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Conceptualizing and Measuring the Optimal Experience of the eLearning Environment*

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ABSTRACT

Online learning (eLearning) has become a global phenomenon as many organizations and educational institutions worldwide have entered the field in an attempt to enhance the students' experience of learning. While numerous studies have focused on the effectiveness and benefits of eLearning, few have focused on understanding and measuring the user experience and relating this to the actual student usage of the eLearning system. This study addresses this gap by conceptualizing and measuring the eLearners' experience from two integrated perspectives: (1) the learners' affective perceptions using the flow model and (2) the learners' technology acceptance using the Technology Acceptance Model. The integrated perspective proposes that the users' acceptance and the affective responses toward a particular system are two important factors in determining the users' intentional and actual behaviors, which in turn, influence user participation and engagement with the system. The data was collected in 2004 directly from 964 students using a Web-based eLearning system called CECIL (www.cecil.edu) at the University of Auckland. The conclusions drawn from the results of the study using a structural equation model support the use of the integrated model for investigating eLearner behavior. The research implications of our findings are discussed.

Subject Areas: eLearner Experience, Effectiveness, Flow, System Usage, and Technology Acceptance Model (TAM).

INTRODUCTION

The Internet grew exponentially from 40 million users in 1996 to more than 300 million users in 2000. By the end of 2005, there will be approximately one billion Internet users worldwide (Angus Reid, 2000). Closely following the dramatic growth in Internet usage has been the rise in eLearning (Rungtusanatham, Ellram, & Siferd, 2004; Janicki & Steinberg, 2003), which has revolutionized the way in which information and educational content can be delivered. As Flynn (2003,

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p. i) argues, this transformation of the classroom has been significant and "there are few of us who have not been affected by this debate . . ." The U.S. Department of Education quantifies the level of change by stating that more than 3 million people were enrolled in online classes in the United States in 2001 and that 6 million are projected for 2006 (Conhaim, 2003) because it gives the opportunity to students "who could not otherwise further their education because of distance, employment and family responsibilities" (Bruce & Hwang, 2001, p. 621). The advance of information and communication technologies, together with the recent emergence of Internet technologies, has provided unprecedented opportunity for institutions of higher education to meet the educational needs of a greater portion of the population than ever before (Post & Whisenand, 2005). "There is little doubt that more and more college classes will be placed online in the future, and we are fast approaching the point when it will be the norm to have several courses online at the universities throughout the nation" (Giegerich, 2003; Bennett & Green, 2001, p. 495).

eLearning is also moving to the forefront to meet the training needs of corporations as the growth of the Internet brings online education to people in the workplace. The training industry was estimated to be worth $60 billion worldwide in 2004, with $6.6 billion coming from eLearning. Overall, the eLearning market is expected to be worth $23.7 billion by 2006 (CRM Today, 2003). "Emerging technologies, especially the World Wide Web, offer promising new avenues for providing staff development activities to update the knowledge and skills of practitioners, especially in rural and remote areas"(Ludlow, Foshay, Brannan, Duff, & Dennison, 2002, p. 33).

In sum, eLearning is often described as having the potential to overcome the place and time limits of the traditional face-to-face teaching methods (Webb, Gill, & Poe, 2005) and many researchers have cited its usefulness in enhancing the experience of the learning environment (Roed, 2003; Atack & Rankin, 2002; King, 2001). However, this view has been balanced by several studies that show the relatively high dropout rates for eLearning when compared to those of traditional face-to-face classes (McLaren, 2004). Frankola (2001) found evidence of higher dropout rates for distance learners and it was concluded that eLearning dropout behavior could be attributed to a less than optimal online experience (James Madison University, 2003). Therefore, one of the major research questions focusing on the effectiveness of eLearning should be to understand how to motivate students to be experientially involved in the learning process. There is a need for a model that can be used to identify factors that affect the students' online learning experiences and the psychological state effects on online behavior. However, Hara and Kling (1999) claim that many of the studies on online learning remain anecdotal and that they come from the point of view of the teacher and focus on the positive aspects only. They conclude that researchers need to consider the actual experiences of the learners. Song, Singleton, Hill, and Koh (2004, p. 60) also argue that "online learning is not grounded in convincing empirical evidence that is beneficial for learning and that there is a need for continuing research studies related to their overall perceptions."

While there is much literature focused on technical issues, less attention has been given to students' experiences (Schrum, 1998). For this reason, studies of the learners' perspectives of the eLearning environment are needed in order to build more effective Web-based instruction that can optimize the learning experience and to encourage enduring use. It is only with greater learner perseverance that the true potential of eLearning will be fully achieved and its growth rate maintained.

In response, this study focused on the effectiveness of eLearners' experiences from two integrated perspectives to be discussed further in the conceptual foundations, that is; (1) the learners' affective perceptions using the flow model (Novak, Hoffman, & Yung, 2000) such as the experience of flow (intrinsic enjoyment, loss of self-consciousness), behavioral properties of the flow activity (seamless sequence of responses facilitated by interactivity with the computer and self-reinforcement), and its antecedents (skill/challenge balance, focused attention, and telepresence) and (2) the learners' technology acceptance (Gefen, Karahanna, & Straub, 2003; Davis, 1989). The integrated perspective proposes that users' acceptance and their affective responses toward a particular system are two important factors in determining the users' intentional and actual behaviors, which in turn, influence user participation and engagement with the system.

We listen to Flynn (2003, p. i) who argues for studies that "investigate this issue from a number of perspectives." Also Baugher, Varanelli, and Weisbord (2003) call for new measures in determining the changing role of Web-based courseware in student performance. This approach is also consistent with Roussev and Rousseva (2004) in their examination of cognitive skills and active learning. Therefore, the research questions that focus our study are:

RQ1: What factors contribute to the learners' experience of the cognitive state of flow in an eLearning environment?

RQ2: What factors contribute to the experience of the learners' cognitive acceptance of technology in an eLearning environment?

RQ3: What is the empirical relationship between the learners' cognitive state of flow and acceptance of technology in an eLearning environment?

Besides the lack of attention paid to the empirical relationship between flow and technology acceptance (Liaw & Huang, 2003), there has been relatively little work that focuses on the antecedents as well as the consequences of flow and technology acceptance in the eLearning context. This study provides empirical evidence regarding the observed relationships and has implications for business practice. The results of the study can be used as benchmarking to provide quantitative indicators and as a means of comparison when evaluating the importance of different eLearning issues.

This article takes the following form. We begin with a description of the conceptual foundations of this research. To develop this we first define eLearning. Upon this foundation our focus is then on understanding the optimal elearning experience and integrated conceptual model. Subsequently, we describe our methodology and results. The article concludes with a discussion of the results as well as the research implications of this contribution.

CONCEPTUAL FOUNDATIONS

Defining eLearning

According to Bose (2003) eLearning involves the use of the Internet and other related information technologies to create experiences that foster and support the process of education. Apart from enhancing the convenient experience, which is often cited as the most compelling reason to implement and use such systems, several authors contend that the most critical elements of online learning are the ability to foster interaction among students and interaction between instructors and students (Box, 1999; Kirby, 1999). "Meaning is not imposed or transmitted by direct instruction, but is created by the students' learning activities, [by] their 'approaches to learning . . ." (Biggs, 1999, p. 12). Moore (1989) argued that there are three primary types of interaction that can occur either synchronously or asynchronously: learner–content interaction, learner–instructor interaction, and learner–learner interaction (Hardaway & Scamell, 2003; Moore, 1989). These types of interactions are important in eLearning because they also facilitate peer interactions, collaborative learning, and peer review. According to Schrage (1991) the goal is to produce a shared experience rather than an experience that is shared. Working with others often increases involvement in learning by allowing sharing of individuals' ideas and responding to others' reactions and the collaboration improves thinking and deepens understanding (Klipowicz & Laniak, 1999; Regalbuto, 1999).

When students are given opportunities to discuss and to interact, they can adapt their understandings and reflect upon them (Hall, 2002). Peer interactions are crucial to learning because they set up circumstances in which learners perceive an internal need to reconcile different perspectives to resolve conflicts of interpretation (Vygotsky, 1986), that is, learners become part of the learning process. This type of interaction has benefits for problem-solving situations (Adelskold, Alklett, Axelsson, & Blomgren, 1999) and contributes to learner satisfaction and frequency of interaction in online learning (Jung, Choi, Lim, & Leem, 2002; Gunawardena & Zittle, 1997).

While the recent emergence of networked technologies has expanded the delivery mechanism for education, it has also changed the way students have traditionally experienced the learning environment. Because online courses delivered via the World Wide Web offer widespread accessibility and asynchronous learning, eLearners no longer need to meet face to face with classmates and instructors (Webb, Gill, & Poe, 2005; Clouse & Evans, 2003). Interaction between students, instructors, and learning content via the computer-mediated communication in an online environment requires a shift from oral discourse to a dependence on written and visual communication. eLearners also become more responsible for completing instructional tasks without the explicit oral instructions provided in face-to-face settings. Cheung and Kan (2002) and others found that the level of ownership of the learning process has a positive association with student performance (Chan & Shum, 1997). These situational differences in the eLearning environment, when compared with traditional learning settings, hold substantial implications for educators and eLearning designers who are responsible for providing online instructional environments.

As a result, it is important to examine eLearners' experiences in order to provide an optimal learning environment (Howland & Moore, 2002). These authors revealed that many of the students did not realize how much they needed to know about using the features of the online course management tools, such as the discussion board and chat room. They found that many students who perceived the Internet course as being difficult reported technical challenges with their online learning experience. These challenges can not only limit the amount of participation and engagement with online learning activities when the student is feeling uncomfortable with the online environment, but it also makes the educational organization fail to effectively utilize the expected pedagogical gains and organizational benefits delivered by eLearning systems.

Because eLearning shifts control from instructor to learner, there is nothing the instructor can do to prevent students from putting off performing online learning activities when the rest of the Web is merely a click away. As a result, in order to succeed in eLearning, Rossett and Schafer (2003) advise that online students must rely on themselves to take an active role in the online environment. Otherwise, they may be easily betrayed by the anywhere, anytime concept of online courses and get behind (Rossett, 2000) until they find that they are not able to complete the online course within the allotted time frame (Hiltz, 1994). Moreover, as noted by Lee (1986), the availability of the technology does not guarantee increased utilization. The patterns of usage can vary substantially when use is optional (Lee, 1986). Consequentially, more organizations are requiring evidence that the eLearning system will be widely accepted and effectively utilized by its intended users before implementing it. This is because most system usages are voluntary due to limitations of control from the instructors in the online environment. Therefore, approaches need to be put in place to encourage students to play a greater role in their learning environment online. For example, courses that have group work can encourage students to use the online environment to manage and facilitate group interactions.

The Optimal eLearning Experience

In this study we argue that the evidence of the success of an eLearning system can be defined by the three core components of the students' optimal experience, that is: (1) system use, (2) technology acceptance, and (3) the flow experience. System use is the consequence of the students' technology acceptance and flow experience.

System Use

In this study, the eLearning system's success is measured by eLearner participation and engagement in terms of eLearning system usage. Among the various theories and models researching such information technology–enabled system success, the predictor of success that has received the most attention is system use, either intended or actual. While authors like Seddon (1997) argue that the critical factor for system success measurement is not the system use but the net benefits derived from use. However, he also argues that by simply measuring system use as an indicator of success, researchers will have to assume that a positive relationship between time spent using a system and the benefit it provides exists. As Szajna (1993) has pointed out, this assumption is not necessarily correct. While usage is clearly not the same as eLearning system success, it has been considered by many researchers to be a necessary precursor and important issue to all stakeholders (DeLone & McLean, 1992). Others, like Al-Gahtani and King (1999) state that system use has been used by a number of researchers in the past two decades (Davis et al., 1989; Trice & Treacy, 1988; Srinivasan, 1985; Robey & Zeller, 1978;

Lucas, 1975) as a surrogate indicator of system success (Al-Gahtani & King, 1999). Consequently, we speculate, on the basis of previous research, that system use is a key variable in understanding and measuring the outcome of eLearning system success.

Technology Acceptance Model (TAM)

However, in response to the concern that usage is not enough to measure the outcome of success, our attention moves toward understanding and explaining individual attitudes toward new information technology adoption and acceptance. This component of the conceptual model focuses on the eLearners' perceptions of technology acceptance using the TAM (Venkatesh & Davis, 2000; Davis, 1989; Davis, Bagozzi, & Warshaw, 1989). This model has been widely used to predict the acceptance of information technology and the validity has been demonstrated across a wide variety of information technology systems (Lederer, Maupin, Sena, & Zhuang, 2000). The model postulates that the two variables, perceived usefulness and perceived ease of use, jointly determine an individual's behavioral intention to use a technology, which in turn, affects actual use (Hackbarth, Grover, & Yi, 2003). In addition, perceived usefulness is expected to be influenced by perceived ease of use because, other things being equal, the easier a technology is to use, the more useful it can be (Venkatesh, 1999). From the standpoint of its definition, theoretical development and operationalization, perceived ease of use can be regarded as process expectancy because it is a construct focused on an individual's perception about the level of effort needed to use a system. It represents the user's subjective evaluation of the process of interaction with a system.

In contrast, perceived usefulness can be regarded as outcome expectancy because it is a construct measuring the user's subjective perception of the extent to which using a particular information system will aid work performance and enhance productivity (Davis, 1989). According to Agarwal and Karahanna (2000), users' perceptions are important not only because they influence subsequent behavior, but also because they are amenable to strategic managerial manipulation through appropriate interventions, such as system design and training. However, Venkatesh, Morris, and Davis (2003) insist that, in order to develop a more comprehensive but parsimonious model for conducting empirical tests, researchers must choose from many different types of models and their constructs. Consequently, most theoretical models are bound to have their limitations because some contributions from alternative models have to be ignored. Because the goal of the TAM is "to provide an explanation of the determinants of computer acceptance that is generally capable of explaining user behavior across a broad range of end-user computing technologies and user populations, while at the same time being both parsimonious and theoretically justified" (Davis, 1989, p. 985), the TAM proposed by Davis (1989) cannot be an exception. One of the major criticisms of the TAM is that it has not explored how and why these perceptions start to develop in the first place (Agarwal & Karahanna, 2000).

In response to that, researchers have begun developing and testing more complex models seeking to provide an explanation for the formation of initial user perceptions by looking at the relationship between perceptions and their antecedents.

In doing so, researchers have tended to draw on other disciplines and well developed theories for guiding their research so that they can not only develop and test more comprehensive integrated models to fill the missing causal links, but also gain the benefit of using other well-established streams of research to supplement their arguments and rationales (Karahanna & Straub, 1999). For example, Venkatesh and Davis (2000) also followed their earlier effort by providing a better understanding about the antecedents of the perceived ease of use and the role of computer self-efficacy as a determinant of perceived ease of use. They extended the original TAM model to explain perceived usefulness and usage intentions in terms of social influence (subjective norm, voluntariness, and image) and cognitive instrumental processes (job relevance, output quality, and result demonstrability). The extended model, referred to as the TAM2, was tested using longitudinal data in both voluntary and mandatory settings. The results strongly supported the validity of the TAM2 and the extended model provided a detailed account of the key factors influencing the formation of perceived usefulness (Venkatesh & Davis, 2000). They argue that individual behavior will be influenced by social forces (subjective norm, voluntariness, and image), that is, the influence of others (lecturers, classmates, etc.) through the effect of compliance, identification, and internalization (Kelman, 1958). Therefore, in sum, we have deployed the TAM2 model and argue that the eLearners' experiences of technology acceptance are hypothesized to be as follows:

- H1a: Subjective norm will have a positive effect on intention to use when eLearning system use is perceived to be voluntary.
- H1b: Voluntariness will moderate the effect of subjective norm on intention to use.
- H1c: Subjective norm will have a positive direct effect on perceived usefulness.
- H1d: Subjective norm will have a positive effect on image.
- H1e: Image will have a positive effect on perceived usefulness.
- H1f: Job relevance will have a positive effect on perceived usefulness.
- H1g: Output quality will have a positive effect on perceived usefulness.
- H1h: Result demonstrability will have a positive effect on perceived usefulness.
- H1i: Perceived ease of use will have a positive effect on perceived usefulness.
- H1j: Perceived usefulness will have a positive effect on the intention to use.
- H1k: Perceived ease of use will have a positive effect on the intention to use.
- H1l: Intention to use an eLearning system will have a positive effect on usage behavior.

Flow Experience

Following Venkatesh, Morris, and Davis (2003), we extend the application of the TAM through Csikszentmihalyi's (1990, 1975) concept of flow defined as: a psychological state that occurs when one's skills are neither overmatched nor underutilized to meet a given challenge. In other words, the optimal experience of flow occurs when there is a balance between challenge and skill. We argue that the flow model is appropriate to the research context on the assumption that the achievement of optimal experience is dependent on the development of the necessary skills to overcome course-related challenges and the ability to learn to master the use of the eLearning system itself (Howland & Moore, 2002; Cheung & Kan, 2002). Therefore, the balance between challenges and skills is important. According to Csikszentmihalyi (1975), the original theory of flow postulates that the overall positivity of the subjective experience, as represented by flow indicators such as positive affect, arousal, concentration, involvement, intrinsic or autotelic motivation, feelings of control over actions and environment, momentary loss of anxiety and constraint, and enjoyment or pleasure (Cybinski & Selvanathan, 2005), is a function of this balance (Jones, Hollenhorst, Perna, & Selin, 2000). Csikszentmihalyi coined the term flow to refer to optimal experience events, in which people are so intensely involved in an activity that nothing else seems to matter; the experience itself is so enjoyable that people will do it even at great cost, for the sheer sake of doing it.

While the concept of flow has been studied in a wide range of endeavors spanning the disciplines of psychology, human–computer interactions, information systems, and education (Agarwal & Karahanna, 2000; Chen, Wigand, & Nilan, 1999; Webster, Trevino, & Ryan, 1993), a comprehensive flow measurement procedure focused on user consumption of a Web-based environment was proposed Novak, Hoffman, and Yung (2000) that included the:

1. Antecedent condition of flow: skills and challenges, focused attention.
2. Consequences of flow: consumer learning, perceived behavior control, exploration behavior, positive subjective experiences, distortion in time perception, and negative consequences of flow.
3. Variables related to the psychological experience of flow: losing track of time and self-awareness, concentration, mood, and control.

Their results revealed that the flow constructs are reliable indicators for measuring flow and suggested that the model of flow can be used to identify factors facilitating the emergence of flow. Within the model, the overall structure of flow is defined in terms of the experience of flow (intrinsic enjoyment, loss of self-consciousness), behavioral properties of the flow activity (seamless sequence of responses facilitated by interactivity with the computer and self-reinforcement), and its antecedents (skill/challenge balance, focused attention, and telepresence).

When users achieve the flow state during system use, their experience can be identified by the following indicators: (1) seamless sequence of responses facilitated by machine interactivity, (2) intrinsically enjoyable experience, (3) accompanied by a loss of self-consciousness, (4) and a self-reinforcing quality to the activity. Therefore, to extend the TAM, the following relationships are hypothesized:

H2a: Greater skill and perceived control corresponds to greater flow.

H2b: Greater challenge and arousal correspond to greater flow.

H2c: Greater telepresence/time distortion correspond to greater flow.

H2d: Greater focused attention corresponds to greater telepresence/time distortion.

H2e: Greater involvement corresponds to greater focused attention.

H2f: Greater flow corresponds to greater exploratory behavior.

H2g: Greater flow corresponds to greater positive affect.

H2h: Greater interactive speed corresponds to greater focused attention.

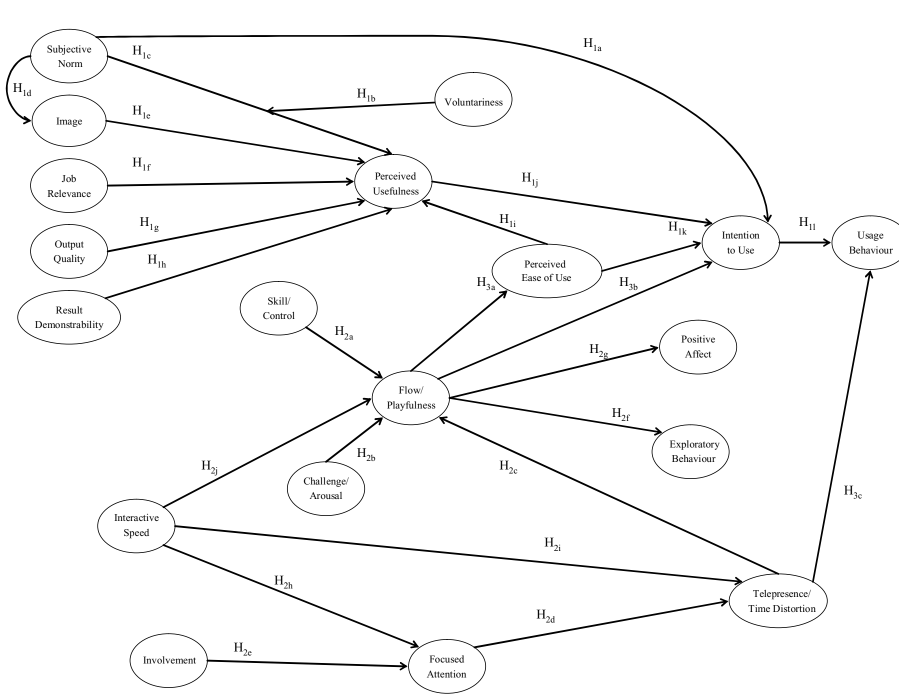
H2i: Greater interactive speed corresponds to greater challenge/arousal.

H2j: Greater interactive speed corresponds to greater flow.

Integrating Flow and the TAM

Drawing on two established research streams in the areas of psychology and technology acceptance has helped to develop a conceptual model that provides an integrated view that can be applied across different eLearning systems, whether the use is mandated in a complete online course or it is voluntary as a supplement to the traditional face-to-face setting (see Figure 1). While the TAM takes an eLearners' perception of system into account, the model of flow takes the eLearners' affective state through direct experiences with the system into consideration. Prior work in individual psychology has suggested that holistic experiences with technology, as captured in constructs such as enjoyment and flow, are potentially

Figure 1: Integrated conceptual model.



important explanatory variables in technology acceptance theories (Agarwal & Karahanna, 2000; Venkatesh, Speier, & Morris, 2002; Koufaris, 2002). Similarly, Davis, Bagozzi, and Warshaw (1992) found that intrinsic motivation (enjoyment), which is based on the performing of an activity purely for the enjoyment of the activity itself, is one of the key drivers of behavioral intention to use computers (Liaw & Huang, 2003). Because intrinsic motivation emphasizes the pleasure and inherent satisfaction derived from a specific activity, eLearners who have a more enjoyable experience during the learning process are more likely to sustain their participation and perceive the system to be easier to use due to increased time spent interacting with the system.

Liaw and Huang (2003) identified predictors of individual attitudes toward Internet search engines as a tool for information retrieval. In order to gain an understanding of how individual computer experience and perception affect individual use of search engines, they developed a conceptual model that integrated individual computer experience and perceptions, a system quality perspective, a TAM perspective, and motivation perspective. They concluded that, when users enjoy using search engines to find information, they also regard search engines as being easy to use and are willing to use them in the future (Liaw & Huang, 2003). The findings of the study can be used to suggest that, if the eLearners can experience flow during the online learning activities, not only will they engage in the interactions with the eLearning system, but they will also have intrinsic motivation to seek and replicate these positive feelings by participating in eLearning in a continuing pattern. In addition, the presence of telepresence and time distortion leads to a distorted sense of time resulting from being absorbed in the activity. Individuals tend to spend more time than they expect as they become inattentive to time. For this reason, telepresence and time distortion will have a direct impact on actual time use. The study of the relevant research discussed above leads to three additional hypotheses that blend the TAM and the flow models empirically:

- H3a: The experience of flow will have a direct impact on the ease of use of the system.
- H3b: The experience of flow will have a direct impact on intention to use.
- H3c: The presence of telepresence/time distortion will positively affect time use.

METHOD

The eLearning system chosen for the study is called CECIL, the Web-based, online enterprise Learning Management System used and developed by the University of Auckland, New Zealand (www.cecil.edu). The prime aim of CECIL is to support academics and their students by means of a highly flexible and reliable system for information and communication. CECIL is an appropriate subject for this study because it covers all aspects of most common eLearning activities, hence enhancing the generalizability of the study. Second, CECIL is a multifunctional and pervasive eLearning system available to all students enrolled at the University of Auckland. Only undergraduate students were selected in the study because a similar survey was conducted in the same month targeting the postgraduate student population.

Rather than excluding individuals from participation through sampling criteria, variables that were considered to be liable to confound the results were measured and statistically controlled during data analysis. These variables included age, gender, and ethnicity. Therefore, a sample of undergraduate students in multiple faculties within the university was the population for this study. All undergraduate students in nine faculties, including Arts, Business & Economics, Creative Arts & Industries, Education, Engineering, Law, Medical & Health Sciences, Science, and Theology, were selected for inclusion in this study. There were two major reasons: First, data was being collected online so it was easy to target participants without any discrimination. Second, while online surveys offer a great potential to reach the participants, response rates tend to be low. In order to ensure that there would be sufficient sample size for the present study, a larger sample population size was necessary to compensate for the expected lower response. The online survey lasted for 2 weeks and 21,994 students were enrolled in the survey.

Instrumentation

Basic assumptions and theoretical concepts underpinning the development of the questionnaire were adopted from existing theories because all the constructs and related indicators used in this study were derived from the original models of flow and the TAM2. All the adopted indicators used a seven-point scale with 1 representing *strongly disagree* and 7 representing *strongly agree*. They were refined in order to suit an eLearning context and are shown in Table 1a and 1b, which categorizes the constructs into exogenous and endogenous variables. A self-administered online questionnaire, which contained 106 questions, was used to collect data (see Table 2).

Prior to data collection for this study, an initial version of the questionnaire was tested by a sample of 76 students. This pilot administration of the survey was given in order to discover how long the survey would take for students to complete. In addition, the pilot study gave the researcher a chance not only to identify any question that might be problematic or ambiguous but also to check any predetermined response choices that might have been omitted. As a result of the pilot test, a decision was made to delete two questions because they might not be a direct measure of future behavior.

The final data set was collected through CECIL in October 2004. Participants had to log on to CECIL in order to find out that there was a survey on eLearning and participate in the study. One XBOX and four PC games donated by Microsoft NZ were in a random draw to be won by those who completed the questionnaire. A total of 2,865 undergraduate students participated in the survey but approximately 34% completed the entire questionnaire leaving only 964 usable responses.

Model Development

The confirmatory data analysis was performed using SPSS, while the confirmatory phase was conducted using AMOS. Cronbach alpha coefficients were used to measure the reliability of the items. Item reliabilities were assessed based on suggested levels of alpha coefficient levels (Nunnally, 1978). Before the analysis of the structural models, the reliability and validity of the constructs were tested. Five measurement models, including four second-order factors, were analyzed to

Table 1a. Measurement constructs (part one).

Construct	Measure	Source
Subjective Norm $	SN1: People who influence my behavior think that I should use CECIL. SN2: People who are important to me think that I should use CECIL.	TAM2
Job Relevance $	JR1: In my learning, usage of CECIL is important JR2: In my learning, usage of CECIL is relevant	TAM2
Output Quality $	OQ1: The quality of the output I get from CECIL is high OQ2: I have no problem with the quality of CECIL's Output	TAM2
Results Demonstrability $	RD1: I have no difficulty telling others about the results of using CECIL regarding how it has improved the quality of my learning. RD2: I believe I could communicate to others the consequences of using CECIL. RD3: The results of using CECIL related to my learning are apparent to me. RD4: I would have difficulty explaining why using CECIL may or may not be beneficial.	TAM2
Image $	IM1: People in my class who use CECIL have more prestige than those who do not. IM2: People in my class who use CECIL have a high profile IM3: Having CECIL is a status symbol in my university	TAM2
Voluntariness $	VO1: My use of CECIL is voluntary VO2: My lecturers do not require me to use CECIL VO3: Although it might be helpful, using CECIL is certainly not compulsory in my learning.	TAM2
Involvement $	IN1: Important/Unimportant IN2: Irrelevant/Relevant IN3: Means a lot to me/Means nothing to me IN4: Matters to me/Doesn't matter IN5: Of no concern me/Of concern me IN6: For me, using CECIL has become an activity that is worth doing for its own sake. IN7: It is often difficult to pull myself away from the computer once I start surfing CECIL.	FLOW
Interactive Speed $	I1: When I use CECIL there is very little waiting time between my actions and the computer's response. I2: Interacting with CECIL is slow and tedious I3: Pages on CECIL sites I visit usually load quickly	FLOW

Table 1a. (continued)

Construct	Measure	Source
Perceived Usefulness*	PU1: Using CECIL in my learning increases my Productivity. PU2: Using CECIL enhances the effectiveness of my Learning. PU3: I find CECIL to be useful in my learning PU4: My interaction with CECIL is clear and Understandable.	TAM2
Perceived Ease of Use*	PE1: My interaction with CECIL is clear and Understandable. PE2: Interacting with CECIL does not require a lot of my mental effort. PE3: I find CECIL to be easy to use PE4: I find it easy to get CECIL to do what I want to do	TAM2
Focused Attention*	FA1: Not deeply engrossed/Deeply engrossed FA2: Absorbed intently/Not absorbed intently FA3: My attention is not focused/My attention is Focused. FA4: I concentrate fully/I do not concentrate fully	FLOW
Exploratory Behavior*	E1: I enjoy visiting unfamiliar Web sites just for the sake of variety. E2: I rarely visit Web sites I know nothing about E3: Even though there are many Web sites, I tend to visit the same Web sites again and again. E4: When I hear about a new Web site, I'm eager to check it out. E5: Surfing CECIL to see what's new is a waste of time E6: I like to browse CECIL and find out about the latest Information. E7: I often click on a link just out of curiosity.	FLOW
Intention to Use*	IU1: In the coming year, how much do you expect to use CECIL, compared to your current level of usage.	FLOW
Usage Behavior*	UB1: How much time would you estimate that you personally use CECIL.	FLOW
Positive Affect*	PA1: Happy/Unhappy PA2: Annoyed/Pleased PA3: Satisfied/Unsatisfied PA4: Melancholic/Contented	FLOW

$Denotes exogenous variable.
*Denotes endogenous variable.

ensure the validity of the constructs. The fit of the confirmatory factor analysis (CFA) models was assessed with a number of fit indices. Chi-square fit index, goodness of fit index (GFI; Jöreskog & Sörbom, 1989), the non-normed fit index (NNFI; Hu & Bentler, 1999; 1995), comparative fit index (CFI; Bentler, 1990), and root mean square error of approximation (RMSEA; Bollen, 1989)

Table 1b. Measurement constructs (part two).

Construct	Measure	Source
Flow/Playful*	Indicator 1: Flow F1:Do you think you have ever experienced flow on CECIL. F2:In general, how frequently would you say you have experienced flow when you use CECIL? F3:Most of the time I use CECIL I feel that I am in Flow. F4:For me, using CECIL is a compelling experience. Indicator 2: Playful P1: I feel unimaginative when I use CECIL. P2: I feel flexible when I use CECIL. P3: I feel unoriginal when I use CECIL. P4: I feel uninventive when I use CECIL. P5: I feel creative when I use CECIL. P6: I feel playful when I use CECIL. P7: I feel spontaneous when I use CECIL.	FLOW
Skill/Control*	Indicator 1: Skill S1:I am extremely skilled at using CECIL. S2:I consider myself knowledgeable about good search techniques on CECIL. S3:I know somewhat less about using CECIL than most users. S4:I know how to find what I am looking for on CECIL. S5:How would you rate your skill at using CECIL, compared to other things you do on the computer. S6:How would you rate your skill at using CECIL, compared to the sport or game you are best at. S7:I could probably teach myself most of the things I need to know about using CECIL. S8:I can make my Web browser do what I want it to do. S9:If I have a problem using CECIL, I can solve it one way or another. S10:I would prefer to learn how to use CECIL on my own. S11:I need an experienced person nearby when I use CECIL. S12:I need someone to tell me the best way to use CECIL. Indicator 2: Control CO1:Controlling/Controlled CO2:Influenced/Influential CO3:Dominant/Submissive CO4:Guided/Autonomous CO5:I am in complete control when I use CECIL	FLOW

Table 1b. (continued)

Construct	Measure	Source
Challenge/Arousal*	Indicator 1: Challenge C1:Using CECIL does not challenge me. C2:Using CECIL challenges me to perform to the best of my ability. C3:Using CECIL provides a good test of my skills. C4:I find that using CECIL stretches my capabilities to my limits. C5:How much does CECIL challenge you, compared to other things you do on the computer. Indicator 2: Arousal A1:Stimulated/Relaxed A2:Calm/Excited A3:Frenzied/Sluggish A4:Unaroused/Aroused	FLOW
Telepresence/ Time Distortion*	Indicator 1: Telepresence T1:I forget about my immediate surroundings when I use CECIL. T2:Using CECIL often makes me forget where I am. T3:After using CECIL, I feel like I come back to the "real world" after a journey. T4:Using CECIL creates a new world for me, and this world suddenly disappears when I stop browsing. T5:When I use CECIL, I feel I am in a world created by the Web sites I visit. T6:When I use CECIL, my body is in the room, but my mind is inside the world created by the pages I visit. T7:When I use CECIL, the world generated by the pages I visit is more real for me than the world I live in. T8:When I use CECIL I forget about personal concerns or mundane matters. Indicator 2: Time Distortion TD1:Time seems to go by very quickly when I use CECIL. TD2:When I use CECIL, I tend to lose track of time.	FLOW

*Denotes endogenous variable.

were the main fit indexes used to evaluate the proposed models. The chi-square fit index ranges from zero to infinity and smaller values indicate good fit. GFI, CFI, and NNFI values range from zero to one where values close to one indicate a good fit (Byrne, 1989). RMSEA values usually range from zero to 0.08, and values close to zero indicate better fit. The structural models were analyzed using each individual valid item as the indicator of its construct.

Table 2: Questionnaire description.

The purpose of the questionnaire was to measure and examine the relationships between user perception, user experience, and expected and actual usage of CECIL. The survey instrument was divided into 12 parts.
Part one contained questions about the participant's usage of CECIL.
Part two focused on the role of CECIL in participants' learning.
Part three included questions about user feeling when working online.
Part four contained questions asking about participants' skill at using CECIL when compared to other activities.
Part five contained questions regarding attitudes and perceptions about using CECIL.
Part six was made up of questions about how users feel when interacting with CECIL.
Part seven contained questions asking participants to report their general experiences of using CECIL.
Part eight directly related to the occurrence of flow state when using CECIL.
Part nine aimed to uncover the participant's beliefs and perceptions about the outcome of using CECIL.
Part ten included questions asking participants to reflect on the social influence and personal image associated with CECIL.
Part twelve was made up of questions about the general background of the participants.

The proposed integrated conceptual model was tested after four second-order models were tested separately. There were two reasons for doing this. First, testing the second-order models before complex models has important statistical advantages in structural equation modeling (SEM) analysis (Byrne, 1989) as model complexity may create a number of problems including unacceptable model fits. Second, the results of the preliminary test can be used to modify the measurement model before processing to structural model tests. Because a structural model includes the relationships that are of major concern to the purposes of this study (i.e., relationships that have not been analyzed previously or those that have limited empirical support), it was better if the problem associated with model complexity was dealt with to prevent any unacceptable fit index that might lead to rejection of the new conceptual model.

RESULTS

A total of 964 online surveys (out of 2,865) were completed (see Table 2.). The cases that had missing cells were deleted from the data file for several reasons. First, about 99% of incomplete surveys had responded to only a few questions. Most of the items (95%) were not answered. The participants whose returns had minimal data clearly wanted to be excluded from the study. Finally, SEM does not compute some fit indexes if the data file has missing cells. Therefore, a decision was made to exclude incomplete cases. A preliminary data analysis effectively revealed that only 10% of students had less than 6 months of experience with CECIL. The majority of students were 20 years old or younger (58.6%) with 52.2% reporting that they were full-time students at the university. There were approximately equal numbers of male and female participants.

Table 3: Sample demographic profile.

Item	Item Description	Frequency	Percent
GENDER	Male	513	53.2
	Female	451	46.8
AGE	<=20	565	58.6
	>20	399	41.4
ETHNICITY	NZ Pakeha (European)	345	35.8
	Maori	23	2.4
	Pacific Islander	30	3.1
	Asian	402	41.7
	European	72	7.5
	Other	92	9.5
Occupational STATUS	Part-Time	413	42.8
	Full Time Permanent	33	3.4
	Self Employed	7	0.7
	Just Student	503	52.2
	Homemaker	8	0.8
INCOME	<30,000	905	93.9
	30,000–40,000	26	2.7
	40,000–50,000	9	0.9
	50,000–60,000	5	0.5
	60,000–70,000	3	0.3
	70,000–80,000	1	0.1
	>80,000	15	1.6
YEARS of CECIL USE	Less than 6 months	98	10.2
	Over 6 months and up to a year	421	43.7
	Over 1 year and up to 2 years	199	20.6
	Over 2 years and up to 3 years	155	16.1
	Over 3 years	91	9.4

Means for the scales of the flow model ranged from 2.79 ($SD = 1.33$) to 4.99 ($SD = .85$) and for the scales of the TAM2 from 2.88 ($SD = 1.59$) to 5.42 ($SD = 1.14$). The skewness and kurtosis values of the scales of the flow model and the TAM2 model were less than one, which indicated normal distribution of the scores. Table 3 shows means, standard deviations, skewness, and kurtosis value of all scales or constructs used in the study.

The Pearson Product Moment correlation was computed to provide preliminary evidence of bivariate correlations or linearity among the scales. Within the scales of the flow model and the TAM2 model, most of the correlations were significant and the magnitude of correlations was low to moderate. Therefore, there were no signs of multicollinearity, which is one of the assumptions of valid SEM analysis. There is other evidence (Table 4) that fewer than 8% of the correlations had values greater than ±0.5. In other words, constructs between the TAM2 model and the flow model were correlated but not highly correlated. Most of the correlations between the scales of the flow model and the TAM2 model were statistically significant, indicating that they influence one another. Moreover, two dependent variables (Usage Behavior and Intention to Use) were moderately correlated, which was expected from the assumption of linearity.

Table 4: Descriptive statistics (scales).

Construct	Mean	Standard Deviation	Skewness	Kurtosis
Arousal	4.5283	.8587	−0.081	0.790
Challenge	2.8112	1.0794	0.471	−0.011
Control	3.9385	.7237	−0.161	1.235
Exploratory Behavior	3.9447	.9477	−0.288	0.130
Flow	2.9948	1.3500	0.205	−0.622
Focused Attention	4.0858	1.0897	−0.267	0.246
Interactive speed	3.9063	1.365	0.047	−0.526
Involvement	2.7898	1.3326	0.685	0.279
Playfulness	3.5090	0.9141	0.102	0.142
Positive Affect	4.5687	.9517	−0.329	0.959
Skill	4.9928	.8536	−0.467	0.436
Telepresence	2.9970	.9025	0.768	0.778
Time Distortion	3.3107	1.3695	0.299	−0.453
Perceived Usefulness	5.0070	1.3700	−0.752	0.403
Perceived Ease of Use	5.4209	1.1407	−0.952	1.224
Subjective Norm	3.3890	1.5959	0.067	−0.642
Image	2.8842	1.5862	0.355	−0.821
Voluntariness	3.9457	1.4480	0.051	−0.368
Job Relevance	5.1463	1.4167	−0.819	0.437
Output Quality	4.8377	1.2637	−0.524	0.322
Result Demonstrability	4.7355	1.2064	−0.227	−0.001

Before proceeding to the measurement model in SEM, a series of alpha reliability analyses was performed to verify the consistency of responses to the items of each scale used in the study. Items with negative and low correlation were deleted in order to increase the value of alpha. Because construct reliability is measured in terms of Cronbach's alpha, increasing the value of alpha could help prevent the problem from arising when it comes to examining the measurement model at a later stage. As suggested by Hair, Anderson, Tatham, and Black (1998), the acceptable value of Cronbach's alpha is at least 0.7 (Selim, 2003). Based on this suggestion, there were five constructs that exhibited a relatively low degree of internal consistency within their corresponding construct when these items were being used to measure the relevant construct: Arousal, Control, Exploratory Behavior, Playfulness, and Time Distortion.

CFA Model

The purpose of this analysis was to test how well the items, which act as observable indicators for the unobservable constructs, could be used to measure the corresponding construct. This was done by using CFA models which evaluate measurement models. It focuses on the extent to which the operationalization of a construct actually measures what it is intended to measure. There are two different approaches that can be employed to evaluate the measurement models: first-order models and second-order models. In this study both these models were constructed and evaluated. In the first-order model, the items were directly loaded onto a latent

Table 5: The overall fit measures—Individual second-order models.

Second-Order Model	Chi-Square	Degrees of Freedom	*p*	CFI	GFI	AGFI	NFI	RMSEA
Skill/Control	1152.2	104	.000	.69	.86	.81	.67	.10
Telepresence/ Time Distortion	307.05	20	.000	.91	.92	.86	.90	.12
Flow/Playfulness	738.19	27	.000	.80	.84	.74	.79	.17
Challenge/Arousal	755.7	35	.000	.73	.86	.77	.72	.15

construct and in the second-order model, more than two or at least two first-order constructs were loaded on to a hierarchical or second-order construct. In the SEM, 4 second-order and 14 first-order models were used. The second-order models were analyzed separately before running the whole SEM to make sure that each of the models did fit the data. To evaluate the measurement models individually, CFAs were run using the AMOS 5 statistical package (Arbuckle & Wothke, 1999). Table 5 shows how the results of the fit indexes depict the results of the four second–order models.

The results from the four second-order models show that, except for Telepresence/Time distortion, all models did not show good fit on any of the criteria. The result suggests that the composite models of Flow/Playfulness, Skill/Control, and Challenge/Arousal should be rejected. However, most of the CFIs and GFIs of those models were not very far from the acceptable range of 0.90, and most of the parameter estimates exceeded 0.4. So it was decided not to modify the models at this stage but to see how these second-order models interacted with one another in the full model. This approach is consistent with Novak, Hoffman, and Yung (2000). For this reason, even though the results indicated that only Telepresence/Time Distortion was a good-fitting model, the decision was made to keep them intact and combine each individual measurement model into a full model to allow for further analysis and confirmation of the results.

SEM

The results of the full model showed fit of the model in terms of RMSEA. The chi-square was significant and all the goodness-of-fit indexes were lower than the acceptable range. Some parameter estimates and item loadings were low and nonsignificant. So the next step was to have these parameter estimates and items deleted from the initial structural model, one by one, in order to improve the fit of the model. Some item errors were highly correlated, as indicated by the modification indices. Therefore, two correlations were imposed on four item errors (eb1 and eb4). After all the modifications, a final revised model was run. The revised model showed a slightly improved value of RMSEA from 0.067 to 0.064. Loadings of all second-order factors were moderate to high with path coefficients being valid under *p*, 0.001, and the results were close to the ones obtained by Novak, Hoffman, and Yung (2000). This implies that the measurement scale can be directly applied in the New Zealand context to study learners' online behavior. While most of the parameter estimates indicated the relationships between the latent constructs were significant and in the expected direction, the factor loadings were high and

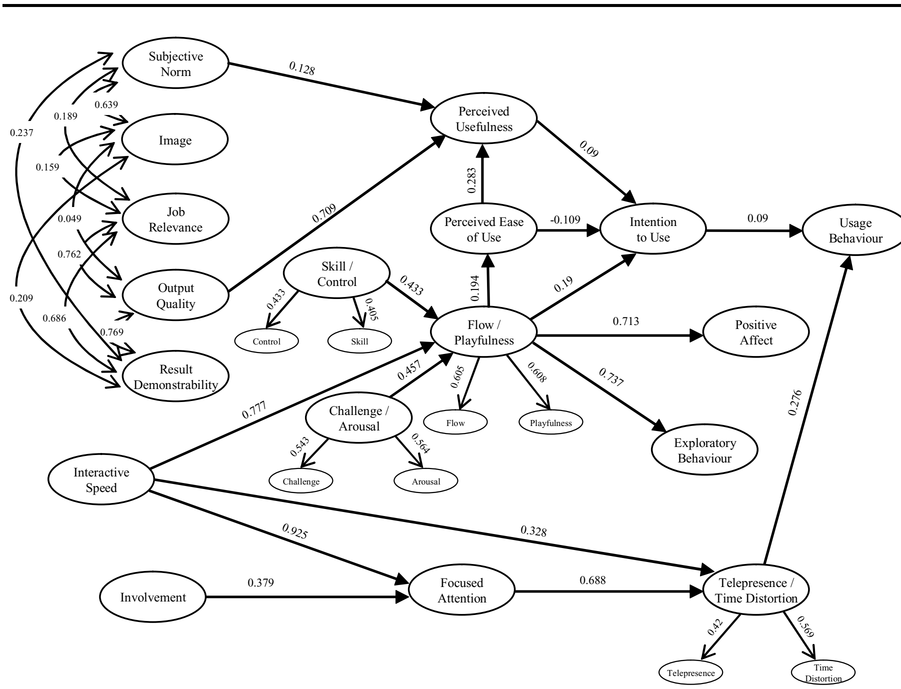
Table 6: Overall fit measures for initial and revised model.

Structural Model	Chi-Square	Degrees of Freedom	*p*	CFI	GFI	AGFI	NFI	RMSEA
Initial model	19161.61	3632	.000	.651	.577	.554	.603	.067
Revised model	15652.62	3217	.000	.711	.643	.622	.663	.063

significant. However, the GFI, AGFI, and CFI were not within the acceptable range. The fit of the model is shown in Table 6. The results indicated that the absolute fit indexes, including CFI, GFI, AGFI, and NFI, had been improved slightly but they were not within the acceptable range. However, given the complexity of the integrated model, RMSEA suggested that the revised model was a fair fit.

Figure 2 depicts all the statistically significant relationships found in SEM, that is, the factors that were found to contribute to the learners' experience in the eLearning environment, CECIL. The moderating effect of Voluntariness between Subjective Norm and Intention to Use was deleted because no direct or indirect effect between Subjective Norm and Voluntariness was detected. Voluntariness was also dropped from the model because no relationship was found to be significant. The result of SEM suggested that the crucial linkage (Flow/Playfulness → Perceived Ease of Use) between two original theoretical models was supported.

Figure 2: Final structural model.



However, one of the relationships appeared to be negative (Perceived Ease of Use → Intention to Use).

Although incremental fit indexes and absolute fit indexes was not within the acceptable range and indicated that the model should be rejected, the RMSEA suggested that the revised final model was a fair fit, given the complexity of the integrated model. The RMSEA, which assesses how well a model reproduces the sample data, have been recommended by Hu and Bentler (1999) to evaluate model fit for a complex model. They conducted a study to evaluate the sensitivity of various types of incremental fit index and absolute fit indexes derived from Maximum likelihood, generalized least squares, and asymptotically distribution-free estimators to an under-parameterized model (relations between constructs were underestimated) under different data conditions, including conditions in which distributional, assumed independence, and asymptotic sample size requirement were violated. Based on the results of their study, they argued that GFI, AGFI, and NFI should not be used to assess model fit for a complex model because they are likely to generate bias and perform poorly due to model complexity (Hu & Bentler, 1999). In addition, while Steiger (1989) and Browne and Cudeck (1993) recommend that the value of RMSEA less than 0.05 be considered as indicative of close fit; Browne and Cudeck (1993) suggest that values in the range of 0.05 to 0.08 indicate fair fit. MacCallum, Brown, and Sugawara (1996) even considered values in the range of 0.08 to 0.1 to indicate mediocre fit (Hu & Bentler, 1999). Based on these suggestions and recommendations, it was decided by these researchers that RMSEA would be a preferred indicator for evaluating model fit because of the model complexity.

CONCLUSION

Overall, we conclude that the learners' experience and their usage of an eLearning environment is affected by the integration of their affective state and their technology acceptance. Our findings have helped us to establish the significant factors that contribute to the eLearners' affective (RQ1) and technology acceptance (RQ2) as well as their integrated empirical relationship (RQ3). Therefore, we argue that the eLearners' intended and actual usage behavior is influenced by the nature of this affective and technology-related experience.

The results indicate the following factors contribute to the learners' experience of the an eLearning environment:

1. Perceived usefulness is affected by subjective norm (H1c) and job relevance (H1f).
2. Perceived usefulness (H1i) and intention to use (H1k) are affected by perceived ease of use.
3. Intention to use is affected by perceived usefulness (H1j).
4. Usage behavior is affected by intention to use (H1l).
5. The experience of flow is affected by skill/perceived control (H2a).
6. The experience of flow is affected by challenge/arousal (H2b).

7. Ease of use (H3a) and the intention to use (H3b) are affected by the experience of flow.
8. Exploratory behavior (H2f) and positive affect (H2g) are affected by the experience of flow.
9. Telepresence/time distortion is affected by focused attention (H2d).
10. Focused attention is affected by involvement (H2e).
11. Focused attention (H2h), telepresence/time distortion (H2i), and flow (H2j) are affected by interactive speed.
12. Usage behavior is affected by telepresence/time distortion (H3c).

The results from the current study suggest that only subjective norm and job relevance are significant antecedents of perceived usefulness, with job relevance having a stronger effect. However, there are strong and significant correlations among subjective norm, job relevance, and other determinants of perceived usefulness, indicating that, although image, output quality, and result demonstrability may not directly influence the eLearners' perception of the system, they may still exert indirect influence though their relationships with subjective norm and job relevance. Regarding H1d, subjective norm does not seem to have a positive effect on image. The possible explanation is that it is not easy for eLearners to establish or maintain a favorable image in the virtual environment in which peer-to-peer interactions are limited.

For similar reasons, lack of direct contact in the online courses make it difficult for the individual, such as the instructor or tutor, to exercise his social influence in the attempt to influence eLearner behavior. While voluntariness does not have a statistically significant relationship with subjective norm and perceived usefulness, its negative relationship with perceived usefulness suggests that, when the use of an eLearning system is believed to be voluntary, the compliance-based effect on perceived usefulness will diminish. In contrast, H1f and H1g were tests of the effect of output quality and result demonstrability on perceived usefulness. How important they are depends on whether they can be immediately displayed or revealed at will. In an eLearning context, this is not likely to be the case, and learners have to wait for the test or exam in order to demonstrate what they have learned. This might be the reason why they are not supported.

The most striking finding of the study is the negative relationship between perceived ease of use and intention to use, as proposed in H1k. In an eLearning context, this might be explained by the lack of motivation associated with an online course. If the learner believes that the particular eLearning system is very user-friendly and can be picked up anytime, anywhere, there will be less incentive for him to get familiar with the system at once. He might tend to wait until he realizes that he can never complete the online course on schedule. In other words, being capable of performing certain tasks does not necessarily lead to actual performance or intention to perform. This is the reason why eLearning requires self-discipline and self-monitoring for it to succeed. With respect to the flow theory, the results of the study indicate that greater telepresence and time distortion do not necessarily correspond to greater flow. In an eLearning context, telepresence and time distortion might be viewed as negative effects by eLearners because their minds become so distracted and absorbed that they cannot concentrate on their primary goal, which is learning. Regarding the important linkages between two original models, the study found that it is appropriate to have two models combined so that a better model can be developed to predict eLearner online behavior as well as factors affecting this behavior.

Managerial Implications

The results indicate that intentional usage of an eLearning system is significantly affected by perceived usefulness and flow. Hence, the practitioners seeking to facilitate the adoption of an eLearning system should emphasize how to better match learning relevance needs and requirements. In addition, educational institutions might need to develop some strategies for gaining instructors' involvement and support. Because they are the people who are important to the learners, they are in the best position to effectively exercise their social influence in affecting learners' usage behavior. Another important strategic consideration is the identification and acquisition of an eLearning system that is suitable to eLearners' learning needs and able to be used to educate and entertain the users simultaneously. The flow state is another important factor affecting eLearner behavioral intention. The data from the results suggested that an affective state, such as flow, is more important than eLearners' beliefs about the usefulness of a particular eLearning system in determining their intention to use. For this reason, eLearning content providers and system designers should work with instructors and innovative organizations collaboratively to come up with designs that can provide appealing learning experiences for their online learners.

While innovative organizations need to provide the infrastructure for successful implementation of eLearning systems, instructors need to upload the important and relevant learning materials online. In addition, the importance of these learning materials should be brought to eLearners' attention explicitly so that this message can act as a powerful driving force to motivate eLearners to use the system. Finally, the model suggests that speed and involvement (importance) are two important factors that can be used to facilitate eLearners' experience of flow. Therefore, the most effective way to ensure active participation and deep involvement in the online lecture materials and courses is to develop systems that can interact spontaneously with the user while providing important and interesting content.

Research Implications

In interpreting the findings, the reader must keep in mind that the study has several limitations. First, the sample size was slightly smaller than the five cases per parameter estimate recommended by Bentler and Chou (1987). Although the sample size for the study was acceptable based on the results of the descriptive data analysis, SEM requires a large sample size if an accurate computation of significant test and model fit indexes is to be made. The second limitation relates to the use of a convenience sample. One of the major criticisms of using a convenience sample is that the generalizability of the results will be limited if the sample size cannot be considered as truly representative of the target population. Better results could have been obtained if a representative sample from each faculty had been acquired. For example, the Faculty of Business was an early adopter of the CECIL system. Students in this faculty also are regularly using information technology in their learning. Therefore, better results may have been obtained from this group. This may be different for Faculty of Arts students. However, while the results may not be applicable to other populations or environments, for example, organizations using eLearning for training purposes, the results of the study are important because the participants are university students who not only have a high inclination to use online learning systems for current educational needs but also are likely to have a similar demand for eLearning as a training tool when they enter the workforce in the near future.

The third significant limitation is that personal characteristics were not measured in the study. As pointed out by Webster and Martocchio (1992) and Agarwal and Karahanna (2000), while individual traits of cognitive playfulness can be a significant antecedent of the state of flow, personal innovativeness is a crucial factor affecting the likelihood of the flow state emerging. It must be placed in the balance against the parsimony of the current model. Warr (1980) described the Christmas tree analogy, in which the initial structure of a model becomes lost through the addition of decorations and refinements so that it eventually lacks the coherence of a purposeful configuration. The fourth limitation involves model specification issues: according to Trevino and Webster (1992), perceived ease of use would amplify the flow experience. The other limitation concerns the use of self-reported usage for measuring actual usage instead of a possibly more reliable and objective measure. While self-reported usage can be inaccurate as indicated by Szajna (1996), it has numerous advantages, such as being inexpensive to gather and easy to incorporate into questionnaires. Due to privacy reasons, actual usage data was not compiled for use in the current study. The final limitation involves the research design. While the optimal way to understand the relationship between eLearners' intentional and actual behavior would have been through the use of a longitudinal study, this study utilized a cross-sectional analysis in which participants were asked to reflect upon their current behavior and their behavior a few months before.

Further research needs to examine or revise this conceptual model in order to further investigate individual attitudes toward eLearning systems and how they can affect individual belief and subsequent behavior. Future research could also test this integrated model across a broader set of technologies (information systems) and user populations to determine its predictive robustness and generalizability. The research focused on three particular constructs because of their strong theoretical linkage to the human behavior that framed the study. Future research may usefully examine other potential user acceptance enhancers (driver/driving force) to extend the created model within the information technology acceptance domain by considering, for example, personal characteristics, gender, and cultural differences. While this study investigated the adoption of eLearning from the learner perspective, future research utilizing the same methodology could consider adopting the instructor's perspective. This is important because eLearning is unlikely to develop well without the direct involvement and contribution of both parties. In addition, future studies could utilize the model and methodology employed in this study to investigate other Web applications such as the use of enterprise resource planning in the Web environment. The study did not investigate the impact of positive affect and exploratory behavior, so future research could examine whether these aspects have a positive relationship on learner performance. Future studies incorporating a longitudinal design may also provide deeper insight into the complex underlying interactions involved during the eLearning adoption process. For example, the introduction of a new eLearning system in an educational institution could be examined at various stages, from the implementation process to the final deployment stage.

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