages exchanged among college students tend to have a "high intimacy and high relational" rather than "practical" orientation. This tech-cultural mismatch and the low acceptance rate of Campus Alerts suggest that using SMS for official emergency communication may not be an attractive idea to most of the students.

CONCLUSION

This study provides a basis for a critical assessment of the TAM model in the perspective of emergency response system adoption. Drawing attention to the holistic nature of motivation-behavior in technology acceptance, the study balances the over-individualized conceptions of acceptance in the IS tradition. The examination of theoretical constructs of TAM not only served a starting point for developing new theories and practices for community emergency response, but also provided a basis for deepening our understanding of technology acceptance behavior in general. The study also highlights some limiting aspects of SMS-based alert technology in relation to the technological characteristics of SMS and the cultural traits of the intended user group. Overall, the study establishes a good foundation for challenging new lines of research that more closely examine the motivations and barriers to user acceptance of emergency response technology.

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