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An Analysis of the Technology Acceptance Model in Understanding University Students' Behavioral Intention to Use e-Learning

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ABSTRACT
Many universities implement e-learning for various reasons. It is obvious that the number of e-learning opportunities provided by higher educational institutes continues to grow in Korea. Yet little research has been done to verify the process of how university students adopt and use e-learning. A sample of 628 university students took part in the research. The structural equation modeling (SEM) technique was employed with the LISREL program to explain the adoption process. The general structural model, which included e-learning self-efficacy, subjective norm, system accessibility, perceived usefulness, perceived ease of use, attitude, and behavioral intention to use e-learning, was developed based on the technology acceptance model (TAM). The result proved TAM to be a good theoretical tool to understand users' acceptance of e-learning. E-learning self-efficacy was the most important construct, followed by subjective norm in explicating the causal process in the model.

Keywords
e-Learning, Technology acceptance model, Structural equation modeling, Self-efficacy

Introduction

A recent trend in higher education has been to set up e-learning systems that provide students with online access and learning content. What drives this trend are changes in students' demographic factors, in educational delivery market conditions, and in innovation technology itself (Concannon, Flynn, & Campbell, 2005). There are, however, numerous barriers to the integration of instructional technology into higher education, such as technology infrastructure, faculty effort, technology satisfaction, and graduates competency (Surry, Ensminger, & Haab, 2005). Even many higher online educational institutions have failed due to the high cost of technology, poor decisions, competition, and the absence of a business strategy (Elloumi, 2004). Many universities that provide e-learning face enormous difficulty in achieving successful strategies, including the delivery, effectiveness, and acceptance of the courses (Saadé, 2003). Merely offering any conceivable course and attempting to replicate classroom experience online cannot meet the students' needs and may cause unexpected failure (Kilmurray, 2003). University students' persistent frustration in web-based education is another problem in terms of online learning. This drives more student-centered research of online education (Hara, 2000). With the growing reliance on information systems and increasing rapidity of the introduction of new technologies into learning environment, identifying the critical factors related to user acceptance of technology continues to be an important issue (Yi & Hwang, 2003).

Korea takes full advantage of ICT in supporting all levels of education and human-resource development, and e-learning is considered one of the important alternatives for current knowledge-based society (Kim & Santiago, 2005). Korea's e-learning readiness was ranked fifth in the world based on a report of the Economist Intelligence Unit (2003). Most universities have continued to offer partial, blended, or fully online e-learning courses since the late 1990s. At present, most off-line universities have either introduced an e-learning plan or have implemented e-learning. Despite quantitative growth of e-learning, there is growing concern that stresses quality assessment for e-learning in higher education in Korea (Lee, 2006). In addition, barriers in terms of e-learning utilization in universities or colleges still exist (Leem & Lim, 2007).

Consequently, developers and deliverers of e-learning need more understanding of how students perceive and react to elements of e-learning along with how to most effectively apply an e-learning approach to enhance learning (Koohang & Durante, 2003). In addition, knowing students' intentions and understanding the factors that influence students' beliefs about e-learning can help academic administrators and managers to create mechanisms for attracting more students to adopt this learning environment (Grandon, Alshare, & Kwan, 2005). Therefore, it is necessary to conduct research that deals more intensively with learners' perception of, attitude towards, and intention to use e-learning. However, little research has been done in Korea to empirically determine the relationship of university students' e-learning use with personal factors such as perceived usefulness, easiness, attitude, intention to use, and self-efficacy, with social factors such as subjective norm and organizational factors such as system accessibility.

Objectives

This study proposed an integrated theoretical framework of university students' e-learning acceptance and intention to use based mainly on the technology acceptance model (TAM). The objectives of the study were to analyze the relationship of university students' intention to use e-learning with selected constructs such as their attitude, perceived usefulness, perceived ease of use, self-efficacy of e-learning, subjective norm and system accessibility, and to develop a general linear structural model of e-learning acceptance of university students that would provide a school manager or an educator with implications for better implementing e-learning. Also determined were some descriptive characteristics of e-learning use and those selected constructs.

Research hypotheses

In accordance with the previously stated objectives and consistent with related literature, this study tested the following hypotheses:

- H_1: University students' behavioral intention to use e-learning is affected by their attitude (H_{11}), perceived usefulness (H_{12}), perceived easy of use (H_{13}), e-learning self-efficacy (H_{14}), subjective norm (H_{15}), and system accessibility (H_{16}).
- H_2: University students' e-learning attitude is affected by their perceived usefulness (H_{21}), perceived ease of use (H_{22}), e-learning self-efficacy (H_{23}), subjective norm (H_{24}), and system accessibility (H_{25}).
- H_3: University students' perceived usefulness of e-learning is affected by their perceived ease of use (H_{31}), e-learning self-efficacy (H_{32}), subjective norm (H_{33}), and system accessibility (H_{34}).
- H_4: University students' perceived ease of use of e-learning is affected by their e-learning self-efficacy (H_{41}), subjective norm (H_{42}), and system accessibility (H_{43}).

Literature review and theoretical framework

One of the well-known models related to technology acceptance and use is the technology acceptance model (TAM), originally proposed by Davis in 1986. TAM has proven to be a theoretical model in helping to explain and predict user behavior of information technology (Legris, Ingham, & Collerette, 2003). TAM is considered an influential extension of theory of reasoned action (TRA), according to Ajzen and Fishbein (1980). Davis (1989) and Davis, Bagozzi, and Warshaw (1989) proposed TAM to explain why a user accepts or rejects information technology by adapting TRA. TAM provides a basis with which one traces how external variables influence belief, attitude, and intention to use. Two cognitive beliefs are posited by TAM: perceived usefulness and perceived ease of use. According to TAM, one's actual use of a technology system is influenced directly or indirectly by the user's behavioral intentions, attitude, perceived usefulness of the system, and perceived ease of the system. TAM also proposes that external factors affect intention and actual use through mediated effects on perceived usefulness and perceived ease of use. Figure 1 depicts the original TAM (Davis, 1989).

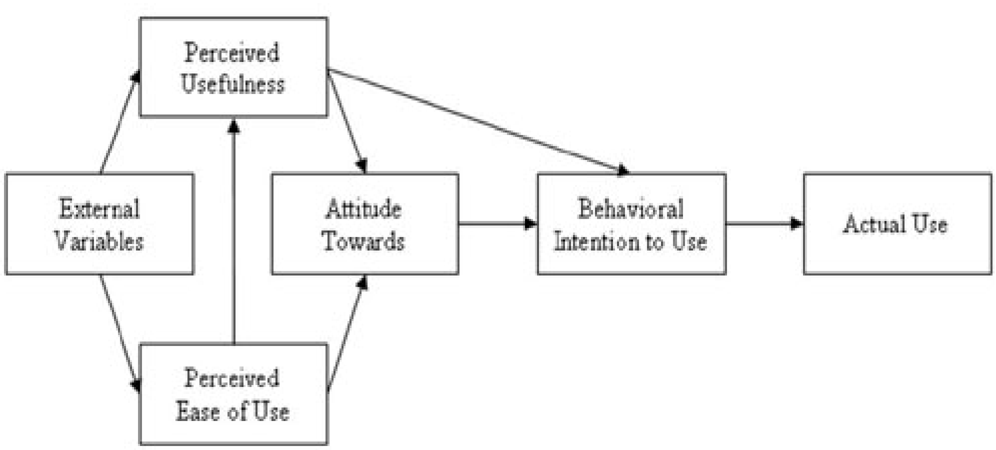

Figure 1. Original technology acceptance model (TAM)

TAM appears to be able to account for 40 percent to 50 percent of user acceptance. TAM has evolved over time. TAM2 extended the original model to explain perceived usefulness and usage intentions including social influence (subjective norm, voluntariness, and image), cognitive instrumental processes (job relevance, output quality, and result demonstrability) and experience. The new model was tested in both voluntary and mandatory settings. The results strongly supported TAM2 and explained 60 percent of user adoption using this updated version of TAM (Venkatesh & Davis, 2000). This study adopted TAM2 as the baseline model in addition to TAM.

Several studies have examined TAM as a model to explain how people adopt and use e-learning. Selim (2003) stated that there was a need to investigate TAM with web-based learning. He put forward the course website acceptance model (CWAM) and tested the relationships among perceived usefulness, perceived ease of use and intention to use with university students using the structural equation modeling techniques of the LISREL program. He concluded that the model fit the collected data and that the usefulness and ease of use turned out to be good determinants of the acceptance and use of a course website as an effective and efficient learning technology. Perceived usefulness can be defined as the extent to which a university student believes using e-learning will boost his or her learning. Meanwhile perceived ease of use is defined as the extent to which one believes using e-learning will be free of cognitive effort. In this study, e-learning refers to pure, web-based, asynchronous learning through an Internet site operated by the university. It is also supported by the learning management system (LMS) of the university

Lee, Cheung, & Chen (2005) did similar research with the LISREL program to investigate university students' adoption behavior towards an Internet-based learning medium (ILM) introducing TAM, but they integrated TAM with motivational theory. They included perceived enjoyment as an intrinsic motivator in addition to perceived usefulness and perceived ease of use into the TAM. According to their results, perceived usefulness and perceived enjoyment had an impact on both students' attitude toward and intention to use ILM. However, perceived ease of use was found to be unrelated to attitude. Meanwhile, Liu, Liao, and Peng (2005) integrated TAM with flow theory that emphasizes concentration on the structural model. They argued that university e-learning system users should be regarded as both system users and learners. In addition, Liu, Liao, and Peng adopted e-learning presentation type as an external variable into the model. They concluded that e-learning presentation type and users' intention to use e-learning were related to one another, and concentration and perceived usefulness were considered intermediate variables. Pituch and Lee (2006) added system and learner characteristics as external variables that were hypothesized to impact perceived usefulness, perceived ease of use, and use of an e-learning system. After conducting a structural equation modeling technique with LISREL, they concluded that system characteristics were important determinants to perceived usefulness, perceived ease of use, and use of an e-learning system, and that the theoretical model based on TAM was well supported. Saadé, Nebebe, and Tan (2007) also insisted that university students' participation and involvement were important to successful e-learning systems and therefore students' acceptance behavior should be assessed. They suggested that TAM was a solid theoretical model where its validity can extend to the multimedia and e-learning context.

Venkatesh and Davis (1996) focused on understanding the antecedents of the perceived ease of use. They concluded that computer self-efficacy acts as a determinant of perceived ease of use both before and after hands-on use and that the objective usability was found to be a determinant of ease of use only after direct experience with a system. In the meantime, Grandon, Alshare, and Kwan (2005) insisted that e-learning self-efficacy was found to have indirect effect on students' intentions through perceived ease of use. In addition, Mungania and Reio (2005) found a significant relationship between dispositional barriers and e-learning self-efficacy. They argued that educational practitioners should take into consideration the learners' dispositions and find ways through which e-learning self-efficacy could be improved. In this study, e-learning self-efficacy is generally represented as the personal confidence in finding information and communicating with an instructor within the e-learning system and the necessary skills for using the system.

As suggested in TAM2, subjective norm, one of the social influence variables, refers to the perceived social pressure to perform or not to perform the behavior (Ajzen, 1991). It seems important to determine how social influences affect the commitment of the user toward use of the information system for understanding, explaining, and predicting system usage and acceptance behavior (Malhotra & Galletta, 1999). According to the study done by Gradon, Alshare, and Kwan (2005), subjective norm was found to be a significant factor in affecting university students' intention to use e-learning. In contrast, the study done by Ndubisi (2006) showed that subjective norm had no significant effect on university students' intention to use e-learning. This kind of inconsistency may be resolved through the structural equation modeling (SEM), which indicates spurious effects and indirect effects as well as direct effects (Sobel, 1987).

In general, variables related to the behavioral intention to use information technology or to the actual use of information technology could be grouped into four categories: individual context, system context, social context, and organizational context. While social context means social influence on personal acceptance of information technology use, organizational context emphasizes any organization's influence or support on one's information technology use. Thong, Hong, and Tam (2002) identified relevance, system visibility, and system accessibility as organizational context variables. They reported that the organizational context affects both perceived usefulness and perceived ease of use of a digital library. Lin and Lu (2000) similarly reported that higher information accessibility brings about higher use of information and higher perception of ease of use. In this study, e-learning accessibility refers to the degree of ease with which a university student can access and use a campus e-learning system as an organizational factor.

Research design

Based on the previous research, a theoretical model was developed. Figure 2 represents a theoretically interesting model to be tested and analyzed. The arrows linking constructs (latent variables) specify hypothesized causal relationships in the direction of arrows. The arrows between constructs and indicators (observed variables) symbolize measurement validity. Perceived ease of use and perceived usefulness can be considered cognitive constructs. Attitude might be considered an affective construct. Meanwhile, intention to use could be regarded as a behavioral construct. In the model, *x* represents observed exogenous indicators and *y* represents observed endogenous indicators. To make the model simple to comply with space constraints, error terms for all observed indicators are excluded from the figure.

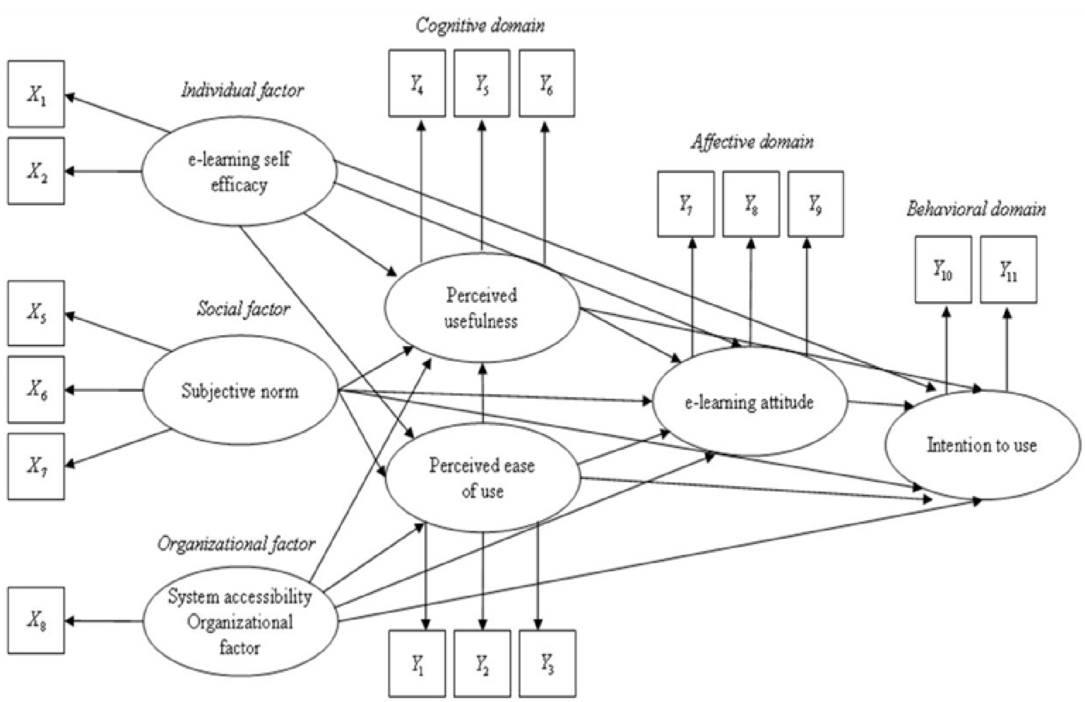

Figure 2. Theoretically interesting model

Method

Sample and procedure

The population in the study consist of university students at Konkuk University's Seoul Campus. There were 13,906 undergraduate students at the Seoul Campus. Among them 6,953 students took at least one e-learning course in the spring semester of 2007. Normally, a sample size of 200 subjects would be an appropriate minimum, if one wanted to use LISREL (Marsh, Balla, & MacDonald, 1988). Similarly, Newcomb (1992) insisted that no one should use LISREL with fewer than 100 subjects. Considering those statements and the number of parameter estimates, the number of sample subjects was set at 650, about 9 percent of the 6,953 students who were taking e-learning courses.

After deciding the number of sample subjects, the researcher adopted a cluster sampling method to choose e-learning courses. Twelve e-learning courses were randomly selected from the 39 e-learning courses offered by the university. Six hundred fifty questionnaires were distributed to the students with the aid of professors in charge of each e-learning course during the mid-term exam period and collected immediately after the mid-term exam because some courses did not have a final exam. Six hundred twenty-eight students from the selected e-learning courses voluntarily participated in the study. All written exams were executed at the assigned times and places in the campus to prevent cheating, even though all learning activities took place completely online. Table 1 presents the demographic profile of the sample.

Table 1. Demographic information of the sample

Variables	Number (*N*)	Percent (%)
School year		
Freshman	73	11.62
Sophomore	194	30.89
Junior	135	21.50
Senior	226	35.99
Gender		
Male	416	66.24
Female	212	33.76
Number of e-learning courses taken this semester		
1	379	60.35
2	181	28.82
3	55	8.76
4 or more	13	2.07
Number of e-learning courses taken previously		
None	221	35.19
1	105	16.72
2	125	19.90
3	76	12.10
4	47	7.48
5 or more	54	8.60
Availability of high-speed Internet at home		
Yes	594	94.59
No	34	5.41
Total	628	100.00

Instrumentation

The instrument was developed by the researcher based on the objectives of the study and previous literature review. Content validity was established by pilot testing the instrument with 25 people: two e-learning administrative staff members, three graduate students in the Department of Educational Technology, and 20 students in Konkuk University. The completed instrument consisted of four parts. Part I was designed to identify demographic attributes of the respondents. It contained demographic items such as academic years, gender, the number of e-learning courses currently being taken, the number of e-learning courses previously taken, e-learning experience from other educational institutes, and the availability of high-speed Internet at home.

The questions in Part II were not only made based on Davis's prior studies with modifications to fit the specific context of the e-learning but also mainly adapted from the three studies for the objectives of the study: Lee, Cheung, & Chen, (2005); Ndubisi (2006); and Malhotra & Galletta (1999). Part II consisted of four sub-sections, as follows: perceived ease of use (PE), perceived usefulness (PU), attitude (AT), and behavioral intention (BI). The questions in Part III were developed by the researcher to measure e-learning self-efficacy (SE). It was measured by two indicators: confidence in finding information in the e-learning system and degree of necessary skills for using an e-learning system. The questions in Part IV were divided into two sections: subjective norms (SN) and system accessibility (SA). Subjective norms as social influence factors were measured mainly by adapting the scales done by Malhotra and Galletta (1999). Since most students have computers with Internet at home, system accessibility as an organizational factor was measured by only one indicator in the study, which was the difficulty in accessing and using e-learning systems in the university. All constructs were measured on seven-point Likert-type scales, from 1 = strongly disagree to 7 = strongly agree.

Statistical procedure

Data collected by the questionnaire were coded by research assistants. The data were recorded first in an MS Excel program and later transferred to Statistical Analysis System (SAS), Windows version 9.3. A random sample of five percent of the entered data was checked for coding accuracy. Descriptive statistical analyses such as mean, standard deviation, frequency, percent, and correlation were implemented using SAS. In order to test the hypotheses by structural equation modeling (SEM), LISREL Windows version 8.3 was employed.

Result

Analysis of measurement model

In the measurement model, both convergent and discriminant validity were checked. Convergent validity implies the extent to which the indicators of a factor that are theoretically related should correlate highly. All factor loadings (lambda *x* and lambda *y)* exceeded .70, which accounts for 50 percent of variance. Considering the sample size of the study, these scores are significant at a .05 significance level and a power level of 80 percent (Hair, Anderson, Tatham, & Black, 1998). Discriminant validity was confirmed by examining correlations among the constructs. As a rule of thumb, a .85 correlation or larger indicates poor discriminant validity in structural equation modeling (David, 1998). None of the correlations presents above .85. The result suggests an adequate discriminant validity of the measurement. The correlation matrix between constructs is shown in Appendix A. The correlation matrix between observed indicators is shown in Appendix B.

Two reliability tests were carried out to secure accuracy and consistency. Composite reliability (α) was obtained for each construct. Another measure of reliability calculated was the variance extracted measure (ρ). In general, a commonly used threshold value for acceptable composite reliability is .70. Meanwhile, guidelines recommend that the variance extracted value should exceed .50 for a construct. All measures fulfill the suggested levels with composite reliability ranges from .76 to .94 and variance extracted value ranges from .63 to .82. Table 2 shows the result of a confirmatory factor analysis and reliability test with some descriptive statistics, mean, and standard deviation. Figure 3 also describes graphically the relationships between constructs and observed indicators, presenting loadings and residuals.

Table 2. Summary of means, standard deviations, construct loadings, and reliabilities

Construct	Measurement instrument	Mean (STD)	Loading	α/ρ
Perceived ease of use (PE)	I find e-learning system easy to use (E_1).	5.36 (1.16)	.84	
	Learning how to use an e-learning system is easy for me (E_2).	5.62 (1.18)	.95	.93/.82
	It is easy to become skillful at using an e-learning system (E_3).	5.65 (1.16)	.92	

Perceived usefulness (PU)	E-learning would improve my learning performance (U_1).	4.27 (1.29)	.91	
	E-learning would increase academic productivity (U_2).	4.30 (1.31)	.93	.88/.74
	E-learning could make it easier to study course content (U_3)	4.20 (1.39)	.72	
Attitude (AT)	Studying through e-learning is a good idea (A_1).	4.69 (1.43)	.95	
	Studying through e-learning is a wise idea (A_2).	4.51 (1.41)	.93	.94/.84
	I am positive toward e-learning (A_3).	4.16 (1.39)	.86	
Behavioral intention (BI)	I intend to check announcements from e-learning systems frequently (B_1).	4.88 (1.07)	.74	.79/.66
	I intend to be a heavy user of e-learning system (B_2).	4.52 (1.22)	.88	
e-learning self-efficacy (SE)	I feel confident finding information in the e-learning system (S_1).	4.57 (1.16)	.85	.76/.63
	I have the necessary skills for using an e-learning system (S_2).	4.92 (1.23)	.73	
Subjective norm (SN)	What e-learning stands for is important for me as a university student (N_1).	4.07 (1.27)	.84	
	I like using e-learning based on the similarity of my values and society values underlying its use (N_2).	3.85 (1.37)	.86	.89/.73
	In order for me to prepare for future job, it is necessary to take e-learning courses (N_3).	4.02 (1.41)	.84	
System accessibility (SA)	I have no difficulty accessing and using an e-learning system in the university (SA).	5.01 (1.53)	1.0	n/a

Scale: 1 = strongly disagree ~ 7 = strongly agree. All loadings were significant based on t-*values.*

Table 3 shows a summary of the overall model fit measures. Except for the χ^2 test result, all absolute measures were significant and considered acceptable. Since χ^2 statistics are sensitive to the number of subjects and require assumption of multivariate normal distribution, other measures are better to consider as criteria for model fitting. Truly, it is difficult to accept null hypothesis from the χ^2 test result with large sample size, even though the model fits well the collected data (Kelloway, 1998).

In addition to absolute values which are the root mean squared residual (RMR), the root mean squared error of approximation (RMSEA), the goodness-of-fit index (GFI), and the adjusted goodness-of-fit index (AGFI), NFI as comparative fit measures, and the critical N (CN) were examined. NFI ranges from 0 to l, with values exceeding .9 indicating a good fit (Bentler & Bonnet, 1980). CN is a simple index and tentative acceptance criterion that, by focusing on sample size, provides an improved method for assessing goodness-of-fit (Hoelter, 1983). CN favors often large samples over small ones (Bollen, 1990). The researcher included this measure because of the relatively large size of the sample, 628. A fixed cutoff value is 200, and above 200 is generally regarded as a good fit to the data. Assessing all measures, the full general structural model was accepted and believed to be good enough to analyze the parameter estimates.

The general structural model was used to test the simple bivariate relationships between the constructs included in the model. Hypotheses testing was conducted within the context of the structural model. This simplified the interpretation of the results because a relationship between two constructs could be examined while holding constant other constructs in the model.

Table 3. Goodness-of-fit measures for SEM

Fit measures	Values	Recommended value
χ^2	223.4 (p = .00)	p > .05
RMR	.033	< .05
RMSEA	.045	< .10
GFI	.959	> .90
AGFI	.937	> .90
NFI	.972	> .90
CN	363.880	> 200

Gamma (from exogenous construct to endogenous construct) and Beta (from endogenous construct to endogenous construct) estimates which were statistically significant are denoted by asterisks. A *t*-value was used as a criterion to test the significance of the parameters at the .05 level. A *t*-value was defined as the ratio between the parameter estimate and its standard error (Jöreskog & Sörbom, 1989). *T*-values larger than two in magnitude were judged to be significantly different from zero in this study. A *t*-value larger than three was represented by two asterisks, while one asterisk represented a *t*-value between two and three.

Hypotheses were examined by confirming the presence of a statistically significant relationship in the predicted direction. As far as behavioral intention is concerned, attitude, e-learning self-efficacy, and subjective norms were identified to be significant. In terms of attitude, perceived usefulness, perceived ease of use, and subjective norms turned out to be significant. System accessibility had no effect on perceived usefulness. On the other hand, subjective norm had no significant relationship with perceived ease of use. The parameter estimates for the hypothesized paths, their *t*-values, and result of hypotheses are summarized in Table 4.

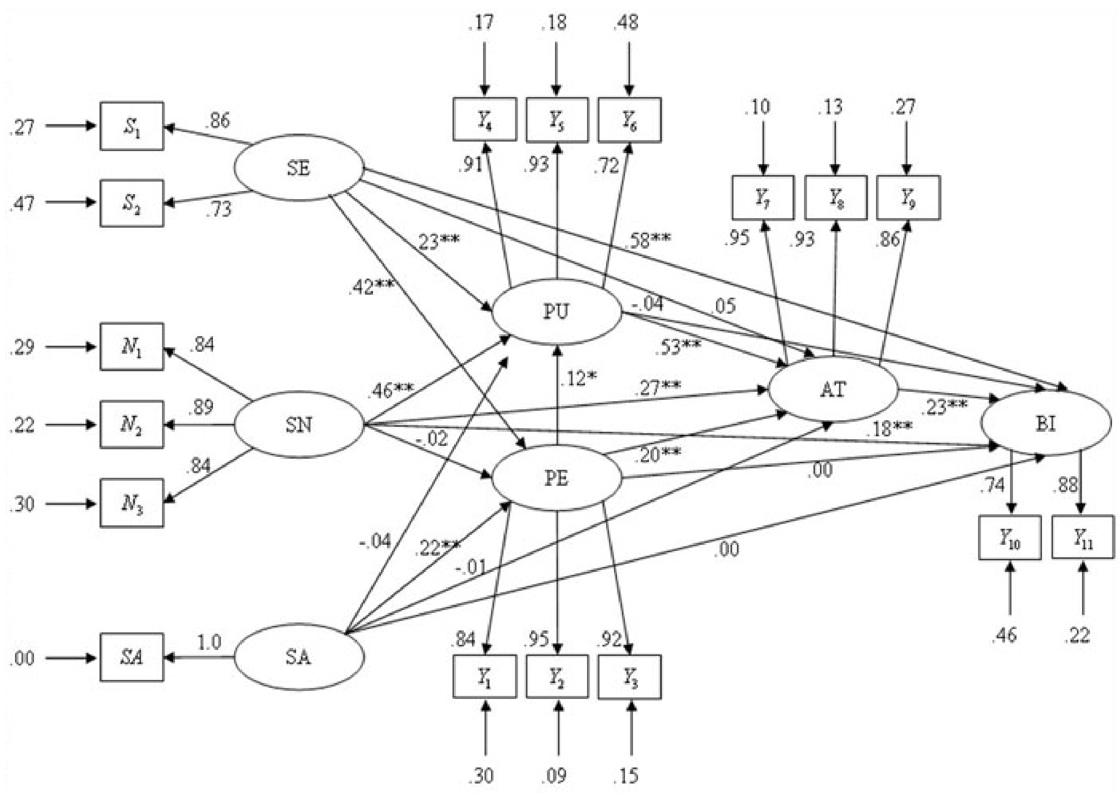

Figure 3. Parameter estimates of general structural model

Several trends were evident in the magnitude of the bivariate relationships proposed by the model. In the context of behavioral intention, key endogenous constructs of the study, all the relationships among the constructs were significant except parameter estimates from perceived usefulness, perceived ease of use, and system accessibility to behavioral intention to use. The strongest magnitude was found in a relationship between e-learning self-efficacy and behavioral intention ($\gamma_{41} = .58$), followed by attitude ($\beta_{43} = .23$).

In contrast, both perceived usefulness and perceived ease of use were found significant in affecting user attitude. Perceived usefulness ($\beta_{32} = .53$) had the largest effect on user attitude. According to the direct effect estimates, the subjective norm was identified as the largest determinant to perceived usefulness ($\gamma_{22} = .46$), and e-learning self-efficacy had the largest effect on perceived ease of use ($\gamma_{11} = .42$). Finally, system accessibility was found to be non-significant to all constructs except perceived ease of use.

Considering the above statements, e-learning self-efficacy was the most important variable, followed by subjective norm, in influencing behavioral intention to use e-learning. In fact, these constructs were also identified as important to attitude, according to the total effect estimates.

Table 4. Parameter estimates, *t*-value, and results of hypotheses

Hypothesized path	Standardized estimate				Result of hypotheses
	Direct effect	(t-value)	Indirect effect	Total effect	
AT → BI (H_{11})	.225	(3.31 **)		.225	Supported
PU → BI (H_{12})	−.04	(−.60)	.118	.082	Not supported
PE → BI (H_{13})	.002	(.10)	.052	.057	Not supported
SE → BI (H_{14})	.579	(7.08**)	.054	.633	Supported
SN → BI (H_{15})	.184	(3.44**)	.096	.280	Supported
SA → BI (H_{16})	.002	(−.12)	.006	.00	Not supported
PU → AT (H_{21})	.526	(11.36**)		.526	Supported
PE → AT (H_{22})	.199	(5.57**)	.052	.251	Supported
SE → AT (H_{23})	.049	(1.11)	.229	.278	Not supported
SN → AT (H_{24})	.265	(6.49**)	.238	.503	Supported
SA → AT (H_{25})	−.01	(−.30)	.036	.021	Not supported
PE → PU (H_{31})	.116	(2.65*)		.116	Supported
SE → PU (H_{32})	.234	(3.96**)	.049	.283	Supported
SN → PU (H_{33})	.461	(9.17**)	.238	.459	Supported
SA → PU (H_{34})	−.04	(.93)	.026	−.011	Not supported
SE → PE (H_{41})	.422	(6.78**)			Supported
SN → PE (H_{42})	−.02	(−.36)			Not supported
SA → PE (H_{43})	.222	(6.19**)			Supported

Conclusion and discussion

Similar to earlier studies (Lee, Cheung, & Chen, 2005; Saadé, Nebebe, & Tan, 2007), this study confirmed TAM to be a useful theoretical model in helping to understand and explain behavioral intention to use e-learning. Results of the present research led to the conclusion that the model well represented the collected data according to the result of goodness-of-fit test.

One of interesting results of the study is that both e-learning self-efficacy and subjective norm play an important role in affecting attitude towards e-learning and behavioral intention to use e-learning. One possible explanation for this may be justified by motivational theory. E-learning self-efficacy may be considered an intrinsic motivational factor and subjective norm may be an extrinsic motivational factor that could help the university students self-regulate their motivation on e-learning. According to Bandura's social motivational theory, higher self-efficacy results in a more active learning process (1994). On the other hand, subjective norm under the social influence factor pertains to behaviors that are engaged in response to recognition of other people. In Korea, people are encouraged to use IT in every field to catch up with the social change caused by IT. University students may want to adopt e-learning because they think e-learning experience will be beneficial for future job preparation. Or, they feel emotionally afraid of falling behind other students who use e-learning, if they don't take e-learning courses.

System accessibility as an organizational factor was not dominant exogenous construct affecting all endogenous construct except perceived ease of use. This may be a natural result because Korea has a developed infrastructure of IT and almost 95 percent of those in the study's sample have high-speed Internet at home. Hence, it doesn't matter whether the university provides easy access to the student or not. In fact, Konkuk University has already set up ubiquitous learning infrastructure with WIBRO technology for e-learning.

In the context of endogenous constructs, neither perceived usefulness nor perceived ease of use had a significant direct effect on behavioral intention to use e-learning. According to the original TAM, perceived usefulness is hypothesized to affect intention to use, and perceived ease of use is not hypothesized to directly affect intention. Some parts of this research were consistent with previous research, whereas some parts were contrary to previous results. One possible clue is, nowadays, learning to use the Internet is normally considered easy and the benefits from learning through Internet are already well known to students in Korea. Many university students gained enough experience in e-learning through the government (EDUNET, http://edunet4u.net and EBS, http://ebs.co.kr) during their high-school days. Therefore, both cognitive constructs could not directly affect the university students' intention to use e-learning. Rather, those constructs affected attitude towards e-learning and their attitudes affected intention to use.

The result of the study demonstrated that some TAM constructs had a direct and indirect effect on university students' behavioral intention to use e-learning. For that reason, there is potential for practical application in the development and management of e-learning in university. First, educators and managers should make an effort in boosting university students' e-learning self-efficacy. Both on- and off-line support should be provided to build up e-learning self-efficacy. In Konkuk University, an e-learning introduction, e-learning manuals, and an e-learning strategy developed by the Center for Teaching and Learning would be good examples.

Second, subjective norm is the second most important construct that affects both behavioral intention and attitude towards e-learning. Therefore, it is necessary for the university to put more emphasis on e-learning by offering a greater variety of e-learning courses and advertising the benefits of e-learning to attract students.

Third, even though perceived usefulness and ease of use had no direct effect on university students' intention to use e-learning, these constructs were related to the attitudes toward e-learning. Overlooking these constructs could have detrimental effects on the user's acceptance of information technology. Thus, it is necessary that managers and developers of e-learning help students confirm or increase their perception positively through e-learning. One possible solution is to develop more user-friendly and user-oriented e-learning content and LMS. This kind of system will add new perception to the previous attitude and thus bring about more satisfaction. This satisfaction in turn encourages students to optimistically make further use of e-learning.

Finally, this type of research needs to be implemented in other e-learning circumstances or infrastructures. Since the result of the study was limited to only 100 percent asynchronous e-learning, researchers may conduct similar studies to deal with blended learning or synchronous e-learning. Since little research has been done with those types of e-learning, it is highly recommended to carry out research employing TAM.

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Appendix A — Correlation matrix between constructs

Constructs	BI	AT	PE	PU	SE	SN	SA
Behavioral Intention (BI)	1.00						
Attitude toward e-learning (AT)	.644	1.00					
Perceived ease of use (PE)	.440	.465	1.00				
Perceived usefulness (PU)	.556	.776	.347	1.00			
E-learning self-efficacy (SE)	.786	.561	.510	.528	1.00		
Subjective norm (SN)	.624	.661	.275	.610	.543	1.00	
System accessibility (SA)	.361	.288	.402	.246	.440	.288	1.00

Appendix B — Correlation matrix between observed indicators

Indicator	B1	B2	A1	A2	A3	U1	U2	U3	E1	E2	E3	S1	S2	N1	N2	N3	SA
B1	1.0																
B2	.65	1.0															
A1	.40	.53	1.0														
A2	.43	.56	.89	1.0													
A3	.42	.52	.81	.80	1.0												
U1	.38	.46	.67	.64	.60	1.0											
U2	.36	.44	.69	.67	.61	.85	1.0										
U3	.30	.40	.57	.55	.51	.65	.66	1.0									
E1	.38	.38	.47	.38	.40	.35	.33	.28	1.0								
E2	.35	.33	.44	.35	.39	.29	.28	.23	.80	1.0							
E3	.35	.33	.42	.35	.37	.29	.30	.22	.76	.88	1.0						
S1	.52	.60	.47	.46	.39	.43	.42	.35	.42	.35	.38	1.0					
S2	.43	.46	.37	.35	.36	.33	.32	.29	.44	.39	.43	.62	1.0				
N1	.38	.50	.54	.55	.53	.48	.47	.39	.28	.23	.21	.43	.28	1.0			
N2	.36	.48	.53	.55	.52	.49	.50	.41	.25	.20	.19	.44	.30	.74	1.0		
N3	.35	.48	.50	.51	.49	.47	.46	.37	.25	.23	.21	.39	.28	.70	.75	1.0	
SA	.31	.30	.26	.27	.29	.24	.21	.20	.37	.38	.36	.34	.39	.24	.25	.25	1.0