UNDERSTANDING DROPOUT

OF ADULT LEARNERS IN E-LEARNING

by

JUSUNG JUN

(Under the Direction of Ronald M. Cervero)

ABSTRACT

Although many studies related to e-learning have been conducted in the field of adult education and human resource and organization development, relatively little attention has been given to why adult learners actually drop out. The purpose of this study was to determine which specific set of variables can best predict the dropout of adult learners from e-learning courses in the workplace. Based on Keller's (1987) ARCS model, a self-completion forced choice survey instrument scale was developed to obtain information about learners' motivation to participate in e-learning in the workplace. The sample used for this study was a non-random convenience sample of employees in a South Korea company. Two hundred fifty-nine usable surveys were returned, yielding a final response rate of 12.26 percent.

A logistic regression model was proposed to accomplish the purpose of the study. The primary results were:

(1) The overall assessment of the proposed logistic regression model consisting of individual background variables (Number of e-learning courses completed, Age, Gender, Educational level, Marital status, Number of learning hours for the course, Mandatory/voluntary attendance, and Hours worked per week) and motivational variables

(Attention, Relevance, Confidence, and Feedback) revealed that the model had a moderate association between the predictor variables and Dropout (Nagelkerke's R-Square, .456).

(2) The Gender, Number of e-learning courses completed, and Attention predictor variables had a substantive relationship to the dropout of adult learners from an e-learning course (B_{yx}* = .40, 36, and .22, respectively).

(3) The logistic regression model consisting of the Number of e-learning courses completed, Gender, Learning hours for the course per week, Hours worked per week, and Attention variables was chosen due to its efficient predictability of dropout of adult learners. This model correctly classified 48.6% of the completers and 97.9% of the dropouts, for an overall accuracy rate of 84.5% for the model.

INDEX WORDS: Adult Education, Adult learners, Dropout, E-learning, Exploratory factor analysis, Individual background predictors, Logistic regression, Motivation predictors (Attention, Relevance, Confidence, and Feedback).

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DEDICATION

This dissertation is lovingly dedicated to my wonderful wife,

Soyoung Kim

and children Yewon and Yeram.

Your love, support, encouragement, sacrifice,

and faith has made this journey possible.

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긴 항해를 마치며...

그동안 멀리서, 그리고 가까이에서 물심양면 도와주신 많은 분들께 진심으로

감사의 말씀을 전합니다. 먼저 스승님이신 송광용 선생님과 나일주 선생님께 깊은 감사의 말씀을 드립니다.

그분들의 큰 격려가 이 항해를 온전히 마칠 수 있게 한 발판이였습니다.

그리고 자료 수집을 위해 마치 자신의 일인 양 큰 도움을 주신 주재식, Tony Kim,

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또한 자료 분석에 귀중한 시간을 내어주신 UGA 김석호 교수님께도 큰 감사의 뜻을 표합니다.

마지막으로 언제나 정신적, 물질적 후원을 아끼지 않으신 양가 부모님 및

가족께 깊은 감사의 뜻을 전합니다. Hallelujah!!!

TABLE OF CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

CHAPTER I

INTRODUCTION

> Our society is continuously moving towards a knowledge-based economy: an economy in which the application of knowledge replaces capital, raw materials, and labor as the main means of production. The synergy of combining new information and communication technologies with human skills has dramatically altered job content and skills requirements at the workplace. (The Canadian Vocational Association and UNEVOC-Canada, 2002, ¶ 1)

Background of the Study

The so-called information revolution triggered by advanced communication technologies such as the internet has had a significant influence on our daily lives. The arenas of education and training are no exception. The rapid rate of change demands an ability to learn to adjust quickly and assimilate large amounts of conflicting information. In this environment, an ability to learn continuously will become imperative. The learning environment for today's learners is no longer set within the walls of a school, but rather is everywhere, especially the Web and e-mail. These advanced information technologies allow learners to access a variety of learning activities beyond the limitations of time and place.

Many adult learners are taking advantage of advanced technologies for their learning. E-learning, in particular, gained a pivotal position in the field of human resource and organization development (HROD) as well as public arenas such as university education. E-learning can be defined as instructional content or learning experiences delivered or enabled by electronic technology (ASTD/NGA, 2001). Specifically, e-leaning is defined as “a wide set of applications and processes such as Web-based learning, computer-based learning, virtual classrooms, and digital collaboration. It includes the delivery of content via Internet, intranet/extranet (LAN/WAN), audio- and videotape, satellite broadcast, interactive TV, and CD-ROM" (Kaplan-Leiserson, 2001, ¶ 2). In a word, e-learning is technology-based learning. More typically, "e-learning has come to indicate Web-based or online delivery of education and training" (National Alliance of Business [NAB], 2000, p. 1). The use of the Web in teaching and learning within the field of HROD and public arenas such as university and K-12 education is now commonplace. Web-Based Training (WBT) is the term that is used most often to describe the use of Web technologies for learning within industry, while the term Web-based instruction (WBI) is more common within universities (Horton, 2000). Horton (2000) defines WBT as "any purposeful, considered application of Web technologies to the task of educating a fellow human being" (p. 2). Khan (1997) defines WBI as "an innovative approach for delivering instruction to a remote audience, using the Web as the medium" (p. 5). These definitions of WBT and WBI have the effective uses of Web technologies for teaching and learning in common, but they apply to different educational settings. In the context of this study, WBT will be used because the primary emphasis of this study is the kind of training provided by business organizations.

Education and training via the Web are growing rapidly because they have the potential to meet the needs of those who seek to find a way to learn more efficiently and conveniently. E-learning provides many potential benefits to both companies and workers in today's fast-paced, just-in-time work environment by allowing learning to become a continuous process of inquiry and improvement that keeps pace with the speed of change in business and society. With e-learning, the employees have convenient, just-in-time access to needed knowledge and information, with specific contents assembled and delivered according to their specific needs. In addition, E-learning offers many advantages as businesses grow internationally, face ongoing cost-containment pressures, and encounter a highly competitive job market (NAB, 2000, pp. 4-5). These advantages are: a) lower delivery costs and minimized productivity losses, b) just-in-time information, c) personalized learning, d) ease of distribution, e) anywhere, anytime availability, f) unhampered by geography, and g) ability to track progress and performance.

Brown (2000) also points out that "reduced training costs, world-wide accessibility, and improved technological capabilities have made electronic instructional delivery to adult learners a viable alternative to classroom instruction" (p. 1). Specially, she notes, "the flexibility of time, place, and programs offered via Web training is appealing to learners who are trying to balance school with work and home responsibilities" (p. 1). Unlike traditional classroom training, e-learning can be learner-focused, emphasize solutions and learning results, happen anytime and anywhere, and create new models for the provision of learning based on today's e-learning environment (ASTD/NGA, 2001).

One of the characteristics of e-learning is that "it has blurred the distinction between who is a content user and who is a provider, throwing off balance another pillar of training-the role of instructor" (Galagan, 2000, p. 28). In other words, e-leaning can also allow learners to do a collaborative sharing of knowledge. Adult learners have a wealth of real-life experience and by bringing it to training can be a resource for learning (Driscoll, 1998). In sum, in comparison with traditional face-to-face training, e-learning is a better fit for many of today's workplace environments.

Although e-learning has some advantages as an efficient and effective learning delivery media, the big problem of e-learning in terms of time and cost spent is learner dropouts. While e-learning seems to answer a lot of learner's needs, drop-out rates are higher than those for face-to-face course (Knowledgenet, 2001). Svetcov (2000) claims, "It is generally agreed that attrition rates from online schools are higher than from traditional schools … the online student dropout rate [is] around 35 percent, [which is] 15 percent higher than traditional schools….The fact is, much of what passes for online education today would put most of us to sleep" (p. 3). More skeptically, Murphy (2001) argues that e-learning courses without classroom training have low success rates--only about 10 percent of employees complete online-only courses. The "anytime, anywhere" nature of at-your-laptop learning all too easily becomes "no time, nowhere"; the average dropout rate for online courses can run as high as 50 or 75 percent, depending on the source (Ganzel, 2000).

Of course, the reasons for dropout among learners are numerous and complex. Accordingly, the phenomenon of adult learner dropout cannot be understood just by using one or two variables. Theory in the area of learner dropout supports a multivariate framework to account for the complexity inherent in analyzing the learner's participation in multiple spheres of activity (Osborn, 2001). In order to build a model that accounts for the phenomenon of adult learners' dropout in e-learning in the workplace, a study needs to be conducted that examines variables identified in the literature to determine which variables most clearly differentiated completers from dropouts, identifies the relationships among the variables, and builds a model for adult learners' dropout. For the purpose of this study, an e-learning dropout is defined as anyone who doesn't complete a course or leave without reaching the goals of an e-learning course. The dropout problem carries enormous direct and indirect costs including in lost hours and money.

Dropout Studies in Adult Education and Distance Education

Darkenwald and Gavin (1987) point out that comprehensive review of dropout research in adult education has concluded that the findings of such studies have been largely contradictory or inconclusive. In addition, many of the studies on learner dropout and retention in adult education have used psychological, individual-level characteristics as their main independent variables (Ashar & Skenes, 1993). In a similar vein, Dirkx and Jha (1994) report that research on student attrition in adult education has focused on (1) identifying the motives or reason that adult learners have for leaving educational programs, (2) comparing those who dropped out with those who completed, and (3) investigating the influence of different institutional or contextual factors on attrition rate.

In distance education, there have been a number of studies on attrition conducted in higher education settings that inform this study. Based on the multivariate framework of student attrition developed by leading researchers in the field of distance education and instructional technology, Osborn (2001) conducted a study to select a set of key variables related to a student's ability to complete a distance learning course. To do this, he extracted three broad constructs such as entry characteristics, social integration, and academic integration including nine indicators of completion and seven predictors based on four models of student attrition. These models are Billings' (1988) Model of Correspondence Course Completion, Tinto's (1997) Model of Student Persistence, Kennedy and Powell's (1976) Descriptive Model, and Kember's (1995) Open Learning Model. Findings of the study show that the primary variables responsible for discriminating between completers and noncompleters included three factors: study environment, motivation, and computer confidence. Compared to the completing students, at-risk students had less-stable study environments, lower motivation, and less computer confidence. In addition, four single-item predictors were important discriminating variables: educational level, GPA, number of credit hours taken in the current semester, and number of previous distance learning courses.

Kember, Lai, Murphy, Siaw, and Yuen (1994) conducted a replication study originated by the work of Kember (1989). The essence of the model is that social and academic integration of students are viewed as intervening variables between initial background characteristics and outcome measures (e.g., academic achievement and persistence). The results show that social and academic integration had a significant effect on academic achievement and persistence. In addition, successful part timers were able to integrate school, work, family, and social demands; those who had difficulties often blamed external factors.

Fjortoft (1995) conducted a study to test a predictive model developed to examine the important parameters in adult student persistence in distance learning programs. The results of the study reveal that the independent variables in the model were significant in predicting persistence, explaining 23 percent of the variance in persistence. Univariate tests show that intrinsic benefits related to enhanced performance and satisfaction on the job, age, and level of student ease with individual learning were significant factors. However, extrinsic benefits, which were described as enhanced salary and career mobility, were not significant factors related to persistence. Adults in this study appear to be significantly motivated by intrinsic job-related benefits to persist in distance learning programs, with an individual learner focus.

In the meantime, many studies related to e-learning in the workplace have mostly focused on such subjects as (1) the comparisons among instructional strategies for the success of e-learning, (2) the satisfaction of adult learners with e-learning programs, and (3) the Return On Investment (ROI) of e-learning programs. However, relatively little concern has been given to why adult learners drop out in e-learning in the workplace.

Whatever the setting, it is difficult to comprehend why learners dropout of adult education and training programs because the reasons among learners are numerous and complex. Accordingly, the phenomenon of adult learner dropout cannot be understood just by one or two variables. Theory in the area of learner dropout supports a multivariate framework to account for the complex inherent in analyzing the learner’s participation in multiple spheres of activity (Osborn, 2001).

In order to determine whether a specific set of factors could be used to predict an adult learner's success in completing a work-related e-learning course, this study examines variables identified in the literature to determine which ones most clearly differentiate dropouts from completers and explores relative importance of the variables used in a model for logistic discriminant analysis. In examining these variables and relationships among variables this study employs the theoretical framework based on the following models: Boshier’s (1973) congruency model, Rubenson and Hoghielm’s (1978) expectancy-valence model of dropout, Bean and Metzner’s (1985) model of nontraditional undergraduate student attrition, Keller’s (1987) ARCS model, Billings’ (1988) model for completion of correspondence courses, and Kember’s (1995) open learning model.

Problem Statement

Although many studies related to e-learning have been conducted in the field of adult education and HROD, relatively little attention has been given to why adult learners actually drop out. In addition, there is scarce research-based evidence about how and why the learners in e-learning programs drop out. Hence, at both a practical and an academic level, it is important to know what characteristics or factors discriminate dropouts from non-dropouts for e-learning courses. This study provides an understanding of the dropout phenomenon of adult learners in e-learning in the workplace by testing a logistic regression model.

Purpose and Research Questions

The purpose of this study was to determine which specific set of variables can best predict the dropout of adult learners from e-learning courses in the workplace. The following research questions were a guide to the study purpose:

1. To what extent does a model consisting of individual background and motivational variables predict the dropout of adult learners from an e-learning course?

2. Which individual and motivational variables have a substantive relationship to the dropout of adult learners from an e-learning course?
3. Which is the best model to predict the dropout of adult learners from an e-learning course?

Significance of the Study

This study has the potential for both theoretical and practical contributions to the field of adult education, especially e-learning in the workplace. Theoretically, it offers an understanding of the dropout dynamic of adult learners in e-learning by providing a specific set of factors could be used to predict an adult learner's success in completing a work-related e-learning course. More specifically, the results of this study expand the knowledge base related to understanding dropout of adult learners in e-learning programs. As will be seen in the literature review, the majority of studies of dropout have focused on traditional educational settings such as face-to-face classroom-based programs. This study provides adult education and distance education scholars with empirical evidence delineating the dropout of adult learners in e-learning in the workplace. In addition, this study provides a more holistic understanding of dropout of adult learners in terms of theoretical perspective. As noted earlier, many studies have pointed out the fact that the phenomenon of adult learner dropout cannot be understood just by one or two variables. This study provides a multivariate framework showing useful information about the most important variables of dropout of adult learners in e-leaning in the workplace.

This study offers practical significance as well. Based on the research results, this study presents some important information such as prescriptive strategies for the e-learning course designers and instructors. This study strongly recommends that they take into account a variety of strategies that can prevent adult learners in e-learning from dropping out. For instance, e-learning course designers and instructors can provide adult learners with learning opportunities by using a variety of learning strategies to assure their understanding, integration, and retention of course concepts. Or, they may need to encourage them to use communication techniques for more interactive learning in e-learning courses. In addition, the study can urge designers and instructors to pay attention to student support services or communication environment as the important factors for the success of e-learning program and the reduction of dropout rate of the adult learner.

CHAPTER II

REVIEW OF THE LITERATURE

The purpose of this study was to determine which specific set of variables can best predict the dropout of adult learners from e-learning courses in the workplace. In order to achieve the study purpose, this literature review provides a framework of the underlying concepts for the study. This literature review divides into five major areas: e-learning in the workplace, corporate e-learning in South Korea, variables related to dropout of adult learners, models of dropout in adult education, and some implications for the study of dropout of adult learners in e-learning.

The origin of the literature review represents several disciplines and fields. The main literature comes from the fields of adult and continuing education, human resource and organization development (HROD), distance education, and instructional technology. This literature review searched the following data bases in the University of Georgia's GALILEO: Educational Resources Information Center (ERIC), Dissertation Abstracts International (DAI), and PsycINFO. The World Wide Web also provided a huge amount of sources of literature through some search engines such as Google, Yahoo, and Altavista. This searching task also included a hand and eye review of various academic journals, such as *Adult Education Quarterly* (AEQ), *International Journal of Lifelong Education*, *Training & Development*, *Training*, *Educational Technology*, *The American Journal of Distance Education*, and *Distance Education-An International journal*. I used a variety of search terms for this literature review, either singly or in combinations: "e-learning," "distance education," "distance learning," "web-based learning," "web-based training," "web-based instruction," "adult dropout," "adult attrition," "e-dropout," "deterrent factor," "adult retention," and "adult persistence."

E-learning in the Workplace

The so-called information revolution triggered by advanced communication technologies such as the internet has changed many things. The arenas of education and training are no exception. Whiteman (2001) notes that businesses are recognizing innovative ways to increase productivity by redesigning entire critical business processes and using technology to support the new designs. He continues that business "programs must respond to corporate and personal development needs by designing curriculum that embraces the management skills required by a changing business world" (pp. 1-2).

Based on the belief that e-learning programs can provide a more individualized, self-paced, self-directed learning experience for the learner and substantially reduce the educational cost of participants in those programs, e-leaning has gained a pivotal position in the field of HROD, as well as, public arenas such as university education. Alex Pass (as cited in Dobbs, 2000), project manager for Motorola's education-assistance program, asserts:

> There is a need for training in the moment that you have to deliver content to someone who can apply it immediately. That's the overriding need. The model is changing, and we have to keep up with it. It's all about e-learning and that means completely altering the way education is delivered, valued, and measured. (p. 56)

Gilroy (2001) argues that "after many years of development e-learning has become an important business process for corporations, which are now exploring how to better educate and manage their employees who rely on fresh knowledge to perform" (p. 1). He maintains that "e-learning is also at the top of the agenda of public and private universities, which are looking for ways to extend their influence and reach new types of customers" (p. 1). Murphy (2001) also points out that e-learning can be a more efficient and inexpensive way for companies to train their staff because they do not have to fly staff members to a central location for classroom training or pay for hotels, instructors, or for staff time away from work. Additionally, "e-learning courses can be customized to fit a company's needs and be administered to every staff member, including hourly workers" (p. 1).

Out of several reasons, the cost savings explains a large proportion of why e-learning is growing rapidly. According to Nauman (as cited in Murphy, 2001), a senior manager in the Chicago office of Ernst & Young LLP who consults with client companies making the switch, "the cost savings is the No. 1 reason that e-learning is growing in popularity…If a corporation wants to teach several thousand employees spread around the country a new subject, it can be very expensive to fly them into a central point to a classroom and pay for hotels and instructors, not to mention the time away from work. An e-learning seminar can reach those people far more efficiently at a fraction of the cost" (¶ 4). Michael Brennan (as cited in Murphy, 2001), a senior analyst at Framingham, Mass-based International Data Corp, argues that "companies can save 75% and more with e-learning vs. traditional classroom instruction" (¶ 5). But what kinds of costs are saved? Horton (2000) gives us some instances: travel expenses for training, training facilities and supplies, training administrative costs, salaries, and lost opportunity costs. In addition to this, he enumerates the major examples of organizations' substantial savings:

- *Hewlett-Packard* cut the cost of training 700 engineers on a new chip from $7 million USD to $1.5 million. The training was performed in 30 days instead of the year projected for on-site classroom training.

- *MetLife* was able to train 9000 fields' sales representatives to use a new computer application for $30 USD each.
- *Cisco* reduced the $1200 - $1800 USD cost per learner of instructor-led training to $120 with WBT
- *Novell* certification can be an expensive process. The price of a four-day classroom course for Novell Certification was $1800 USD, not including travel, lodging, meals and time away from the job. The same training now costs $700 to $900 delivered by WBT. (pp. 21-22)

In the United States, the education enterprise, from cradle to grave is the second largest segment of the economy after health care, and the education market is estimated by the investment firm W.R. Hambrecht + Company to total $772 billion (Galagan, 2000). Out of this education market, the total U.S. training budget in 2000 was about $63 billion (National Alliance of Business [NAB], 2000).

"A combination of rapid-fire technological advances and trends such as globalization, changing demographics and the need for higher-level skills in today's knowledge-based economy has nurtured an emerging e-learning marketplace that is primed for explosive growth in the years ahead" (ASTD/NGA, 2001, p. 10). The following statistics from ASTD/NGA (2001) show what the e-learning marketplace looks like today, as well as what the future holds for this rapidly growing segment of the U.S economy:

- Corporate e-learning in the United States is a $1.2 billion market in 1999 and is expected to grow to a $7 billion market by 2003. According to NAB (2000), it is expected to grow to about $11.5 billion market by 2003.

- The global e-learning industry comprises approximately 5,000 suppliers offering every imaginable method of e-learning. The vast majority of these suppliers are private; no single competitor in the e-learning market accounts for 5 percent market share or more- a fact that is contributing to growing market consolidation.
- According to ASTD’s State of the Industry Report 2001, firms participating in the organization’s Benchmarking Service projected a 117-percent increase, on average, in the use of learning technologies between 1999 and 2002. ASTD found that the percentage of organizations using the Internet for training purposes grew from 3 percent in 1996 to 38 percent in 1999. For intranets, the rate of growth was even higher, from 3.5 percent to nearly 40 percent.
- A recent survey by International Data Corporation affirmed the growing popularity of the World Wide Web as a training medium. WBT, according to the survey, is expected to surge by more that 900 percent between 1999 and 2003. A key reason, according to a Business Week report on the findings, is that online training is far cheaper that bringing in a live instructor, let alone sending employees to an offsite training location. And productivity doesn’t suffer as much when employees get their how-to at their own computer. (p. 10)

E-learning is changing the way corporations deliver training in nearly all segments of the business process. Furthermore, e-learning has been changing the image of training in the workplace.

According to the American Society for Training and Development (as cited in Bierema, 2001), “workplace learning is coming of age during a time when information is the currency of the new economy, attention has shifted from training to learning” (p. 41). Bierema (2001) urges that organizations always pursue change and growth, and these changes and growth never happen without learning. She maintains that "learning is pivotal in the quest to seek organizational effectiveness for individual, team, and ultimately the organization itself" (p. 41). Table 1 presents the trend of today's work environment. As shown in this table, the kernel of the trend is a paradigm shift from training to learning. Learning in the workplace is "shifting from formalized, short-term instruction by an expert to informal, strategically focused learning facilitation by stakeholders and internal employees" (Bierema, 2001, p. 41).

Table 1

From Training to Learning

From Training		**To Learning**
Focus on short term	→	Focus on lifelong learning/development
Skill based	→	Core competency based
Driven by individual request	→	Driven by corporate strategy
Concentrates on managers and executives	→	Concentrates on all employees
Assessment done by HR and /or Mangers	→	Assessment done by affected individuals
Training happens offsite	→	Learning happens anyplace
Training is scheduled periodically	→	Learning happens in real time
Training based on knowledge delivery	→	Learning based on creating new meaning about sharing experiences in workplace
Instructor driven; designed by specialists	→	Self-directed
Generalized, prescriptions	→	Specific, trainees determine
Trainers deliver, trainer-centered	→	Facilitated jointly, learner-centered

Note. From "Practice of organizational learning," by L. L. Bierema, 2001, In J. W. Gilley, P. J. Dean, & L. L. Bierema, *Philosophy and practice of organizational learning, performance, and change* (pp. 41-66). Cambridge, MA: Perseus Publishing.

According to Drucker (2000), the only trigger for the changes taking place in training is the new technologies. He notes three root causes:

> One is the radical shift in the structure of the workforce. Another root cause is the rapid restructuring of traditional work, whether in the factory or in large-scale repetitive

> clerical operations, which are actually production work. …A third root cause is new learning theory. Let me explain: Traditional training is a product of World War I, perfected in World War II. It arose out of the application of the basic concepts of Frederick Taylor's scientific management, to the German invention around 1840 of apprenticeship. …That kind of training hasn't become obsolete-far from it. But it is being transformed by the application of learning theories developed in the past 30 to 40 years, particularly in connection with Deming's total quality management. I could summarize that by saying that learning as we practice it still puts the teaching process at the center. Increasingly, we must instead put the learning process at the center. (p. 27)

He continues that "new technologies make it possible to reach learners wherever they and whenever they find it convenient, instead of bringing inadequately small groups to a central location away from their work" (p. 27). According to ASTD/NGA (2001), e-learning is "adult-centered and work-related" (p. 7). More broadly, it is "technology-enabled learning that is designed to increase worker's knowledge and skills so they can be more productive, find and keep high-quality jobs, advance in their careers, and have a positive impact on the success of their employers, their families and their communities" (p. 7). E-learning has been considered as the most appropriate tool for the demand of the new work environment. This implies that we have to throw away the past assumptions of training and encourage workers as lifelong learners. At this point, we cannot help looking at a big issue related to e-learning's limitations.

Corporate E-learning in South Korea

The corporate e-learning market in South Korea has recently been growing rapidly over the past several years. This growth has been propelled by both the supply and demand sides. Corporate e-learning providers (in-house training department or outside e-learning vendors) have improved the quality of e-learning and resolved customization issues to successfully overcome clients' reluctance to use e-learning. More reliable information and communication technology (ICT) and declining telecommunication costs have also contributed to the growth of the market. Table 2 shows the market size of e-learning in years of 2003 and 2004.

Table 2

Market Size of E-learning in South Korea

Areas	2003		2004		
	Market Size (millions US $)	Component Ratio (%)	Market Size (millions US $)	Component Ratio (%)	Rate of Increment
Content Area	221.38	22.61	261.36	22.14	18.06
Solution Area	195.46	19.96	202.69	17.17	3.70
Service Area	562.29	57.43	716.39	60.69	27.41
Total	979.13	100	1180.44	100	20.56

Note. From "Korea e-learning initiative: Research on e-learning industry and policy in Korea," by Y. Kang, 2005.

As seen in the Table 2, the e-learning market increased 20.56% from 2003 to 2004. With a growth rate of 27.41%, the service market appears to lead the whole e-learning industry. The growth of e-learning is particularly visible among large corporations, where both in-house programs and outsourcing programs supplied by e-learning companies operate side by side (Lee, 2003). According to Ministry of Commerce, Industry, and Energy (2004), 56.81% of large enterprises are introducing e-learning courses, compared to only 24.71% of small and medium enterprises.

Today, as a methodological strategy, corporate training divisions employ blended e-learning environments to maximize the learning effect, rather than using supplementary or pure e-learning environments. This allows the training divisions to focus on designing a customized educational system that contributes to the company's competitiveness while meeting individual learner's needs and demands (Ministry of Commerce, Industry, and Energy, 2003). In 1999, the Ministry of Labor added Web-based training to the Vocational Training Promotion Act as a new form of vocational training and education. The Ministry has been subsidizing part of the training expenses for employers who, in compliance with the Employment Insurance Act, have their employees take Web-based training courses (Lee, 2003).

Within the area of corporate e-learning, there is currently much discussion regarding its critical issues and future development (Lee, 2003):

> There is a growing demand to expand blended learning to maximize teaching outcomes and to conduct more measurable and specific studies on the effects of e-learning. …Along with the concerns about inefficient information sharing and resources due to a lack of consistent standards, there has also been a growing debate about the standardization of e-learning since 2002, which will be the top priority for future expansion and marketability of e-learning. Similarly, high-quality customized content, improvements of the Internet-based Training System, and the fostering of e-learning professionals have all been receiving much attention. (p. 77)

This discussion, however, has been focused only on technical aspects or content issues of corporate e-learning. There has been little discussion of sociocultural aspects, such as gender or class issues, that are related to the phenomenon of client dropout in e-learning environments.

Variables Related to Dropout of Adult Learners

Although many studies related to e-learning have been conducted in the field of adult education or HROD, relatively little attention has been paid to why adult learners dropout. There is no broad-based quantitative study pointing to evidence of a widespread dropout problem for online training in the corporate world (Zielinski, 2000). In addition, there is not any research-based evidence about how and why adult learners in e-learning programs drop out. Of those studies of dropout of adult learners in e-learning reviewed in this section, only a few provided a comprehensive, theoretically-based, and explanatory framework from which to analyze the problem of dropout. Opinion papers based on the authors' face to face instruction or managing experiences of e-learning are reviewed and are discussed here as well as several theory-based studies, because of their relevance to the conceptual framework and findings of this research.

A study, the Learning Technology Acceptance Study: "If We Build It, Will They Come?", by ASTD and the MASIE Center (2001) reveals the fact that dropout rates for online training are high when learners are put off by one or more several factors. These factors include poor incentives to learn, lack of accountability for completing classes, problems with technology, and the inability of poorly designed courseware to hold a student's attention. Based on its own experience as an e-learning provider, Frontline Group (2001) also provides five reasons why adult learners drop out in e-learning programs: poor design, failure to understand the new medium, not considering a variety of learning styles, lack of supporting systems, and ignoring the self-selecting content needs of learners.

Based on studies conducted by e-learning providers and the opinions of e-learning experts, Frankola (2001b) notes that adult learners drop out in e-learning courses due to the following reasons: students don't have enough time, lack of management oversight, lack of motivation, problems with technology, lack of student support, individual learning preferences, poorly designed courses, and substandard/inexperienced instructors. Interestingly, NYUonline found that "e-learners who took only the asynchronous course were much less likely to complete it than e-learners who also participated in (face to face) live sessions" (as cited in Frankola, 2001b, ¶ 20).

On the other hand, crucial interactivity with faculty and among other students can be important for the success of a course. Studies conducted by Sun Microsystems Inc. show that “only 25% of employees finish learning content that's strictly self-paced, but 75% finish when given similar assignments and access to tutors through e-mail, phone or threaded discussions” (Frankola, 2001b, ¶ 18). Arsham, also points out that interactivity with students is a key factor in explaining students’ retention, based on the experience of teaching two courses of the first all-online accredited Web MBA program (as cited in Elearningpost, 2001).

This fact is also supported by a study (Towles, Ellis, & Spencer, 1993) conducted in the field of distance education. This study sought to evaluate the effect of faculty initiated contacts on student’s persistence within a large video-based distance learning program, and showed that faculty-initiated efforts seem to have the greatest effect on improving course persistence among freshmen students. Vrasidas and McIsaac (1999) examined the nature of interaction in an online course from both teacher and student perspectives. They find that the structure of the course, class size, feedback, and prior experience with computer-mediated communication (CMC) all influenced interaction. In particular, findings showed that some elements of structure, such as required activities, led to more interaction, and students who were new to CMC were not comfortable participating in the online discussion. In addition, “when students do not receive feedback from instructors, they do not continue to post messages. Unless receive immediately feedback, they feel they are posting to the network without any response” (Vrasidas & McIsaac, 1999, p. 33).

According to Gilroy (2001), the CEO of the Otter Group, low enrollments and high attrition rates stem from user dissatisfaction and the cause of this problem is the separation of people in time and space; but it can be overcome by building environments where people talk to one another, build relationships, and teach one another. She continues, “While there is no simple answer, there is one key idea that has been overlooked in the design and implementation of many of the e-learning programs on the market today” (¶ 3). That is, “learning is fundamentally both social and experiential. It is the context of the learning-all of the elements that comprise the experience around the content-that is most important” (¶ 3). Based on the Otter Group's model of how best to teach and learn online, she presents many elements that must be managed to create e-learning programs; Not too much content and too little context, valued learning experience, course as learning communities, personalization, and an open technology source.

A study, “Student support services and success factors for adult on-line learners,” conducted by Greer, Hudson, and Paugh (1998) examined a variety of student support services and four areas for student success from the viewpoint of World Wide Web-based learners in the University of Central Florida College of Education, Vocational Education area. They point out that the most common theme in terms of students' perceptions of success factors were budgeting time, being self-motivated, and having supportive friends and family.

Shepherd (2001) argues that the reason why learners dropout is a simple one of motivation. In addition, motivation has two determining factors: the first factor is a desirable outcome, whether this is the achievement of a personal goal, recognition from others or some form of tangible reward such as money or promotion. There is a flip side to this, in that the learner may be seeking to avoid some penalty, such as a reprimand, disapproval or some financial disincentive. The second factor in motivation is the learner’s perception of the likelihood, given that learners put in sufficient effort, of the learner obtaining their reward or avoiding the penalty. If the means to the end is too tortuous, the motivation will drop regardless of how desirable the outcome may be. He maintains that “even if the incentives are sufficient to get learners started, e-learning can place many obstacles in the way of successful completion. “Removing, or reducing the effect of these obstacles is essential to curing the drop-out problem” (Shepherd, 2001, ¶ 11). These obstacles are inappropriate or inadequate content, lack of time and/or inadequate time to learn, no support for their learning by peers and training mangers, and the assessment of the learner’s learning process by tutors or managers.

Based on a case study, Chyung (2000, 2001a, 2001b) found some reasons for dropout in online distance education. She maintains that adult learners in distance education tend to dropout when they perceive that: (1) online learning environment and instructional presentations are not attractive to them, (2) what they learned from the online instruction was not relevant to their interests or goals, (3) they are not confident enough to become a successful online learner, and (4) they have low satisfaction levels toward the online learning environment. Chyung, Winiecki, and Fenner (1998) found that the satisfaction of adult learners in an on-line course during the first or second classes was the major factor, which determined learners' decisions about whether or not to continue in the program. Forty-two percent of the students who dropped out expressed dissatisfaction with the learning environment as the reason; Another reason given was a discrepancy between professional or personal interests and course structure. In a study by Lim (2001) to develop a predictive model of satisfaction of adult learners in a Web-based distance education course and their intent to participate in the future, she found that computer self-efficacy was the only predictor variable that was statistically significant out of variables included in the predictive model. The variables included in the model were computer self-efficacy, academic self-concept, age, gender, academic status, years of computer use, frequency of computer use, computer training, Internet in a class, and participation in a workshop for Web-based courses.

Some e-learning experts present many strategies or tips for the success of e-learning. Interestingly, Augusto Failde, senior vice president of global development at NYUonline, proposes 11 strategies that companies can use to help ensure high course completion rate (Frankola, 2001a). These strategies are as follows: (1) develop a culture that takes online learning just as seriously as classroom training, (2) do individual comparisons, (3) hold managers accountable for the success of their employees, (4) use managers as role models, (5) create a social dimension to e-learning, (6) make expectations clear up front, (7) provide formal rewards, (8) track performance, (9) get personal, (10) hold a team competition, and (11) launch a communications campaign. He explains that “good companies that recognize the importance of human capital must motivate and support employees as they develop a commitment to life-long learning” (Frankola, 2001a, ¶ 18). Broadbent (2001) also gives e-learning engagers some tips for e-learning success. These tips include; (1) focusing on a clear business objective, (2) don’t set very high expectations, (3) hire consultants or some sort of service provider to handle all of e-learning needs, (4) don’t force e-learning on resisters, (5) don’t evaluate. Black (1998) emphasizes the following; (1) offer short classes, (2) make graphics simple and easy to read, (3) foster collegiality by asking students to contribute information about themselves and their interests, (4) vary the way you interact with learners, (5) avoid superfluous media, and (6) use a combination of synchronous and asynchronous instruction to reinforce new material, design assignments, and improve learner retention. Horton (2000) contends, “Successful virtual classroom courses usually depend more on human interaction than on technological infrastructure” (p. 398). Hence, he points out that selecting a qualified instructor, keeping the class small, and responding promptly and reliably are important in planning a Web-Base Training (WBT) course. In addition to this, he suggests holding a pre-class get-together to overcome initial hurdles; publishing a comprehensive syllabus; preparing learners to participate (e.g., the etiquette for online meetings); managing collaborative activities; teaching the class- rather than just letting it happen (e.g., contact participants individually, help classmates get to know one another, stay on the published schedule, keep office hours, pace learners, do not spend too much time teaching the course software); conducting live events; making participants visible; and staying in touch after the class. Khan and Vega (1997) contend that the Web design should be "logical, user-friendly, and meaningful" (p. 378).

As many researchers point out, motivating learners is a very important factor to retaining them in e-learning courses. "Successful WBT courses rely on the self-discipline and focus of motivated learners" (Horton, 2000, p. 418). He suggests some techniques that designers and instructors can use to keep learners interested, energized, and enthusiastic. These techniques are: (1) set clear expectations, (2) require commitment, (3) feature the WIIFM (what's in it for me?), (4) make WBT fun and interesting, (5) offer bribes, (6) pace and prompt learners, (7) provide encouraging feedback, (8) build a learning community, (9) intervene with unmotivated learners, and (10) redeem troublemakers.

Driscoll (1998) contends, "Designing effective WBT requires knowledge of the unique characteristics of adult learners and an understanding of the facilitator's role" (p. 13). He outlines the characteristics of adult learners as: real-life experience, problem centered learning, continuous learners, varied learning styles, responsibilities beyond the training situation, and meaningful learning.

Osborn's (2001) empirical study, based on the multivariate framework of student attrition developed by leading researchers in the field of distance learning, found that at-risk students who enrolled in Web-based and video conferencing courses in a higher education setting (1) had less stable study environments, lower educational levels, lower motivation, lower GPAs, and less computer confidence; (2) were taking more credit hours in the current semester; and (3) had not taken distance learning courses prior to participation in the study.

As in Tinto's (1975) model, the two dimensions of integration, academic and social, form the core of Kember's (1995) open learning model. This model was developed through the process of validation of the model, utilizing both quantitative and qualitative data from a diversity of sources. This model consists of several constructs that affect outcome of students in open learning courses. The construct of entry characteristics that influences integration variables consists of demographic status, educational qualifications, family status, and employment. Kember (1995) notes that entry characteristic are not good predictors of final outcomes, because they are just a starting point in determining how much difficulty a student is likely to face in coping with a course. He continues, "Many students with apparently adverse circumstances do succeed" (p. 77). The social integration construct consists of enrollment encouragement, study encouragement, and family environment and examines the degree to which students are able to integrate their academic with the often conflicting employment, family and social requirements. Kember (1995) asserts that "social integration can be achieved, even in the face of an inhospitable social environment, if a time and space for study are negotiated" (p. 88). The external attribution construct consists of insufficient time, unexpected events, and distractions. The lower levels of social integration affect the negative academic integration of students. In the model, academic integration is spilt into the positive (academic integration) and negative (academic incompatibility) tracks. Each construct consists of four indicators such as study approach, motivation, course evaluation, and language ability. Academic integration is understood as "encompassing all facets of a course and all elements of contact between an institution and the students whether these are of an academic, administrative or social nature" (Kember, 1995, p. 99). In addition, GPA functions to some extent as an intervening variable between academic incompatibility and dropout. At the final step of the model, a cost/benefit analysis, the student has to make a decision about either dropping-out or completing study. This final step includes a recycling loop that provides a mechanism for switching from one track to the other.

Based on variables (see Table 3) identified from the literature review of dropout in e-learning and the models of dropout dealt with above five constructs were categorized: individual background, motivation, academic integration, social integration, and technological support.

Year after year, e-learning is becoming more popular because it allows training to be available on demand, to be delivered remotely, and to keep up with the rapid pace of economic change. The flexibility of time, place, low delivery cost, and program contents provided via e-learning is very appealing to workers who are trying to improve their careers related to job performance or individual development, as well as to training mangers who are trying to seek effective and efficient instructional delivery. Undoubtedly, e-learning based on the today's advanced technologies has been considered as the best learning delivery media for this purpose. At this point, it needs to understand the dropout of adult learners in e-learning for more effective and efficient e-learning operation.

Models of Dropout in Adult Education

There are many theories and models that explain why adult learners dropout. Bean (1990) notes that "models are important because they tie theory to specific situations" (p. 150). In this section, I will deal with six relevant models of dropout. The models to be discussed are Boshier's (1973) congruency model, Rubenson and Hoghielm's (1978) expectancy-valence model of

Table 3

Five Categories of Variables Identified from the Literature Review of Dropout in E-learning

Studies	Construct				
	Individual Background	Motivation	Academic Integration	Social Integration	Technological Support
ASTD & MASIE Center (2001)		• Incentives • Lack of accountability for completing classes • Poorly designed courseware			• Problems with technology
Augusto Failde (as cited in Frankola, 2001a)		• Extrinsic motivation- formal reward, team competition, clear expectations, etc.		• Social dimension	
Broadbent (2001)		• Clear expectations • Need satisfaction			
Black (1998)		• No evaluation • Challengeable expectations • Clear business objective • Short classes	• Interaction with learner		• Superfluous media
Brown (1996)			• Support from tutor		
Chyung (2000, 2001a, 2001b)		• Attraction • Confidence • Relevance • Satisfaction			
Chyung et al. (1998)		• Satisfaction			
Driscoll (1998)	• Characteristics of adult learners				
Frankola (2001b)	• Individual learning preferences	• Lack of learner control of content • Poorly designed course	• Lack of management/ support • Inexperienced instructor	• Lack of time	• Technical hurdles
Frontline Group (2001)	• Learning styles	• Poorly designed course	• Supporting systems		
Greer, Hudson, & Paugh (1998)		• Self-motivated		• Budgeting time • Supportive friends and family	
Gilroy (2001)		• Satisfaction • Poorly designed course • Personalization	• Learning community		
Horton (2000)		• Live event • Incentive • Pre-class meeting • Staying on the published schedule • Pacing learners • Making participants visible	• Qualified instructors • Interaction individual contact • Prompt feedback		• Technical hurdles
Hossein Arsham (as cited in Elearningpost, 2001)			• Interactivity with student		

Studies	Construct				
	Individual Background	Motivation	Academic Integration	Social Integration	Technological Support
Kember (1995)	• Entry characteristics	• Intrinsic/extrinsic motivation • Positive/negative course evaluation	• Poor/good language skills • Deep/surface approach	• Family environment • Enrollment encouragement • Study encouragement • Insufficient time • Unexpected events • Distractions	
Khan & Vega (1997)		• Poorly designed course			
Lim (2001)		• Self-efficacy			
NYUonline (Cited in Frankola, 2001b)		• Live session			
Osborn (2001)	• Educational level • GPA • Number of credit hours taken in the current semester, and number of previous distance learning courses.	• Computer confidence • Lower motivation		• Less-stable study environments	
Shepherd (2001)		• Incentive • Learner's perception of the likelihood of the learner obtaining their reward or avoiding the penalty • Inadequate contents • Assessment of learner's learning process by trainers	• No support of peer & training managers	• Lack of time	
Sun Microsystems Inc (as cited in Frankola, 2001b)			• Crucial interactivity; faculty and learners		
Towles, Ellis, & Spencer (1993)			• Faculty-initiated interaction		
Vrasidas & McIsaac (1999)	• Prior experience with CMC	• The structure of the course	• Interaction • Class size • Feedback		

dropout, Keller's (1987) ARCS model, Bean and Metzner's (1985) model of nontraditional undergraduate student attrition, Billings' (1988) model for completion of correspondence courses, and Kember's (1995) open learning model. While the first three are motivation-oriented models, the last three are dropout models in distance education settings. Based on these models, I developed a composite model that can explain the dropout of adult learners in e-learning in the workplace.

Boshier's Congruency Model

Boshier's (1973) congruency model based on self-theory is proposed to account for adult education participation and dropout. Boshier asserts that both participation and dropout stem from an "interaction" of internal psychological and external environmental variables. In addition, he understands the dropout of adult learners as an extension of non-participation in some ways; "variables associated with one are associated with the other" (Boshier, 1973, p. 256). In short, this model asserts that "congruence both within the participant and between the participant and his/her educational environment determine participation/non-participation and dropout/persistence" (p. 256). As can be seen in Figure 1, this model is based on "the assumptions that participation and persistence in adult education are determined by how people feel about themselves and the match between the self and educational environment" (Merriam & Caffarella, 1999, p. 62). Therefore, the cumulative effect of these incongruencies is filtered by social and psychological variables such as age, sex, race, and social class as well as subenvironmental variables such as transportation and class size (Merriam & Caffarella, 1999).

Boshier (1973) presents an explanation for ingredients of the model:

- *Internal Psychological Determinants*: Boshier's (1971) factor analysis of 48 statements of "motives for attendance" suggested that participants in non-credit "liberal" adult education classes could be characterized as "deficiency" or "growth" motivated.

  …Determinants impelling the behavior of growth-motivated are primarily inner ones, whilst deficiency-motivated people are impelled by social and environmental pressures.

  …we hypothesize that enrolling for "deficiency" reason is associated with intra-self incongruence, which in turn leads to self/other incongruence and dissatisfaction with the educational environment. Growth motivation is associated with intra-self, and thus self/ other congruence and satisfaction with educational environment.

- *Self/Other Incongruence*: …Adopting Roger's (1959) terminology, incongruences develop within the person (intra-self) and between the person and other-than-self (self-other) experiences. Either type of incongruence leads to anxiety, which is a subjective state of uneasiness, discomfort, or unrest….Bearing in mind the pervasive nature of self-rejection and the development of incongruence, it is now suggested that both adult education participation and dropout can be understood to occur as a function of the magnitude of the discrepancy between the participant's self concept and key aspects (largely people) of the educational environment….Upon finding that unskilled workers' needs (or self-concept) and the adult education institutional arrangements were not congruent, they dropped out.
- *Mediating Variables*: Returning to Figure 1, we hypothesize that participants who enroll for "deficiency" reasons manifest significantly more intra-self (and thus self/other) incongruence than participants enrolling for "growth" reasons. It is now contended that single social, psychological, and institutional variables typically discussed in dropout studies mediated the congruence/dropout relationships. Variables such as transport difficulties, age, and class size trigger dropout, if intra-self or self/other incongruence has developed….Note in Figure 1 that "mediating" variables are linked with enrolling for "growth" or "deficiency" reasons. Deficiency and growth motivation, as well as being associated with age, are differentially distributed by social class, and are associated with other "mediating" variables. (pp. 256-262)

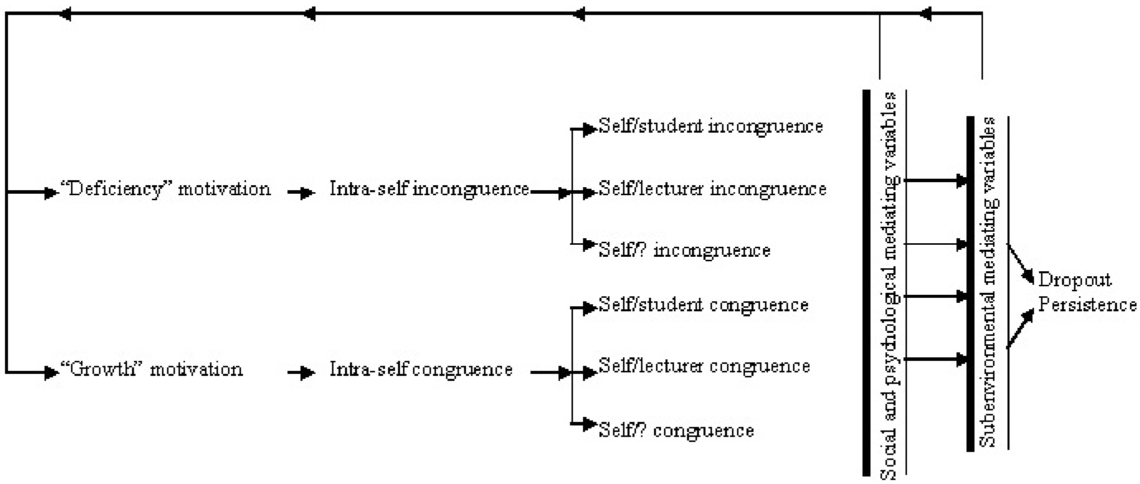

Figure 1. Boshier's model to explain dropout from adult education institutions.

Note. From "Educational participation and dropout: A theoretical model," by R. Boshier, 1973, *Adult Education*, *23*(4), p. 257.

Using Personality and Educational Environment Scales (PEES), which is a modified Semantic Differential measure incorporating 15 reliable and relevant eleven-step scales, Boshier (1973) found that the model is experimentally and administratively suggestive and replete with hypotheses capable of empirical investigation. PEES consists of four concepts: "Other Adult Education Students," "My Adult Education Lecturer," "Myself" and "Myself-As-I-Would-Like-To-Be," and accompanying scales (e.g., stimulating, boring, scholarly, non-scholarly). In addition, PEES consists of three factors stable across concepts: "Personal warmth," "Conventionality," and "Personal effectiveness." He states that "dropping out was a function of the cumulative effect of self/other incongruence which initially resides within the participant" (p. 274). In short, this means that incongruence on self/ideal self, self/others and self/lecturer is correlated substantially with dropout behavior of adult participants.

Boshier's (1973) congruence model was the first to try to explain the phenomenon of persistence/dropout of adult learners in terms of motivation perspective. Even though there are mixed test results of Boshier's model, the model has significant implications for the study of dropout of adult learners.

Borgstrom (1980) points out two weakness of Boshier's (1973) model; the model lacks connection with educational reality, in other words, what goes on in the teaching situation, and the model is focusing only on individual motivational factor as the cause of dropout. According to Garrison (1987), "Boshier's model is far too simplistic to explain complex phenomenon such as dropout in a variety of adult education settings" (p. 214). He continues that "the major difficulty with the congruence model is that it has in effect eliminated from consideration many factors in the adult's school and nonschool environment" (p. 214), pointing out the need for a holistic psychological perspective to better understand the phenomenon of dropout.

Rubenson and Hoghielm's Expectancy-Valence Model of Dropout

Rubenson and Hoghielm's (1978) expectancy-valence model of dropout stemmed from the expectancy valence model developed by Rubenson (1977). Before going on to look at the model, a review of the expectancy theory will provide a base to better understand Rubenson and Hoghielm's expectancy-valence model of dropout. Howard (1989) maintains that expectancy theory originates from the theories of Lewin (1938) and Tolman (1932). This theory assumes that human behavior was "a result of the interaction of the individual and the environment, in the context of a specific situation, and that individual develop beliefs about the probability of various possible outcomes of their behaviors, preferring some outcomes over others" (Howard, 1989, p. 199). In other words, this theory postulates that a person's choice of activities composes an outcome of the value he/she attaches to the result of his/her actions and of his/her expectations of being able to carry out the action in question (Borgstrom, 1980).

Vroom's (1964) valence-instrumentality-expectancy (VIE) theory is also in a very important position in the history of expectancy theory. Building on the work of Lewin, Tolman, and others, he asserts that the force of motivation behind any behavior was a product of valence, instrumentality, and expectancy. As cited by Howard (1989), Vroom defines “expectancy as the individual’s subjective estimation of the likelihood of successfully performing a particular behavior, instrumentality as the individual’s subjective estimation of the likelihood that the behavior would be rewarded, and valence as the positive or negative value that the individual placed on the reward” (p. 200). The three key ingredients of his VIE theory, expectancy, instrumentality, and valence are expressed as probabilities. He spells out three basic assumptions underlying VIE theory: (1) that anticipation of reward energizes individual behavior, (2) that perceived value of various outcomes gives direction to individual behavior, and (3) that learner connections develop between behavior and outcome expectancy (as cited in Howard, 1989, p. 200).

Rubenson (1977) developed Rubenson’ paradigm of recruitment (see Figure 2), applying Vroom’s VIE theory to explain and predict dropout from adult education. Based on this paradigm, Rubenson and Hoghielm’s (1978) built the expectancy-valence model of dropout.

As can be seen in Figure 3, the expectancy-valence model of dropout describes that the strength of the participant’s power (Vroom’s force of motivation) to go on completing or dropping a course results from a function of the product of valence and expectancy (Howard, 1989). While expectancy consists of the expectation of being successful in an educational situation and the expectation that this success will have positive outcomes, valence relates to the values a person puts on being successful (Merriam & Caffarella, 1991).

The strength of the participant’s power is directly affected by the function of the product of valence and expectancy. However, the fact that individual and environmental factors have influence on valence and expectancy should not be overlooked. As mentioned above, their model

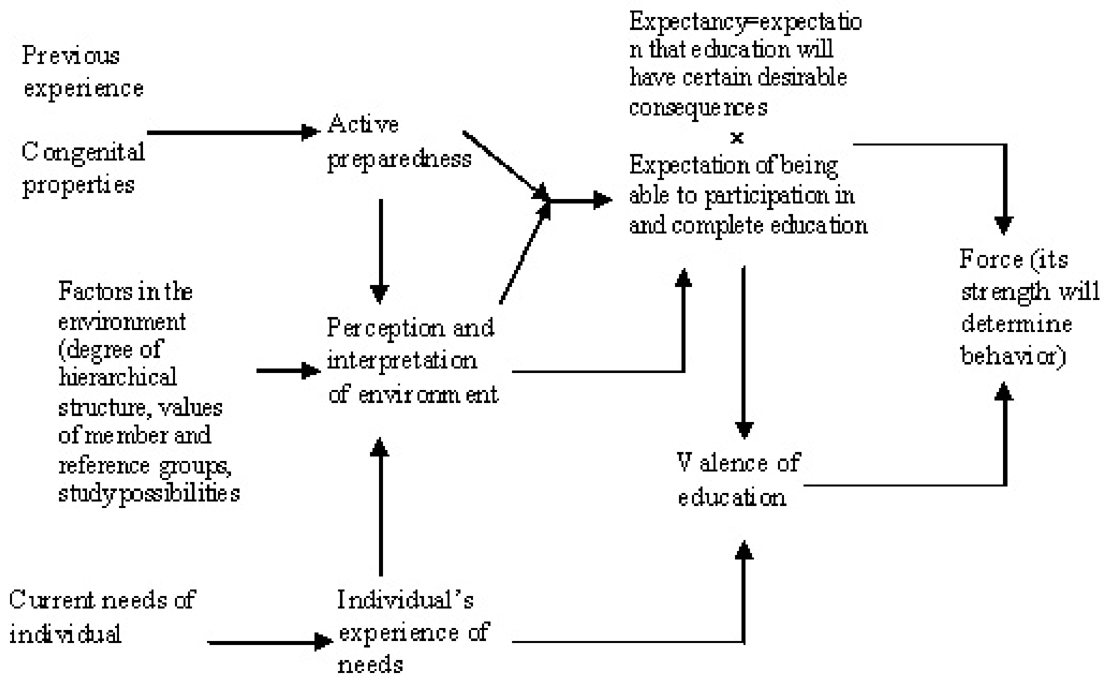

Figure 2. Rubenson's paradigm of recruitment.

Note. From "*Learning in adulthood*," by S. B. Merriam and R. S. Caffarella, 1991, p. 123. San Francisco: Jossey-Bass.

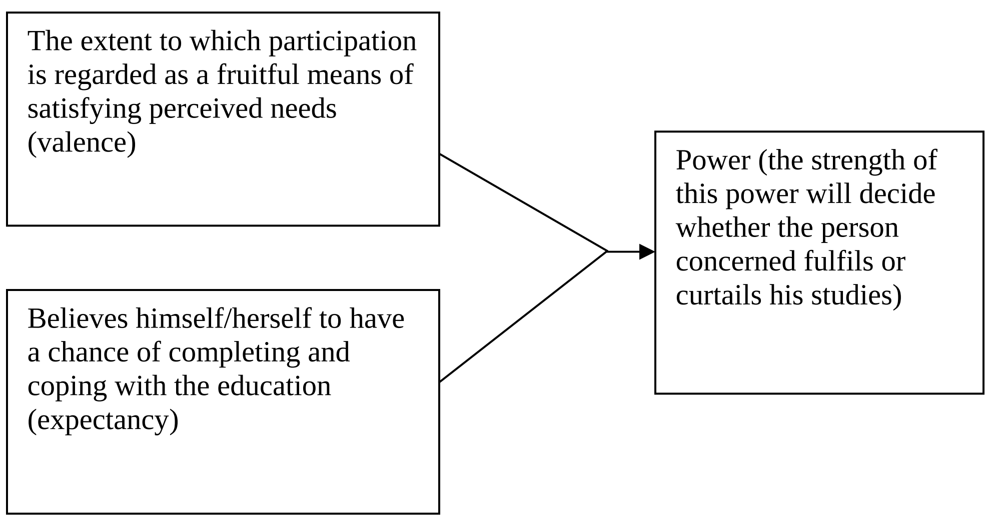

Figure 3. *Rubenson and Hoghielm's model for dropout.*

Note. From "Drop-out in municipal adult schools in the context of allocation policy," by L. Borgstrom, 1980, In R. Hoghielm, & K. Rubenson (Eds.), *Adult education for social change: Research on the Swedish allocation policy* (p. 118). Ordfront, Stockholm: LiberLaomedel Lund.

is based on Rubenson' paradigm of recruitment that draws from psychological motivation theories and, like Vroom's (1964) and Boshier's (1973) models, has its individual and environmental aspects.

While Boshier's (1973) congruence model explains that dropout/persistence is a function of the cumulative effect of self/other incongruence which initially resides within the participant, Rubenson and Hoghielm's (1978) expectancy-valence model of dropout describes that the strength of the participant's power to go on completing or dropping a course results from a function of the product of valence and expectancy. In addition, in Boshier's model, the cumulative effect of the incongruencies is filtered by social and psychological variables as well as subenvironmental variables. However, as can be seen in Figure 3, dropout or completion of adult learners is "contingent upon the interaction of various personal and environmental variables operating in an individual's life" (Silva, Cahalan, & Natalie, 1998, p. 34).

In Rubenson' paradigm of recruitment (see Figure 2), personal variables include prior experience, personal attributes, and current needs, while environmental factors include degree of hierarchical structure of the individual's life-space, values of member and reference groups, and available educational possibilities as institutional factors.

The personal and environmental variables do not themselves explain participants' behavior:

> Rather, the influence of these variables on behavior is mediated by the individual's responses to them. This response in turn gives rise to intermediate variables. Intermediate variables include active preparedness, perception and interpretation of environment, and experience of individual needs. The intermediate variables interact with each other to determine the perceived value of educational activity (valence) and the probability of

> being able to participate in and/or benefit from this activity (expectancy). (Silva, Cahalan, & Natalie, 1998, p. 34)

Accordingly, the individual is the center of the model because everything depends on a person's perception of the environment and the values associated with dropping or completing a course.

In conclusion, Merriam and Caffarella (1991) characterize the characteristics of Rubenson's model as follows: (1) there is attention to societal process through his/her socialization and structural components, (2) the individual's conceptual apparatus is deemed crucial in perceiving needs, the environment, and the value of education, and (3) these two dimensions combined lead to a determination of one's behavior.

Motivating adult learners to do something has always been a critical concern of adult education theorist and practitioners. As mentioned earlier, Rubenson and Hoghielm's expectancy-valence model of dropout starts with psychological theories of motivation; then the strength of the individual's motivation to drop or continue a course is determined by combining positive and negative forces existing in the individual and the environment.

However, this model has some critical weak points. The model placed much less emphasis on so-called external barriers to influence the dropout of adult learners. Even though Rubenson's (1977) paradigm, the background theory of Rubenson and Hoghielm's (1978) expectancy-valence model of dropout, is helpful in shifting attention from demographic variables such as age, sex, and race to more individually based measures such as factors in the environment, it focuses on only motivation that is based on the "perceived" situation, which may or may not be the "real" situation (Cross, 1981). In addition, the model has not been tested empirically. Therefore opportunities exist for testing this model.

Howard (1989) notes the need for a sufficiently comprehensive model that describes the complex relation between both the expectancy process variables and the other variables. He points out that the "results of expectancy research have been mixed; the expectancy basis for motivation is supported but the individual element of the theory are not consistently supported (p. 201). For this purpose, he enumerates three criteria that a comprehensive expectancy motivation model must meet: 1) the accurate description of the dynamics of the fundamental process variables, 2) the placement of expectancy motivation in the context of a cycle that explains not only the influence of expectancy motivation on the actual behavior of individuals but also the influence of actual performance, reward, and need satisfaction on expectancy motivation, and 3) the description of the influence of other variables on the motivation process.

Keller's ARCS Model

In educational technology, Keller's ARCS model (1987) is a well-known motivational design model applying motivation principles to instructional design. Keller (1987) states that "the ARCS model of motivation was developed in response to a desire to find more effective ways of understanding the major influences on the motivation to learn, and for systematic ways of identifying and solving problems with learning motivation" (p. 2). The ARCS model has three distinctive features:

> First, it contains four conceptual categories that subsume many of the specific concepts and variables that characterize human motivation. Second, it includes sets of strategies to use to enhance the motivational appeal of instruction. And third, it incorporates a systematic design (Keller, 1987b), that can be used effectively with traditional instructional design models. (Keller, 1987, p. 2)

The ARCS model consists of four major conditions of attention, relevance, confidence, and satisfaction (an acronym of the model is formed from the four conditions) that are based on an aggregation of motivational concepts and theories according to their shared and discriminative attributes (Song & Keller, 2001). Keller (1987) provides a brief description of each of the four major conditions:

- *Attention*: The first condition, attention, is an element of motivation and is also a prerequisite for learning. The motivational concern is for getting and sustaining attention. As an element of learning, the concern is for directing attention to the appropriate stimuli. At one level, it is fairly easy to gain attention. A dramatic statement, a sharp noise, a quiet pause- all of these and many other devices are used. However, getting attention is not enough. A real challenge is to sustain it, to produce a satisfactory level of attention throughout a period of instruction. To do this, it is necessary to respond to sensation-seeking needs of students (Zuckerman, 1971) and arouse their knowledge-seeking curiosity (Berlyne, 1965), but without overstimulating them. The goal is to find a balance between boredom and indifference versus hyperactivity and anxiety. (p. 3)
- *Relevance*: How many times have we heard students ask, 'why do I have to study this?' When a convincing answer is not forthcoming, there is a relevance problem. To answer this question, many course designers and instructors try to make the instruction seem relevant to present and future career opportunities for the students.…Relevance can come from the way something is taught; it does not have to come from the contents itself….To the extent that a course of instruction offers opportunities for an individual to satisfy these and other needs, the person will have a feeling of perceived relevance. (p. 3)

- *Confidence*: Some people never quite achieve success even when the odds are in their favor; others always seem to excel through no matter what the odds. Differences in confidence, the third major component of the model, can influence a student's persistence and accomplishment. There are several factors that contribute to one's level of confidence, or expectancy for success. For example, confident people tend to attribute the causes of success to things such as ability and effort instead of luck or the difficulty of the task (Dweck, 1986; Weiner, 1974). They also tend to be oriented toward involvement in the task activity and enjoy learning even if it means making mistakes. Also, confident people tend to believe that they can effectively accomplish their goals by means of their a ctions (Bandura, 1977; Bandura & Schunk, 1981). The purpose of most of these strategies is to help the learner form the impression that some level of success is possible if effort is exerted.
- *Satisfaction*: This category incorporates research and practices that help make people feel good about their accomplishments. According to reinforcement theory, people should be more motivated if the task and the reward are defined, and an appropriate reinforcement schedule is used….When a student is required to do something to get a reward that a teacher controls, resentment may occur because the teacher has taken over part of the student's sphere of control over his or her own life. The establishment of external control over an intrinsically satisfying behavior can decrease the person's enjoyment of the activity (Lepper & Greene, 1979).

These four categories that form the basis of the ARCS model include prescriptive motivational sub-strategies to use to enhance the motivational appeal of instruction.

The ARCS model includes a systematic design process that "can be conveniently separated into the steps of define, design, develop, and evaluate" (Keller, 1987, p. 6). Table 4 represents four steps including the related sub-steps of the ARCS model.

Table 4

ARCS Model

Steps	Sub-steps
Define	Classify the motivational problem to be solved Do an audience analysis to identify motivational gaps Prepare motivational objectives
Design	Create a list of potential motivational strategies for each of the objectives Critically review the potential strategies and select the ones to be used
Develop	Create any special materials that are required Integrate them into the instruction
Evaluate	Conduct developmental try-out Assess motivational outcomes (e.g., Use direct measures of persistence, intensity of effort, emotion, and attitude)

Even though the ARCS model was developed to apply motivation principles to instructional design, it is also applicable to the study of learners' dropout. A few studies conducted by Chyung (2000, 2001a, 2001b) are good examples. She found the fact that some motivational factors such as attention, relevance, confidence, and satisfaction affect adult learners' dropout in distance education. She maintains that adult learners in distance education tend to dropout when they perceive that: (1) online learning environment and instructional presentations are not attractive to them, (2) what they learned from the online instruction was not relevant to their interests or goals, (3) they are not confident enough to become a successful online learner, and (4) they have low satisfaction levels toward the online learning environment.

In short, online learners lose their motivation to learn and quit learning when they do not perceive instruction to be interesting or relevant to their goal. They also lose motivation to learn when they are not confident of the learning processes, and /or they are not satisfied with the instructional processes (Chyung, 2001b). In an attempt to reduce potential dropouts, she applied Keller's ARCS model. In her studies, the ARCS model provided guidance in selecting effective instructional inputs and processes and helped improve the motivational appeal of the online instruction. Through the application of the model in practice, she found that the impact of improving the motivational appeal of online instruction was significantly positive in terms of the learner retention rate.

Unlike the two aforementioned models, this model focuses on the provision of motivational design process with prescriptive strategies. The strength of this model is that it contains a four-category synthesis of variables that encompasses most of the areas of research on human motivation. Each category of the model consists of specific subcategories with sample motivational strategy prescriptions in order to improve learning motivation of learners. Even though Keller's model was developed for the purpose of enhancing learning motivation of the learner, it can be applied to the study of dropout of adult learners.

Interestingly, like Boshier's model (1973) and Rubenson and Hoghielm's (1978) model, Keller's (1987) model also originated from expectancy-valence theory:

> In the original model (Keller, 1979, 1983), these two categories were expanded to four. The category called *value* was subdivided into two categories called *interest* and *relevance*. The third category, *expectancy*, remained the same, and a fourth category called *outcomes* was added…. All of these variables have an influence on what people think is important, but *interest* refers more to attentional factors in the environment, and

> *relevance* refers more to goal directed activity. The third category, expectancy, refers to one's expectation for being successful…. The fourth category, outcomes, refers to the reinforcing value of instruction. The outcomes of goal-directed behavior have an influence on subsequent levels of perceived value and expectancy for success and, therefore, form the final category of motivational variables in the ARCS model. (Keller, 1987, p. 3)

Keller (1987) further explains that "all of the strategies used in the development of the model were derived from research findings and from practices that have resulted in motivated learners" (p. 3). In addition, he notes that the classification process and correspondence of judgments for the placement of strategies into categories are acceptable based on the reliability estimate result of (.78) obtained by means of the intraclass correlation method.

Bean and Metzner's Model of Nontraditional Undergraduate Student Attrition

Bean and Metzner's (1985) conceptual model was developed to explain the attrition process for nontraditional students. This model was the first model that tried to explain the dropout process of older, part-time, and commuter students enrolled in higher education. Bean and Metzner's model (1985) (see Figure 4) draws from some theoretical bases: Lewin (1935) who described behavior as a function of the person and environment; Locke (1976) who noted the evaluation of our past experiences gives rise to our attitudes; and Fishbein and Ajzen (1975) which explains that attitudes lead to intentions, which in turn lead to behavior.

This model contains several components that affect dropout of non-traditional students in college either directly or indirectly. The background variables are expected to affect how nontraditional students interact with the institution. The academic variables are regarded as indicators of academic integration and are expected to have indirect effects on dropout through

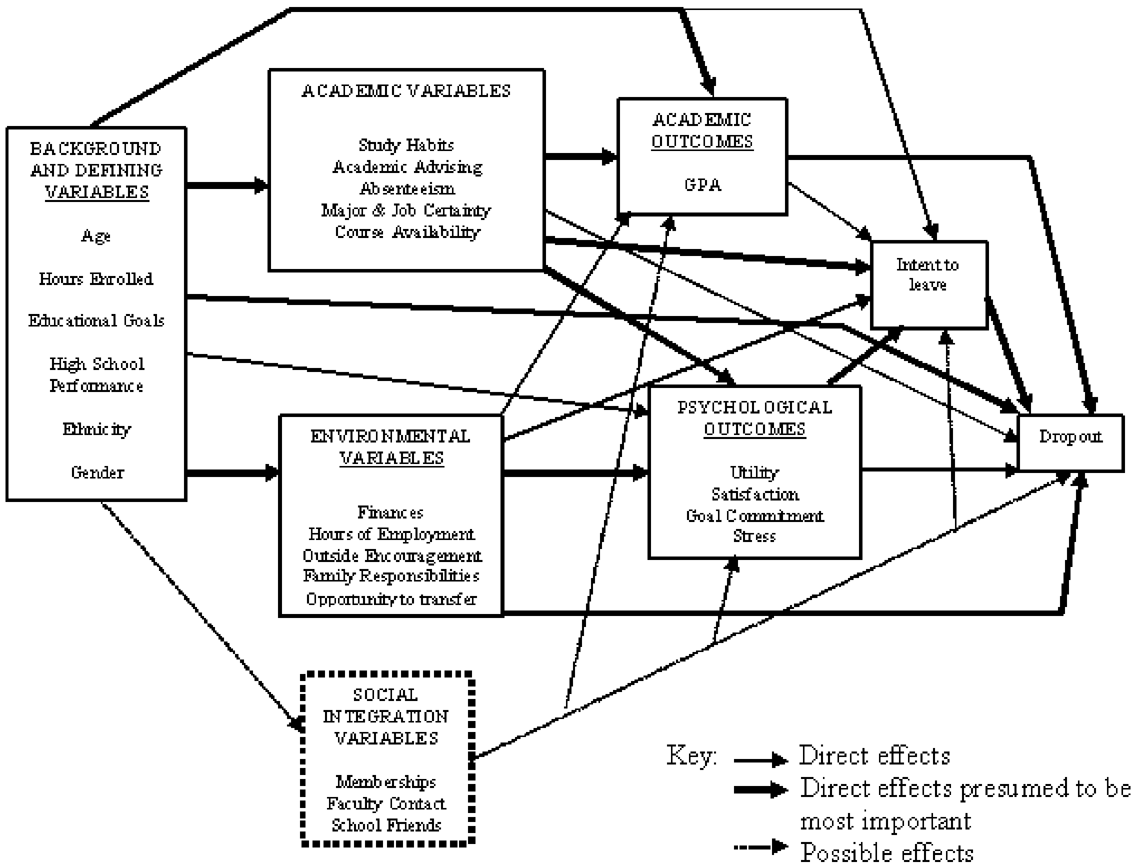

Figure 4. A conceptual model of nontraditional student attrition.

Note. From "A conceptual model of nontraditional undergraduate student attrition," J. P. Bean, & B. S. Metzner, 1985, *Review of Educational Research, 55*(4), p. 491.

GPA, the psychological outcome variables, especially satisfaction, and through intent to leave. The environmental variables indicate factors that might pull the students away from the institution but which the institution has little control over. The social integration variables refer to the extent and quality of students' interaction with the social system of the college environment.

The academic outcomes (e.g., GPA) are expected to affect primarily on the dropout of students, because "students may perceive grades as quasi-economic rewards (Bean, 1982; Tinto, 1975), and the higher the level of this reward, the more likely a student is to remain in school"

(Bean & Metzner, 1985, p. 520). While the psychological outcomes are expected to be primarily the result of the academic and environmental variables, the primary effects of these outcomes are expected to be indirect, acting through intentions that are designated in the model as intent to *leave*. In addition, one of this model's characteristics is that "the indirect effects of a variable on dropout can be calculated and the statistical significance of these effects can be tested" (Bean & Metzner, 1985, p. 490).

This model was tested by some empirical studies. Metzner and Bean (1987) gathered data from nontraditional freshmen at a midwestern urban university. The findings of the study based on multiple regression analysis indicate that dropout was a function of GPA and credit hours enrolled, as well as the utility of education for future employment, satisfaction with the student role, opportunity to transfer, and age affecting dropout through intent to leave. Farabaugh-Dorkins (1991) also conducted a study to test a modified version of the Bean and Metzner model in an effort to understand why older students frequently dropped out of a large public university in the Midwest. The results of the study revealed that intent to leave, followed by GPA and goal commitment were the most important variables in explaining attrition, and that number of children, weekly study hours, and number of hours enrolled in school failed to contribute directly or indirectly to explaining attrition variance. Stahl and Pavel (1992) conducted a study to determine how well the Bean and Metzner's (1985) model fit with community college student data and make theoretically consistent modifications to the model whether the fit was weak, using structural equation modeling. This community college retention model slightly revised from Bean and Metzner (1985) proved to be a plausible model.

Billings' Model for Completion of Correspondence Courses

Billings' (1988) model for completion of correspondence courses was developed to explain why students drop out of correspondence courses. As he mentioned, Billings' model (see Figure 5) is "adapted from Bean's synthetic model of student attrition from Institutions of Higher Education (IHE)" (p. 23). He argues that attrition from correspondence courses is hypothesized to be a causal relationship of the student's background characteristics, organizational settings and the distance education environment of the Independent Study program (ISP), the student's attitudes about education, and the student's intention to complete the course.

Variables for the model were selected from the review of the literature and in accordance with the procedures advocated by Bean (1982), and causally ordered for background variables to precede organizational and environmental variables and for outcome/attitudinal variables to precede intent (Billings, 1988).

This model consists of several ingredients that affect dropout of students in correspondence courses. The background variables represent measures of academic aptitude and achievement noted to influence correspondence course completion. Organizational variables reflect the student's involvement with the organization. These variables are GPA, class level, experience with other correspondence courses, and support from classmates. Environmental variables were emphasized in Billings' (1988) model as well as in Bean and Metzner's model, because of student's background characteristics. For instance, many students are married, have family responsibility, or are employed. These variables consist of employment, employer support, family responsibilities, family support, and distance from the instructor who teaches the course, and determines the impact of the environment on progress toward course completion. Outcomes and attitudinal variables reflect the subjective experience of being a student and are a measure of

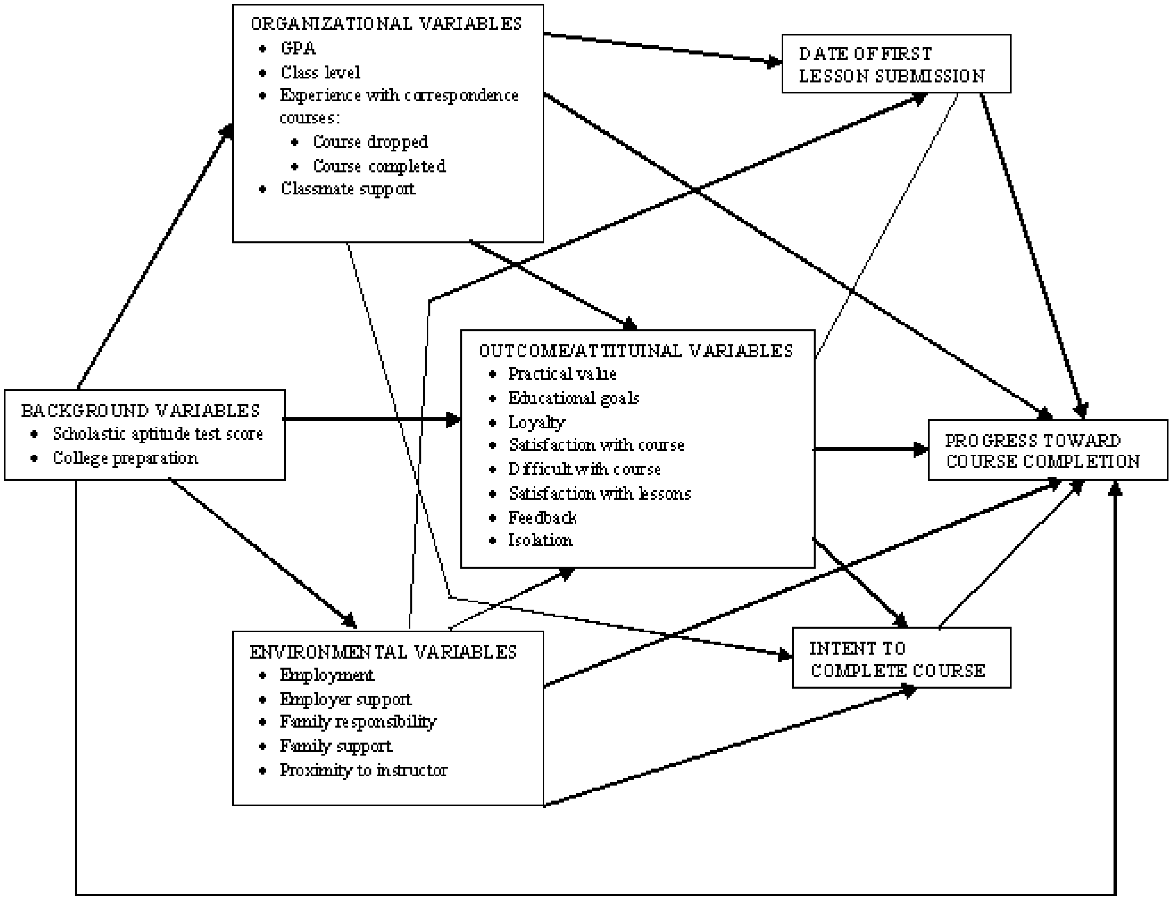

Figure 5. A model for completion of correspondence courses.

Note. From "A conceptual model of correspondence course completion," D. M. Billings, 1988, *American Journal of Distance Education*, *2*(2), p. 25.

how well the student's needs and goals are met by IHE. These variables include loyalty, educational goals, practical value, satisfaction, course difficulty, lesson discussion, feedback, and isolation. Intent to compete course variable is expected to be the consistently best predictor of dropout. Interestingly, the date of first lesson submission was added as a second intervening variable in the model. Progress toward course completion, a measure of student's activity in the course, is the dependent variable in this model. Billings (1988) asserts that this variable requires the student to maintain self-direction in the course and submit lessons regularly. In conclusion, student background characteristics, organizational setting and the environment, attitudes about education, and course instruction are linked with behavioral intent and lesson submission activity to determine variables that influence completion of courses.

As he points out, this conceptual model of correspondence course completion is tentative and needs further testing (Billings, 1988). Even though the model has some significant implications for adult education, especially, distance education, little research has been conducted to test the model. Only Osborn (2001) used Billings' model as one of his theoretical frameworks. Based on the multivariate framework of student attrition developed by leading researchers in the field of distance education and instructional technology, he conducted a study to select a set of key variables related to a student's ability to complete a distance learning course. To do this, he extracted three broad constructs: entry characteristics, social integration, and academic integration including nine indicators of completion and seven predictors based on four models of student attrition. These models are Billings' (1988) Model of Correspondence Course Completion, Tinto's (1997) Model of Student Persistence, Kennedy and Powell's (1976) Descriptive Model, and Kember's (1995) Open Learning Model. Findings of the study show that the primary variables responsible for discriminating between completers and noncompleters include three factors: study environment, motivation, and computer confidence. Compared to the completing students, at-risk students had less-stable study environments, lower motivation, and less computer confidence. In addition, four single-item predictors were important discriminating variables: educational level, GPA, number of credit hours taken in the current semester, and number of previous distance learning courses.

Kember's Open Learning Model

Like Tinto's model (1975), the two dimensions of integration, academic and social, form the core of Kember's open learning model (1995). This model was developed through the process of validation of the model, utilizing both quantitative and qualitative data from a diversity of sources. The model (see Figure 6) derived from Tinto's model of student dropout has two tracks:

> This model suggests that students' entry characteristics direct them towards one of two tracks. Those with favorable situations tend to proceed on the positive track and are able to integrate socially and academically. Others take the lower, negative track where they have greater difficulties achieving social and academic integration. (Kember, 1995, p. 64)

Interestingly, there is a cost/benefit decision step in Kember's model (1995) in which the student periodically weighs the benefits and costs of continuing to study. At this phase a student's decision can result in either dropping-out or completing these studies. Those who decide to complete will then enter a recycling loop for another passage through the cycle, usually with the characteristics and variables somewhat changed. If the results of the cost/benefit analysis continue to show positive benefits a student will eventually complete the course.

This model consists of several constructs that affect outcome of students in open learning courses. The construct of entry characteristics that influences integration variables consists of demographic status, educational qualifications, family status, and employment. Kember (1995) articulates that entry characteristic are not good predictors of final outcomes, because they are just a starting point in determining how much difficulty a student is likely to face in coping with a course. He continues, "Many students with apparently adverse circumstances do succeed" (p. 77). The social integration construct consists of enrollment encouragement, study encouragement, and family environment and examines the degree to which students are able to integrate their academic with the often conflicting employment, family and social requirements. Kember (1995)

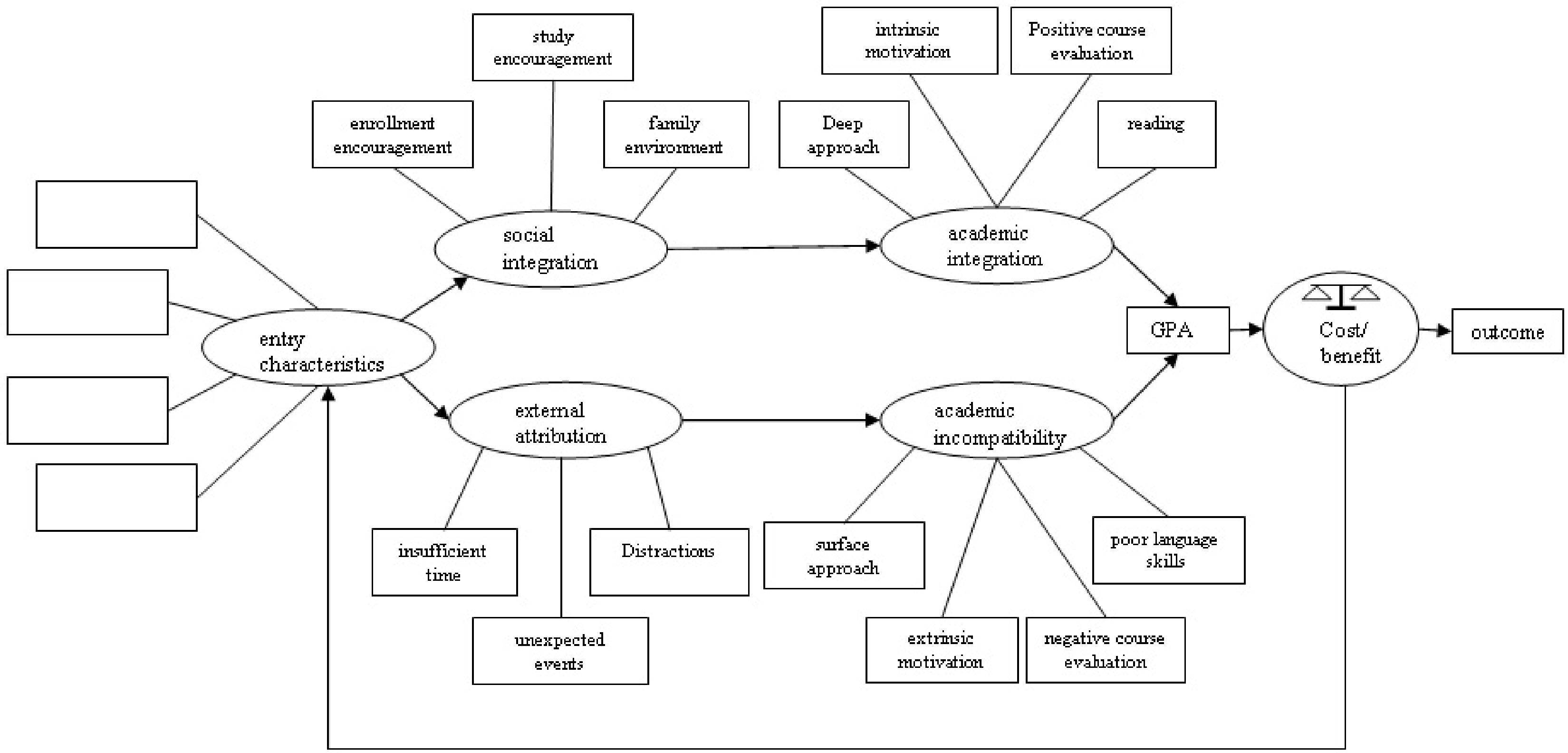

Figure 6. Open learning model.

Note. From "*Open learning courses for adults: A model of student progress*." by D. Kemper, 1995, pp. 222-223. Englewood Cliffs, NJ: Educational Technology Publications.

asserts that “social integration can be achieved, even in the face of an inhospitable social environment, if a time and space for study are negotiated” (p. 88).

The external attribution construct consists of insufficient time, unexpected events, and distractions. The lower levels of social integration affect the negative academic integration of students. In the model, academic integration is spilt into the positive (academic integration) and negative (academic incompatibility) tracks. Each construct consists of four indicators such as study approach, motivation, course evaluation, and language ability. Academic integration is understood as “encompassing all facets of a course and all elements of contact between an institution and the students whether these are of an academic, administrative or social nature” (Kember, 1995, p. 99). In addition, GPA functions to some extent as an intervening variable between academic incompatibility and dropout. At the final step of the model, a cost/benefit analysis, the student has to make a decision about either dropping-out or completing study. This final step includes a recycling loop that provides a mechanism for switching from one track to the other.

Even though Kember’s (1995) open learning model has not been tested by many studies, this model is also useful understanding the process of dropout of adult learners in that it is built on the review of the literature on dropout studies and tested through empirical research methodology.

Some Implications for the Study of Dropout of Adult Learners in E-learning

The six models of dropout have at least two significant implications for the study of dropout of adult learners in e-learning. First, these models can serve as the bases for building a composite model that accounts for the phenomenon of adult learners’ dropout in e-learning. Whatever the setting, it is difficult to comprehend the reason for the learner’s dropout in adult education and training programs because the reasons for dropout among learners are numerous and complex. Theory in the area of learner dropout supports a multivariate framework to account for the complexity inherent in analyzing the learner's participation in multiple spheres of activity (Osborn, 2001). Second, in addition, there is a need for practical contributions of a new model of dropout in the field of adult education, especially, e-learning. This means that any new model based on or including a motivational perspective should have the power to provide practical contributions to the field of adult education. For instance, if adult learners drop out of a course due to motivational factors, some prescriptive strategies developed from a motivational aspect could be provided for adult education practitioners of e-learning programs. Also, it could be used by e-learning program designers and instructors to prevent or decrease the dropout rate in e-learning practice. In addition, the new model of dropout will strongly recommend that they take into account a variety of motivational strategies that could prevent e-learners from dropping out.

CHAPTER III

METHOD

The purpose of this study was to determine which specific set of variables can best predict the dropout of adult learners from e-learning courses in the workplace. The following research questions guided this investigation:

1. To what extent does a model consisting of individual background and motivational variables predict the dropout of adult learners from an e-learning course?
2. Which individual background and motivational variables have a substantive relationship to the dropout of adult learners from an e-learning course?
3. Which is the best model to predict the dropout of adult learners from an e-learning course?

This chapter is organized into seven sections: Conceptual framework, conceptual model, instrument development, study sample, data collection, data preparation, and data analysis.

Conceptual Framework

The framework for the study was developed based on a review of the literature in adult education, human resource development, and distance learning. Specifically, several models related to the dropout of adult learners serve as the conceptual framework of the study. These are Boshier's (1973) congruency model, Rubenson and Hoghielm's (1978) expectancy-valence model of dropout, Bean and Metzner's (1985) model of nontraditional undergraduate student attrition, Keller's (1987) ARCS model, Billings' (1988) model for completion of correspondence courses, and Kember's (1995) open learning model. In general, a model can be defined as a simplified version of reality in which the minutiae and detail are stripped away, leaving what are assumed to be important factors and relationships between these factors (Bean, 1990). Bean notes that “models are important because they tie theory to specific situations” (p. 150). As discussed more fully in Chapter 2, Boshier’s (1973) congruency model, Rubenson and Hoghielm’s (1978) expectancy-valence model of dropout, and Keller’s (1987) ARCS model provide theoretical formulas that explain the phenomenon of dropout of adult learners in adult educational settings in terms of motivation.

Conceptual Model

The aforementioned six models of dropout provided useful theoretical grounds in testing a model for logistic regression of dropout in e-learning. A logistic regression model was proposed for this research. In constructing a model, I relied on the work of these six authors and examined variables based on the relevance to the context of e-learning. In other words, instead of relying on one of these models, none of which were developed specifically for the context in which I was working, I suggested a proposed logistic regression model of dropout for adult learners in e-learning (see Figure 7).

The variables in the proposed model were based on the existing models of dropout and the literature review of dropout of adult learners. Variables included in the model were categorized into eight individual background variables of Number of e-learning courses completed, Age, Gender, Educational level, Marital status, Number of learning hours for the course, Mandatory/voluntary attendance, and Hours worked per week, as well as the four kinds of motivational variables (Attention, Relevance, Confidence, and Satisfaction). These variables reflect partly academic integration, social integration, and technological support variables identified through a review of the literature. Figure 7 presents a model of variable arrangement for the logistic regression analysis.

Predictors **Criterion**

Individual Background Variables

- Number of e-learning courses completed
- Age
- Gender
- Educational level
- Marital status
- Number of learning hours for the course
- Mandatory/voluntary attendance
- Hours worked per week

Motivation Variables

- Attention
- Relevance
- Confidence
- Satisfaction

→

- Dropout (yes or no)

Figure 7. Predictor variables in the proposed logistic regression.

Individual background variables have been considered very important variables in the dropout of adult learners (Bean & Metzner, 1985; Billings, 1988; Boshier, 1973; Driscoll, 1998; Keller, 1987; Kember, 1995; Osborn, 2001; Rubenson & Hoghielm, 1978; Vrasidas & McIsaac, 1999). The matter of which variables should be included in the model depends on the specific situation of the study. In this study, based on the literature review of studies of dropout, I selected Number of e-learning courses completed, Age, Gender, Educational level, Marital status, Number of learning hours for the course, Mandatory/voluntary attendance, and Hours worked per week as important variables. Specially, the Mandatory/voluntary attendance variable is a very important component and has potential to affect the dropout of adult learners in e-learning settings. While the participation of adult learners in adult education activities is often voluntary, employers often influence the participation of adult learners in e-learning courses in the workplace.

Motivation variables are usually considered to be the most important in predicting dropout, as shown in some models of dropout of adult learners (Bean & Metzner, 1985; Billings, 1988; Kember, 1995; Stahl & Pavel, 1992), as motivation is the most powerful variable that affects adult learners' decision to drop out. In this study, based on Keller's (1987) ARCS model, a self-completion forced choice survey instrument was developed because it deals with a comprehensive motivation that is related to the dropout of adult learners.

Instrument Development

The instrument used in this study was designed to obtain information about learners' motivation to participate in e-learning in the workplace, as well as their individual backgrounds. The steps in the process are detailed in Table 5.

Table 5

Steps of Instrument Development

1. Clarification of the concept
2. Development and refinement of the item pool
3. Pre-pilot review of the pilot survey instrument
4. Addition of individual background items
5. Translation
6. Pilot survey

Clarification of the Concept

By using the definitions of motivation provided by Kleinginna and Kleinginna (1981), Franken (1994), and Huitt (2001), motivation can be defined as an internal state or condition that serves to activate or energize behavior and give it direction. It is also (1) the desire or want that energizes and directs goal-oriented behavior, (2) the influence of needs and desires on the intensity and direction of behavior, and (3) the arousal, direction, and persistence of behavior.

The motivation scale for this study was developed based on Keller's (1987) ARCS model, which is a well-known motivational design model applying motivational principles to instructional design. Studies conducted by Chyung (2000, 2001a, 2001b) applied the model to prevent dropout and to reduce the dropout rate of students in a higher education setting. I intended to develop a motivation scale consisting of the four subscales of Attention, Relevance, Confidence, and Satisfaction.

The four arenas referred to are conditions in Keller's (1987) ARCS model and are defined or delineated as:

- *Attention*: Strategies that arouse and sustain curiosity and interest. As an element of motivation and also a prerequisite for learning, the concern is for directing attention to the appropriate stimuli.
- *Relevance*: Strategies that support learner needs, interests, and motives. How many times have we heard students ask, "Why do I have to study this?" When a convincing answer is not forthcoming, there is a relevance problem. To answer this question, many course designers and instructors try to make the instruction seem relevant to present and future career opportunities for the students.
- *Confidence*: Strategies that encourage a positive expectation for successful achievement of a task. Differences in confidence can influence a student's persistence and accomplishment.
- *Satisfaction*: Strategies that promote the extrinsic and intrinsic pleasure of learning through feedback and reinforcement.

Development and Refinement of the Item Pool

Item pools for each motivational subscale were developed based on Keller's (1993) Instructional Materials Motivation Survey (IMMS), Armstrong and Keller's (1993) Motivational Delivery Checklist (MDC), Keller's (1993) Course Interest Survey (CIS), Harroff's (2002) Web-based Adult Education Questionnaire (WAEQ), and motivational strategies to prevent dropout of students developed by Chyung (2000, 2001a, 2001b). Table 6 presents the source of survey items for each motivational scale. Many reviewer groups were convened to develop and validate the instruments involved in this study. These groups were composed of adult educators, experts in educational statistics, and doctoral students in adult education.

Table 6

Survey Item Sources for Each Motivational Subscale

	Attention	**Relevance**	**Confidence**	**Satisfaction**
Keller's (1993) IMMS	12	9	9	6
Armstrong & Keller's (1993) MDC	13	7	16	6
Keller's (1993) CIS	11	5	10	8
Harroff's (2002) WAEQ	3	0	1	10
Chyung's (2000, 2001a, 2001b) motivational strategies	7	11	6	11
Total	46	32	42	41

The first item pool refinement. Reviewer group one, consisting of four adult education advanced doctoral students with survey development experience, participated in the first item critique session. Each item was reviewed for ease of understanding, consistency in wording and academic colloquialisms, and proper classification of each item into the subscales. In this session, the following questions were offered as general issues of discussion: "To whom is the survey going to be administered?", "What is the nature of the e-learning course?", "When is the survey to be given?", and "What is the purpose of the scale that will be developed?" Through this process, I corrected vague wording of items, deleted improper questions in each construct, and related each question to the workplace environment.

The second item pool refinement. The second critique session was conducted by one survey development expert and five adult education doctoral students. In the second item critique session, this critique group first recreated definitions of each component of ARCS. Because Keller's (1987) ARCS were defined from an instructor's perspective to motivate students learning, the definitions needed to be redefined in order to measure adult learners' attitudes and beliefs about an e-learning course.

The following definitions of the ARCS components were recreated:

- *Attention*: Characteristics or ability of the course to get and sustain attention of the learner.
- *Relevance*: Learner's perception of course content and presentation as relevant to present and future career opportunities.
- *Confidence*: Learners' confidence that they will succeed in the course.
- *Satisfaction*: Learner's satisfaction with the quality of the course.

Second, this group reviewed the proper classification of each item into the subscales. For instance, we reviewed if each subscale has the items representing the subscale. Third, this reviewer group also deleted duplicate items, reworded items, and standardized items, as well as checked the relevance between each item and its construct. Finally, I selected an appropriate response format, a 5-point Likert scale (see Table 7) ranging from one (*strongly disagree*) to five (*strongly agree*).

Table 7

Instance of Response Scale

To what extent do you agree or disagree with the statement,	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1. The course stimulated my curiosity. ……………..…	1	2	3	4	5

The third item pool refinement. Through the third item critique session with an adult educator, we refined, reworded, and standardized items. After completing this task, we randomized items and created the pilot survey instrument.

Pre-pilot Review of the Pilot Survey Instrument

The pilot survey instrument was reviewed twice by a survey development expert who is a professor in educational statistics. Based on her comments, I eliminated redundancies, corrected grammatical errors, reworded items with clearly favorable/unfavorable wording, and unstandardized the beginning wording of each item to avoid response set. Table 8 shows items developed through the procedures of survey item pool refinement and pre-pilot review of the pilot survey instrument. Table 9 provides a summary of the survey item pool refinement process and pre-pilot review of the pilot survey instrument.

Addition of Individual Background Items

There is substantial literature on the relationship between individual background variables and dropout of adult learners in adult education, distance education, and e-learning. Based on the literature review, individual background refers to entry characteristics consisting of demographic variables (e.g., Age, Gender, Educational level, and Marital status), Number of e-learning courses completed, Number of learning hours for the course, Mandatory/voluntary attendance, and Hours worked per week. Table 10 shows item examples for individual background variables.

Table 8

Items for the Four Subscales

Subscales	Items
Attention	▪ The quality of the course was sufficient to keep my attention ▪ The course variety held my attention ▪ This course stimulated my curiosity ▪ I felt the web-pages of the course were unappealing ▪ The organization of the course made me enthusiastic ▪ The way the information was arranged on the web-pages helped keep my attention ▪ The course content was too abstract to keep my attention ▪ The course format bored me
Relevance	▪ The topics of the course were irrelevant to my interests ▪ The course content was applicable to my personal interests ▪ The examples used in the course were relevant to my interests ▪ This course was irrelevant to my present career opportunities ▪ The course content was inapplicable to my job ▪ The examples used in the course were relevant to my current job ▪ The topics of the course were unimportant to me ▪ The course content was applicable to my future career opportunities ▪ I felt this course was irrelevant to my goals ▪ The topics of the course were irrelevant to my job performance ▪ The examples used in the course were irrelevant to my future professional goals
Confidence	▪ I felt uncertain that I understood the course objectives ▪ The course materials were too difficult to understand ▪ I felt confident I could learn each lesson ▪ I was unsure about my ability to pass the test(s) in the course ▪ The way the course was organized helped me to gain confidence ▪ I felt confident I would do well in the course ▪ Whether or not I succeeded in the course was up to me ▪ This course provided unmanageable assignments that are too advanced
Satisfaction	▪ I enjoyed working on such a well-designed course ▪ I was unsatisfied with the course content ▪ I got enough feedback to know how well I was doing ▪ This course was unsuccessful in meeting my learning needs ▪ I was unsatisfied with course learning activities ▪ This course provided helpful feedback ▪ Whenever I needed technical support, this course provided help

Table 9

Summary of Survey Item Pool Refinement Process and Pre-pilot Review of the Instrument

Procedures	**Developer/Reviewer**	**Result**	**Number of items left after each refinement**			
			A	**R**	**C**	**S**
Original item pool	Researcher	- Developed item pool	46	32	42	41
The First item pool refinement	Four advanced doctoral students and the researcher	- Refined wording of items - Classified items - Deleted improper items	21	18	18	14
Second item pool refinement	A survey development expert, five adult education doctoral students, and the researcher	- Redefined the constructs - Classified items - Deleted duplicated items - Standardized items - Selected response format	10	12	9	7
Third item pool refinement	An adult educator and the researcher	- Standardized items - Refined wording of items - Reworded items - Created the pilot survey instrument	8	11	8	7
Pre-pilot review of the pilot survey instrument	A survey development expert and the researcher	- Eliminated redundancies - Corrected grammatical errors - Reworded items - Unstandardized the beginning wording of each item	8	11	8	7

Note. A = Attention; R = Relevance; C = Confidence; S = Satisfaction.

Translation

Because the sample of interest for this study was employees who took e-learning courses for improving job skills related to their work in South Korea, the survey instrument developed in English needed to be translated into Korean. The pilot survey instrument was translated into

Table 10

Individual Background Variables

Aspect	Items
Individual Background	1. How many e-learning courses have you ever taken? ( )
	2. In what year were you born? ( )
	3. What is your gender? ❑ Male ❑ Female
	4. What is your highest educational degree?
	❑ High school diploma or GED
	❑ Associate or two-year degree
	❑ Bachelor's degree
	❑ Graduate degree
	5. What is your present marital status? ❑ Married ❑ Single
	6. How many hours per week did you study for the e-learning course? ( ) hrs
	7. Why did you take the e-learning course?
	❑ I had to take this e-learning course
	❑ It was mandatory to take a course, but I chose this course voluntarily
	❑ I attended the e-learning course voluntarily
	8. How many hours per week did you work? ( ) hrs

Korean based on a committee approach method. According to this method, translation from the source to the target is performed by a group of bilinguals. Prieto (1992) recommends some guidelines for translation procedures: (1) employing words and phrases with similar frequency of use in both languages, (2) considering the unique characteristics of the intended audience, (3) utilizing the services of a proofreader unfamiliar with the project to identify discrepancies and provide a check for intelligibility of the target text, and (4) conducting pilot testing of the translation through administration of the instrument to members of the intended audience.

The initial translation of the instrument from English to Korean was performed by the researcher. After the initial translation, six Korean doctoral students with job experience in business settings and other areas at the University of Georgia participated in the translation procedures. Prior to beginning the translation procedure, they were given explicit information regarding the use and intent of the motivational instrument, as well as the above translation guidelines.

For the final review, the Korean version of the survey instrument was sent to two persons in charge of e-learning course operation in Company B and Company C in South Korea. They reworded some items and replaced improper terms in the survey instrument.

Pilot Survey

A pilot test was conducted to assess the construct validity and reliability of the pilot instrument. The sample of interest for this pilot study were employees in South Korea who took e-learning courses for improving job skills related to their work. Respondents in Company D were e-mailed a copy of the survey in April 2004. After two follows-ups, 209 respondents returned usable surveys, yielding a final response rate of 22.0 percent.

Construct-related evidence of validity. I conducted an exploratory factor analysis to find construct-related evidence of validity for the pilot survey instrument consisting of 34 items. The purpose of this factor analysis was to determine the degree to which the test could be considered an appropriate operational definition of the construct. After assessing the dataset for distribution normality and outliers, I found there to be no problems. The exploratory factor analysis was conducted using a principal axis factoring with a rotation technique of direct Oblimin (.2) for construct-validating the four motivational subscales of Attention, Relevance, Confidence, and Satisfaction. Factor loadings of .30 or greater were considered meaningful for the factor analysis. As a rule of thumb, a cut-off of .3 or .4 for factor loadings is typically used to decide whether a variable has a meaningful loading on a factor (Hair, Anderson, Tatham, & Black, 1998).

The analysis began with identifying improper items that were loaded on unexpected factors. Based on the findings of the exploratory factor analysis, I decided to remove 12 of 34 items included in the pilot survey. After eliminating the 12 items, I selected a four-factor solution as the most conceptually meaningful representation of the data, accounting for 45.78% of the total variance (see Appendix A). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy showed that the dataset with 22 items was a very good candidate for factoring (.880). In addition, the Bartlett's test of sphericity ($p = .000$) revealed that the correlation matrix used was worth factoring. The criterion of eigenvalue > 1.0, scree test, and interpretability were used to determine the number of factors.

Factors I to IV represented Relevance, Confidence, Attention, and Satisfaction, respectively. The remaining items for each factor are as follows:

- Factor I (Relevance): Out of 11 items in the pilot survey, 8 items were loaded on this factor, accounting for 30.47% of the variance.

  - The topics of the course were irrelevant to my job performance

  - The examples used in the course were relevant to my current job

  - The examples used in the course were irrelevant to my future professional goals

  - This course was irrelevant to my present career opportunities

  - The course content was inapplicable to my job

  - The course content was applicable to my future career opportunities

  - The topics of the course were unimportant to me

- I felt this course was irrelevant to my goals

- Factor II (Confidence): Out of 8 items in the pilot survey, 6 items were loaded on the factor, accounting for 7.20% of the variance.

  - The course materials were too difficult to understand

  - I was unsure about my ability to pass the test(s) in the course

  - This course provided unmanageable assignments that are too advanced

  - I felt uncertain that I understood the course objectives

  - I felt confident I would do well in the course

  - I felt confident I could learn each lesson

- Factor III (Attention): Out of 8 items in the pilot survey, 5 items were loaded on the factor, accounting for 5.26% of the variance.

  - The quality of the course was sufficient to keep my attention

  - This course stimulated my curiosity

  - The course format bored me

  - The course content was too abstract to keep my attention

  - I felt the web-pages of the course were unappealing

- Factor IV (Satisfaction): Out of 7 items in the pilot survey, only 3 items were loaded on the factor, accounting for 2.85% of the variance.

  - This course provided helpful feedback

  - I got enough feedback to know how well I was doing

  - Whenever I needed technical support, this course provided help

Reliability of each dimension. Internal consistency reliability for Factors I to IV were .89, .78, .74, and .61, respectively, and the overall value of internal consistency for the 22 items selected was .89. In terms of the value of internal consistency, Factor IV (Satisfaction) revealed a poor scale. Under the guidance of my dissertation advisor and methodologist, I added five more items related to the remaining items in the factor and renamed "Satisfaction" to "Feedback" due to the characteristics of the remaining items. To develop the five items that were added to the Feedback dimension, I conducted a literature review of e-learning feedback. Several studies (e.g., Cashion & Palmieri, 2003; Choy, McNickle, & Clayton, 2002; Frey & Alman, 2003; Harroff, 2002; Levin, Waddoups, Levin, & Buell, 2001) indicate that the feedback between the learners and instructor and the feedback among learners are vital factors of a successful learning experience in e-learning environments. Table 11 shows modified items for the final data collection. The modified survey instrument for the final data collection is included in Appendix C.

Study Sample

The sample of interest for this study was employees who took e-learning courses for improving job skills related to their work. The company and the course that were examined in the study were carefully selected with the following specific criteria for inclusion. The selection of the sample implies an operational definition for e-learning. It is much narrower than those presented in earlier chapters.

The sample criteria were as follows:

- the e-learning course is offered to employees in South Korea by an in-house training department or by outside companies,
- the course is work-related,
- the course is of at least 20 hours with one-month duration, and
- the course is instructor-led.

Table 11

Modified Items for the Final Data Collection

	Items Used in the Pilot Study	Item Modification for the Final Survey
A	The quality of the course was sufficient to keep my attention	N/A
	The course variety held my attention	Eliminated
	This course stimulated my curiosity	N/A
	I felt the web-pages of the course were unappealing	N/A
	The organization of the course made me enthusiastic	Eliminated
	The way the information was arranged on the web-pages helped keep my attention	Eliminated
	The course content was too abstract to keep my attention	N/A
	The course format bored me	N/A
R	The topics of the course were irrelevant to my interests	Eliminated
	The course content was applicable to my personal interests	Eliminated
	The examples used in the course were relevant to my interests	Eliminated
	This course was irrelevant to my present career opportunities	N/A
	The course content was inapplicable to my job	N/A
	The examples used in the course were relevant to my current job	N/A
	The topics of the course were unimportant to me	N/A
	The course content was applicable to my future career opportunities	N/A
	I felt this course was irrelevant to my goals	N/A
	The topics of the course were irrelevant to my job performance	N/A
	The examples used in the course were irrelevant to my future professional goals	N/A
C	I felt uncertain that I understood the course objectives	N/A
	The course materials were too difficult to understand	N/A
	I felt confident I could learn each lesson	N/A
	I was unsure about my ability to pass the test(s) in the course	N/A
	The way the course was organized helped me to gain confidence	Eliminated
	I felt confident I would do well in the course	N/A
	Whether or not I succeeded in the course was up to me	Eliminated
	This course provided unmanageable assignments that are too advanced	N/A
S	I enjoyed working on such a well-designed course	Eliminated
	I was unsatisfied with the course content	Eliminated
	I got enough feedback to know how well I was doing	N/A
	This course was unsuccessful in meeting my learning needs	Eliminated
	I was unsatisfied with course learning activities	Eliminated
	This course provided helpful feedback	N/A
	Whenever I needed technical support, this course provided help	N/A
F	I received constructive feedback on assignments and [or] tests	Added
	The instructor responded quickly to my inquiries	Added
	The instructor provided timely feedback	Added
	This course provided regular feedback	Added
	Other students in the course provided helpful feedback	Added

Note. (1) A = Attention; R = Relevance; C = Confidence, S = Satisfaction; F = Feedback.
(2) Based on the pilot study, five items of feedback were added to the Satisfaction dimension, and Satisfaction was renamed Feedback for the final survey.

Therefore, the operational definition of e-learning as it is dealt with in this study is pure web-based or online learning in the workplace for South Korean workers.

Under the condition of the special two-group, multivariate normal, assumed equal-covariance-matrix case, a rule of thumb for minimum sample size in discriminant analysis suggests that the smallest group be comprised of at least 3 · (the number of predictors) units (Huberty, 1994). If the covariance matrices will not be approximately equal, then it is recommended that the smallest group be comprised of at least 5 · (the number of predictors) units.

Keeping the above criteria in mind, I contacted several companies with an in-house training department and e-learning providers that provide employees with e-learning courses. Out of them, only Company A with an in-house training department allowed the researcher to conduct the survey research. The roster obtained from the company identified as the convenience sample for this study a total of 2112 potential candidates (duplicate records for employees who participated in more than one of the e-learning courses in the sample were eliminated) who participated in 20-hour e-learning courses with one-month duration related to improving job skills for their work. The courses were all instructor-led and represented 17 e-learning courses provided by Company A from July to December 2004 (see Table 12). Based on the e-mail survey method, 259 respondents returned usable surveys, yielding a final response rate of 12.26 percent. I represented the descriptive information of individual background variables in the section of *Description of Variables Included in Logistic Regression*.

Data Collection

The questionnaire for data collection was distributed by the e-mail to the sample from December 15, 2004, to January 21, 2005. Approval to conduct the study was granted by the

Table 12

The Number of Participants From Each E-learning Course

E-learning courses	**N**	**%**
6 Sigma Assignment	23	8.9
6 Sigma Methodology	27	10.4
Application of Minitab	22	8.5
Basic MBA	17	6.6
CO2 Welding	19	7.3
E-test Professionals (Theory)	23	8.9
E-test Professionals (Microsoft PowerPoint)	12	4.6
Facility Diagnosis	9	3.5
Fair Trade	14	5.4
Global Business Ethics	4	1.5
Industrial Marketing	10	3.9
Information Security	17	6.6
Knowledge Management	11	4.2
Mechanical Elements	20	7.7
SI (International System) System of Units	17	6.6
Sequence Control	6	2.3
Structure of Database & Computer	8	3.1
Total	259	100.0

University of Georgia Institutional Review Board for Human Subjects Research. I e-mailed the following items to a total of 2112 potential candidates on December 15, 2004, using an e-mail listserv offered by Company A:

- A cover letter stating the purpose of the study and requesting their voluntary participation in this research project (see Appendix B).
- The survey instrument (see Appendix C).

In order to increase response rate, four follow-up reminder e-mails with the above two items were sent every 7 days until the data collection period had concluded. A total of 259 valid responses were returned directly by participants during the data collection period. The final response rate was 12.26% (13.26%, n = 280, if including non-valid responses) of the total sample of 2112 potential participants to whom the survey instruments were e-mailed. Twenty- one surveys were not usable because too many items were left blank.

As soon as I received e-mails with completed surveys from participants, I encoded the values into an SPSS data file. After screening the error coded data, I discarded the e-mails with the completed surveys.

Data Preparation

Logistic regression was chosen for data analysis because of the nature of the data. Logistic regression is much more flexible in its assumptions than discriminant analysis. Logistic regression can handle both categorical and continuous variables, and the predictors do not have to be normally distributed, linearly related, or of equal variance within each group (Tabachnick & Fidell, 1996).

Confirming the Final Instrument

In order to confirm internal construct validity of subscales, an exploratory factor analysis of the participants' responses to the 27 Likert-scale items on the final survey was conducted using the statistical package SPSS 11.5.

Description of data. The Normtest macro developed by DeCarlo (1997) was used to screen the dataset for outliers and normality. Through the outlier test, a total of 14 outliers with the largest Mahalanobis distances were found (cases 105, 143, 231, 197, 119, 103, 187, 179, 156, 41, 24, 86, 167, and 146). The 14 cases had large F values bigger than the critical F values (Critical $F_{(.05/n)\,(df=27,\,231)} = 57.06$). After carefully scrutinizing the pattern of the outliers, I removed only one case (case 105) because the pattern of the case looked very different from the others. However, the remaining outliers were included in the statistical data analyses because there were no marking or coding errors in the dataset and the pattern of the cases looked similar to others. In the statistical analyses, listwise deletion was used as a missing data treatment technique.

For the test of normality of the data with a total of 258 cases, the guidelines used were that if any variables had values for g1 (measure of skewness) or g2 (measures of kurtosis) that were greater than |2.0|, the variables were seriously nonnormally distributed. In light of these guidelines, there were no items that are seriously nonnormally distributed (see Table 13).

Table 13

Descriptive Statistics for the Dataset (N =258)

Statistic / Item	M	SD	Skewness		Kurtosis	
			Statistic (g1)	Std. Error	Statistic (g2)	Std. Error
v01	3.24	1.079	-.397	.152	-.401	.302
v02	3.36	1.047	-.466	.152	-.219	.302
v03	3.45	1.226	-.358	.152	-.886	.302
v04	3.57	1.100	-.196	.152	-.771	.302
v05	3.50	1.060	-.385	.152	-.386	.302
v06	3.41	1.041	-.605	.152	-.173	.302
v07	2.95	1.072	-.102	.152	-.549	.302
v08	3.53	1.084	-.459	.152	-.467	.302
v09	3.18	1.101	-.236	.152	-.581	.302
v10	3.50	1.010	-.269	.152	-.110	.302
v11	3.56	1.132	-.471	.152	-.601	.302
v12	3.27	1.125	-.236	.152	-.605	.302
v13	3.43	1.100	-.447	.152	-.542	.302
v14	3.38	1.011	-.193	.152	-.502	.302
v15	3.27	1.042	-.292	.152	-.316	.302
v16	3.48	1.117	-.593	.152	-.230	.302
v17	3.65	.980	-.330	.152	-.561	.302
v18	3.53	1.095	-.527	.152	-.316	.302
v19	3.52	1.059	-.536	.152	-.272	.302
v20	3.61	1.050	-.463	.152	-.330	.302
v21	3.47	1.077	-.456	.152	-.322	.302
v22	3.26	1.135	-.243	.152	-.824	.302
v23	3.38	1.067	-.341	.152	-.482	.302
v24	3.24	1.125	-.187	.152	-.696	.302
v25	3.29	1.099	-.217	.152	-.722	.302
v26	3.22	1.151	-.264	.152	.740	.302
v27	2.91	1.203	-.011	.152	-.831	.302

An exploratory factor analysis for a four-factor solution. The exploratory factor analysis was conducted using a principal axis factoring with a rotation technique of direct Oblimin (.1) for construct-validating the four motivational subscales of Attention, Relevance, Confidence, and

Feedback. Through a preliminary factor analysis, I first eliminated three items—v27 (Other students in the course provided helpful feedback), v26 (I felt confident I would do well in the course), and v14 (I felt confident I could learn each lesson)—that were loaded on unexpected factors. Next, through an exploratory factor analysis with the remaining 24 items, I obtained a four-factor solution as the most conceptually meaningful representation of the data that is consistent with the finding of the pilot study, accounting for 56.81% of the total variance. The criterion of eigenvalue > 1.0 and interpretability were used to determine the number of factors. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for deciding if the dataset with 24 items was a good candidate for factoring shows that it was very good (.914) (see Table 14). In addition, the Bartlett's test of sphericity ($p = .000$) revealed that the correlation matrix used was worth factoring (see Table 14).

Table 14

KMO and Bartlett's Test

Kaiser-Meyer-Olkin measure of sampling adequacy		.914
Bartlett's test of sphericity	Approx. Chi-Square	3555.365
	df	276
	P	.000

The pattern matrix of a four-factor solution is presented in Table 15. This solution showed relatively the simple factor structure of four factors with only two double loadings (v24 and v22). I kept the two double loadings because if I removed them, the four-factor structure was totally collapsed and the content validity of the Confidence dimension was weakened. Table 16 presents the four factors and the individual items that comprise each factor, as well as the loading values, means, and standard deviations for each item. Internal consistency reliability for Factors I to III were .91, .89, .80, and .84, respectively, and the overall value of internal consistency for

Table 15

Pattern Matrix of a Four-Factor Solution

Construct	Item	Factor I	Factor II	Factor III	Factor IV
R	v18. The examples used in the course were relevant to my current job	.898	-.008	-.101	.081
R	v20. I felt this course was irrelevant to my goals	.805	.052	-.029	-.005
R	v17. The topics of the course were unimportant to me	.756	.040	-.008	-.074
R	v11. This course was irrelevant to my present career opportunities	.753	.060	-.074	-.009
R	v25. The course content was inapplicable to my job	.660	-.100	.159	-.114
R	v08. The topics of the course were irrelevant to my job performance	.602	-.018	.121	.003
R	v23. The examples used in the course were irrelevant to my future professional goals	.564	-.004	.286	-.050
R	v05. The course content was applicable to my future career opportunities	.503	.021	.197	-.196
F	v09. The instructor provided timely feedback	.088	.968	-.130	.114
F	v15. This course provided helpful feedback	.079	.833	-.090	.024
F	v01. I received constructive feedback on assignments and (or) tests	.038	.758	.061	.037
F	v12. This course provided regular feedback	-.040	.731	.093	.075
F	v07. I got enough feedback to know how well I was doing	.008	.699	-.104	-.167
F	v10. The instructor responded quickly to my inquiries	-.074	.580	.021	-.211
F	v19. Whenever I needed technical support, this course provided help	-.145	.397	.166	-.175
C	v03. I was unsure about my ability to pass the test(s) in the course	.010	-.025	.779	.055
C	v04. I felt uncertain that I understood the course objectives	.066	.000	.715	.008
C	v24. This course provided unmanageable assignments that are too advanced	.381	-.008	.438	.001
C	v22. The course materials were too difficult to understand	.337	.091	.435	-.069
A	v06. The quality of the course was sufficient to keep my attention	-.069	-.023	-.028	-.927
A	v16. The course content was too abstract to keep my attention	.228	-.122	-.104	-.681
A	v02. This course stimulated my curiosity	.100	.143	-.051	-.552
A	v21. The course format bored me	-.068	.201	.248	-.511
A	v13. I felt the web-pages of the course were unappealing	.020	.267	.062	-.493

Note. A = Attention; R = Relevance; C = Confidence; F = Feedback; Items v20, v17, v11, v25, v08, v23, v03, v04, v24, v22, v16, v21, and v13 were reverse-coded.

the 24 items selected was .92. Factor loadings of .35 or greater were considered meaningful for the factor analysis.

- Factor I (Relevance): The item loading values for this factor ranged from .503 to .898, accounting for 33.16% of the variance. The item means for this factor ranged from 3.29 to 3.65, with an average of 3.51.

Table 16

Factor Loading, Mean, and Standard Deviation

Factor and Item	Loading Value	Mean	SD
Factor I: Relevance			
v18. The examples used in the course were relevant to my current job	.898	3.53	1.10
v20. I felt this course was irrelevant to my goals	.805	3.61	1.05
v17. The topics of the course were unimportant to me	.756	3.65	.98
v11. This course was irrelevant to my present career opportunities	.753	3.56	1.13
v25. The course content was inapplicable to my job	.660	3.29	1.10
v08. The topics of the course were irrelevant to my job performance	.602	3.53	1.08
v23. The examples used in the course were irrelevant to my future professional goals	.564	3.38	1.07
v05. The course content was applicable to my future career opportunities	.503	3.50	1.06
Factor II: Feedback			
v09. The instructor provided timely feedback	.968	3.18	1.10
v15. This course provided helpful feedback	.833	3.27	1.04
v01. I received constructive feedback on assignments and (or) tests	.758	3.24	1.08
v12. This course provided regular feedback	.731	3.27	1.12
v07. I got enough feedback to know how well I was doing	.699	2.95	1.07
v10. The instructor responded quickly to my inquiries	.580	3.47	1.01
v19. Whenever I needed technical support, this course provided help	.397	3.52	1.06
Factor III: Confidence			
v03. I was unsure about my ability to pass the test(s) in the course	.779	3.45	1.23
v04. I felt uncertain that I understood the course objectives	.715	3.36	1.10
v24. This course provided unmanageable assignments that are too advanced	.438	3.24	1.12
v22. The course materials were too difficult to understand	.435	3.26	1.14
Factor IV: Attention			
v06. The quality of the course was sufficient to keep my attention	-.927	3.45	1.04
v16. The course content was too abstract to keep my attention	-.681	3.36	1.12
v02. This course stimulated my curiosity	-.552	3.24	1.05
v21. The course format bored me	-.511	3.26	1.08
v13. I felt the web-pages of the course were unappealing	-.493	3.45	1.10

Note. Items v20, v17, v11, v25, v08, v23, v03, v04, v24, v22, v16, v21, and v13 were reverse-coded.

- Factor II (Feedback): The item loading values for this factor ranged from .397 to .968, accounting for 16.00% of the variance. The item means for all of these variables were relatively low, ranging from 2.95 to 3.52, with an average of 3.27.
- Factor III (Confidence): The item loading values ranged from .435 to .779, accounting for 4.96% of the variance. The item means for this factor ranged from 3.24 to 3.45, with an average of 3.33.

- Factor IV (Attention): The item loading values for this factor ranged from -.493 to -.927, accounting for 2.69% of the variance. The item means for this factor ranged from 3.24 to 3.45, with an average of 3.35.

In sum, these four factors identified through the exploratory factor analysis were used as motivational variables in logistic regression to predict adult learners' dropout in e-learning courses in the workplace. Each factor score was obtained with the Bartlett's procedure. This procedure modifies the regression method so that the sum of squares of the unique factors in common factor analyses is minimized. Table 17 presents correlations among 24 selected items.

Table 17

Correlations Matrix for 24 Selected Items

v01f	v02a	v03c	v04c	v05r	v06a	v07f	v08r	v09f	v10f	v11r	v12f	v13a	v15f	v16a	v17r	v18r	v19f	v20r	v21a	v22c	v23r	v24c	v25r
1																							
.408[1]	1																						
.182[1]	.080	1																					
.206[1]	.181[1]	.627[1]	1																				
.174[1]	.306[1]	.336[1]	.395[1]	1																			
.365[1]	.621[1]	.084	.162[1]	.448[1]	1																		
.624[1]	.475[1]	.004	.106	.185[1]	.526[1]	1																	
.117	.216[1]	.298[1]	.353[1]	.457[1]	.228[1]	.075	1																
.658[1]	.402[1]	.021	.079	.201[1]	.448[1]	.723[1]	.038	1															
.528[1]	.345[1]	.095	.101	.247[1]	.465[1]	.520[1]	.067	.627[1]	1														
.141*	.322[1]	.225[1]	.245[1]	.477[1]	.257[1]	.125*	.501[1]	.110	.075	1													
.501[1]	.322[1]	.148*	.173[1]	.164[1]	.296[1]	.538[1]	-.026	.617[1]	.456[1]	.094	1												
.454[1]	.449[1]	.110	.179[1]	.355[1]	.548[1]	.452[1]	.240[1]	.460[1]	.509[1]	.229[1]	.343[1]	1											
.603[1]	.358[1]	.062	.105	.227[1]	.441[1]	.619[1]	.103	.693[1]	.563[1]	.164[1]	.598[1]	.499[1]	1										
.249[1]	.472[1]	.113	.132*	.347[1]	.604[1]	.337[1]	.277[1]	.205[1]	.279[1]	.413[1]	.162[1]	.419[1]	.235[1]	1									
.139*	.329[1]	.311[1]	.311[1]	.606[1]	.352[1]	.093	.538[1]	.123*	.205[1]	.542[1]	.129*	.323[1]	.185[1]	.417[1]	1								
.086	.221[1]	.246[1]	.285[1]	.520[1]	.192[1]	.084	.528[1]	.031	.027	.590[1]	-.045	.238[1]	.023	.363[1]	.659[1]	1							
.409[1]	.247[1]	.179[1]	.142*	.108	.317[1]	.343[1]	.103	.408[1]	.453[1]	.072	.366[1]	.378[1]	.433[1]	.221[1]	.125*	-.012	1						
.142*	.289[1]	.293[1]	.296[1]	.591[1]	.320[1]	.116	.521[1]	.104	.126*	.588[1]	.107	.226[1]	.151*	.427[1]	.687[1]	.642[1]	.112	1					
.395[1]	.434[1]	.277[1]	.275[1]	.416[1]	.534[1]	.443[1]	.199[1]	.411[1]	.448[1]	.271[1]	.441[1]	.619[1]	.444[1]	.401[1]	.288[1]	.197[1]	.394[1]	.270[1]	1				
.267[1]	.311[1]	.451[1]	.425[1]	.554[1]	.308[1]	.242[1]	.401[1]	.206[1]	.234[1]	.414[1]	.205[1]	.286[1]	.155*	.296[1]	.427[1]	.366[1]	.204[1]	.469[1]	.315[1]	1			
.164[1]	.321[1]	.391[1]	.451[1]	.517[1]	.260[1]	.120	.507[1]	.101	.137*	.541[1]	.108	.286[1]	.113	.336[1]	.585[1]	.529[1]	.143*	.581[1]	.328[1]	.575[1]	1		
.113	.160*	.420[1]	.456[1]	.474[1]	.204[1]	.130*	.431[1]	.116	.085	.389[1]	.090	.285[1]	.097	.230[1]	.415[1]	.433[1]	.095	.426[1]	.286[1]	.607[1]	.527[1]	1	
.135*	.298[1]	.313[1]	.407[1]	.559[1]	.297[1]	.083	.472[1]	.051	.050	.567[1]	.082	.265[1]	.085	.429[1]	.581[1]	.652[1]	-.004	.573[1]	.300[1]	.536[1]	.586[1]	.570[1]	1

Note. [1] Correlation is significant at the 0.01 level 2-tailed; * Correlation is significant at the 0.05 level 2-tailed.

Description of Variables Included in Logistic Regression

A summary of individual background and motivation variables included in logistic regression is provided in Table 18.

Table 18

Description of Variables Included in Logistic Regression (N = 258)

Variables	Answer Choices	Value (n)
Number of e-learning courses completed		M = 13.79, SD = 13.09 Skewness = 1.50, Kurtosis = 1.90
Age		M = 36.76, SD = 6.77 Skewness = .01, Kurtosis = -.57
Gender	Male	85.3% (220)
	Female	14.7% (38)
Educational level	High school diploma or GED	57.4% (148)
	Associate or two-year degree	12.4% (32)
	Bachelor's degree	25.2% (65)
	Graduate degree	5.0% (13)
Marital status	Married	82.6% (213)
	Single	17.4% (45)
Number of learning hours for the course		M = 3.16, SD = 2.06 Skewness = 1.31, Kurtosis = 1.65
Mandatory/voluntary attendance	I had to take this e-learning course	19.8% (51)
	It was mandatory to take a course, but I chose this course voluntarily	24.8% (64)
	I attended the e-learning course voluntarily	55.4% (143)
Hours worked per week		M = 53.14, SD = 9.26 Skewness = 1.02, Kurtosis = .86
Motivation (Attention)		M = 0, SD = 1.07 Skewness = .57, Kurtosis = -.05
Motivation (Relevance)		M = 0, SD = 1.05 Skewness = -.36, Kurtosis = -.22
Motivation (Confidence)		M = 0, SD = 1.12 Skewness = -.14, Kurtosis = -.45
Motivation (Feedback)		M = 0, SD = 1.04 Skewness = -.27, Kurtosis = -.18
Dropout	Yes	72.9% (188)
	No	27.1% (70)

Note. The descriptive information of the four motivation subscales was calculated with factor scores using the Bartlett's procedure method.

Assumptions

Although logistic analysis does not assume a linear relationship between predictors and criterion, the criterion need not be normally distributed and homoscedastic for each level of the predictors, and error terms need not be normally distributed, other assumptions still apply (Garson, 2003). Before analyzing data, it is important to see if those assumptions are met. This is because if these assumptions are not met, it can affect results significantly. These assumptions are as follows:

- Inclusion of irrelevant variable(s) in the regression model: The inclusion of irrelevant variable(s) can result in poor model fit.
- Influential cases and outliers: To find these, I used the following criteria recommended by Menard (2002):
    - The studentized residuals: values less than -3 or greater than +3
    - The dfbeta: values greater than 1

  For the values of studentized residuals, there were no studentized residuals great than 3 in absolute value. For the dfbeta values, case 237 has dfbeta values larger than 1 in terms of Educational levels. Even though there were many influential cases and outliers in terms of the values of the dfbeta, I decided to keep the cases because those were not miscoded. Menard (2002) notes that "even cases with very large residuals do not necessarily indicate problems in the model, insofar as we are dealing with nondeterministic models in which individual human choice and free will may naturally produce less than perfect prediction of human behavior (p. 90)."

- Presence of multicollinearity: The presence of multicollinearity will not lead to biased coefficients, but the standard errors of the coefficients will be inflated. According to rule of thumb, any r(x, y) greater than .85 may be causing the problem. As shown in Table 19, there are very high correlations among Educational levels (1), (2), and (3). That is because the “Graduate degree” group has only 15 people. Therefore, I collapsed it with an adjacent group, the “Bachelor’s degree” group. As shown in Table 20, there are no predictors that are correlated very highly.

Table 19

Correlation Matrix of Predictor Variables for the Proposed Logistic Regression Model

	Constant	**I1**	**I2**	**I3**	**I4(1)**	**I4(2)**	**I4(3)**	**I5**	**I6**	**I7(1)**	**I7(2)**	**I8**	**R**	**F**	**C**	**A**
Constant	1.000															
I1	-.101	1.000														
I2	-.434	-.010	1.000													
I3	-.060	-.038	-.050	1.000												
I4(1)	-.550	-.015	-.072	-.259	1.000											
I4(2)	-.520	-.001	-.110	-.204	.903	1.000										
I4(3)	-.538	.078	-.049	-.295	.937	.891	1.000									
I5	.099	-.007	-.458	-.409	.058	.097	.116	1.000								
I6	-.019	-.105	-.117	-.055	-.069	-.010	-.049	.082	1.000							
I7(1)	-.254	.258	.011	.328	-.086	-.034	-.050	.076	-.049	1.000						
I7(2)	-.007	.147	-.042	-.044	-.096	-.012	-.030	.150	.044	.265	1.000					
I8	-.567	-.038	-.018	.030	.107	.065	.027	-.074	-.013	.070	-.103	1.000				
R	-.096	.016	.043	.134	-.003	-.045	-.026	-.024	-.150	.129	-.010	.094	1.000			
F	.006	.107	-.050	-.093	.037	.055	.120	.102	.021	.137	.167	-.094	.189	1.000		
C	.058	-.024	.021	-.147	-.002	-.006	-.065	-.047	.059	-.081	-.025	.024	-.434	-.201	1.000	
A	-.094	.154	.047	.119	-.004	-.011	.039	.010	-.051	.019	.114	.002	.374	.567	-.158	1.000

Note. I1 = Number of e-learning courses completed; I2 = Age; I3 = Gender; I4(1) = Educational level (1); I4(2) = Educational level (2); I4(3) = Educational level (3); I5 = Marital status; I6 = Learning hours for the course per week; I7(1) = Mandatory/voluntary attendance (1); I7(2) = Mandatory/voluntary attendance (2); I8 = Hours worked per week; R = Relevance; F = Feedback; C = Confidence; A = Attention.

Table 20

Revised Correlation Matrix of Predictor Variables for the Proposed Logistic Regression Model

	Constant	**I1**	**I2**	**I3**	**I4(1)**	**I4(2)**	**I5**	**I6**	**I7(1)**	**I7(2)**	**I8**	**R**	**F**	**C**	**A**
Constant	1.000														
I1	-.092	1.000													
I2	-.547	.003	1.000												
I3	-.240	-.013	-.074	1.000											
I4(1)	-.159	-.243	-.080	.072	1.000										
I4(2)	-.101	-.151	-.147	.138	.438	1.000									
I5	.233	-.002	-.463	-.442	-.160	-.034	1.000								
I6	-.068	-.103	-.128	-.060	-.064	.077	.081	1.000							
I7(1)	-.330	.280	.006	.328	-.095	.022	.039	-.043	1.000						
I7(2)	-.022	.146	-.052	-.045	-.195	.028	.137	.039	.271	1.000					
I8	-.678	-.031	-.015	.034	.233	.096	-.082	.018	.087	-.090	1.000				
R	-.139	.015	.038	.137	.088	-.028	-.019	-.142	.124	-.002	.094	1.000			
F	.083	.089	-.060	-.057	-.210	-.128	.098	-.018	.147	.148	-.063	.191	1.000		
C	.008	-.024	.035	-.170	.151	.112	-.038	.051	-.064	-.027	.030	-.427	-.186	1.000	
A	-.082	.134	.039	.139	-.094	-.099	.004	-.078	.000	.084	.020	.376	.545	-.131	1.000

Note: I1 = Number of e-learning courses completed; I2 = Age; I3 = Gender; I4(1) = Educational level (1); I4(2) = Educational level (2); I5 = Marital status; I6 = Learning hours for the course per week; I7(1) = Mandatory/voluntary attendance (1); I7(2) = Mandatory/voluntary attendance (2); I8 = Hours worked per week; R = Relevance; F = Feedback; C = Confidence; A = Attention.

Logistic Regression

Logistic regression applies maximum likelihood estimation after transforming the criterion into a logit variable, called the logit of probability (p). Logit (p) is the log of the *odds* or *likelihood ratio* that the criterion is occurring or not (Lea, 1997). It is defined as:

$$\text{Logit } (p) = \log[p/(1-p)].$$

Whereas p can only range from 0 to 1, logit (p) ranges from negative infinity to positive infinity. The logit scale is symmetrical around the logit of 0.5, which is zero.

Logistic regression involves fitting to the data an equation of the form (Lea, 1997):

$$\text{Logit } (p) = a + b_1x_1 + b_2x_2 + b_3x_3 + \ldots .$$

Unlike linear regression which uses a *least-squared deviations* criterion for the best fit, logistic regression uses a *maximum likelihood* method, which maximizes the probability of getting the observed results given the fitted regression coefficients (Lea, 1997).

Meaningful Coding for Categorical Variables

Meaningful coding for categorical variables is important for correct interpretation. Table 21 reveals codings for 4 categorical variables included in the study.

Table 21

Categorical Variables Coding

Variables	**Answer Choices**	**Frequency**	**Parameter coding**	
			(1)	(2)
Gender	(1) Male	220	1	
	(2) Female	38	0	
Educational Level	(1) High school diploma or GED	148	1	0
	(2) Associate or two-year degree	32	0	1
	(3) Bachelor's degree or beyond	78	0	0
Marital Status	(1) Married	213	1	
	(2) Single	45	0	
Mandatory/ voluntary attendance	(1) I had to take this e-learning course	51	1	0
	(2) It was mandatory to take a course, but I chose this course voluntarily	64	0	1
	(3) I attended the e-learning course voluntarily	143	0	0
Dropout	(1) Yes	188	1	
	(2) No	70	0	

Note. Dropout is the criterion.

Data Analysis

Data analysis was conducted using SPSS 12.0 and SAS 9.0 statistical software packages. The statistical analysis provided the information necessary to answer the study's primary research questions. The analysis is hereby described according to the research questions.

Research Question 1

In order to answer Research Question 1 (To what extent does the proposed logistic regression model consisting of both individual background and motivational variables fit in predicting the dropout of adult learners from an e-learning course?), I used the overall fit statistic of model chi-square test (Log-likelihood test of a model), Hosmer and Lemeshow's Goodness of Fit Test, Nagelkerke's R-Square, statistics of percentages correctly classified, and the plot of observed groups and predicted probabilities.

- The model chi-square test – This provides the usual significance test for a logistic model. Model chi-square is a likelihood ratio test that reflects the difference between error not knowing the predictors (initial chi-square) and error when the predictors are included in the model (deviance). Therefore, a significant chi-square value actually means that the model with one or more additional parameters fits significantly better than a model without those parameters.
- Hosmer and Lemeshow's Goodness of Fit Test – This tests the null hypothesis that there is no difference between the observed and model-predicted values of the criterion. If the Hosmer and Lemeshow Goodness of Fit Test statistic is greater than .05, it implies that the model's estimates fit the data at an acceptable level, failing to reject the null hypothesis that there is no difference.
- Nagelkerke's R-Square – This is one of several ways to measure strength of association (effect size). Nagelkerke's R-Square is a further modification of the Cox and Snell coefficient that imitated the interpretation of multiple R-Square based on the likelihood to assure that it can vary from 0 to 1.

- Statistics of percentages correctly classified – Classification tables provide the information of how accurately group membership can be predicted.
- The plot of observed groups and predicted probabilities – This is an alternative way of assessing correct and incorrect predictions under logistic regression. The X axis is the predicted probability from 0.0 to 1.0 of the criterion being classified "1." The Y axis is the frequency of the number of cases classified.

Research Question 2

In order to answer Research Question 2 (Which individual background and motivational variables have a substantive relationship to the dropout of adult learners from an e-learning course?), I used the Wald statistic, the Bayesian Information Criterion (BIC), and the fully standardized coefficient.

The Wald statistic is commonly used to test the significance of individual logistic regression coefficients for each independent variable. However, using the Wald statistic for comparing relative strength of the predictors is not recommended, as there is a flaw in the Wald statistic such that very large effects may lead to large standard errors and small Wald chi-square values (Garson, 2003).

Although the Wald's test statistic is not recommended for comparing relative strength of the predictors, the Wald statistic can answer which variables are statistically significant among all the predictor variables used in the proposed logistic regression. I analyzed Wald's test statistics (Wald = $[\mathbf{B}/_{S.E\boldsymbol{B}}]^2$) for the significance of individual regressors.

- Wald's test statistics – These are commonly used to test hypotheses (H_0: $\beta_i = 0$ and H_1: $\beta_i \neq 0$) of individual logistic regression coefficients for each predictor. It is the ratio of the unstandardized logit coefficient to its standard error.

The BIC was proposed by Raftery (1995) to assess the independent variables in a logistic regression equation. As a rule of thumb, BIC (BIC = z^2 - ln$n$) of 0 to 2 is weak, 2 to 6 is moderate, 6 to 10 is strong, and over 10 is very strong. The BIC in logistic regression should exceed 0 to support retaining the variable in the model.

Standardized logit coefficients of predictors can also be used to identify a substantive relationship to the criterion. However, without standardizing the criterion variable as well, comparison of the effects of the predictors on the criterion does not have the same interpretation as fully standardized coefficients (Pampel, 2000). The standard deviation of the criterion variable can be calculated indirectly using the predicted values of logit (Y) and the explained variance, R^2 (Menard, 2002). The fully standardized logistic regression coefficients can provide the real effects of predictors on the criterion, as well as the relative ranks of the predictors in an equation. The fully standardized logistic regression coefficient is defined as:

$$B^*_{yx} = b_{yx}s_xR/s_{logit(\hat{Y})} .$$

Note. b_{yx} = the logistic regression coefficients; s_x = the standard deviation of X; R = the correlation between the predicted probabilities and the dummy criterion variable; $s_{logit(\hat{Y})}$ = the standard deviation of logit($\hat{Y}$).

The interpretation of the fully standardized logistic regression coefficient is as follows: a 1 standard deviation increase in X produces a B^*_{yx} standard deviation change in logit(Y) (Menard, 2002).

Research Question 3

In order to answer Research Question 3 (Which is the best model to predict the dropout of adult learners from an e-learning course?), I used some criteria to find a best model instead of using stepwise procedures. Although the stepwise procedures are widely used to select variables in order to build a best model within the scientific context of the problem, these procedures often do not correctly identify the best set of predictors (King, 2003). Menard (2002) also notes:

> There appears to be general agreement that the use of computer-controlled stepwise procedures to select variables is inappropriate for theory testing because it capitalizes on random variations in the data, and produces results that tend to be idiosyncratic and difficult to replicate in any sample other than the sample in which they originally were obtained. (p. 63)

An alternative to stepwise selection of predictors for a model is the best subset logistic regression. I used the three criteria of the chi-squared distributed likelihood score statistic, the Akaike's Information Criterion (AIC), and Nagelkerke's R-Square for selecting the best subset models.

- The chi-squared distributed likelihood score statistic – Although this statistic is not as informative as an index that takes into account model parsimony (e.g., Mallow's C_p), it permits best subsets model comparisons. If models have the same number of predictors, the model with a larger value is better than one with a smaller value (SAS Institute, 1999).
- Nagelkerke's R-Square – The measure of effect size used in logistic regression. Since the log likelihood is not really a sum of squares, this statistic should not be interpreted as variance-accounted-for measure (King, 2003). If models have the same number of predictors, the model with a larger value is better.
- Akaike's Information Criterion (AIC) – The AIC (Akaike, 1983) is also useful for comparing model fit in models nested. The AIC values will be smallest for a model that exhibits good fit with a small number of predictors. The AIC is defined as:

$$AIC = -2\log L(M) + 2*K .$$

Note. logL(M) = the maximized log likelihood for the fitted model; K = the number of predictors including an intercept.

King (2003) emphasizes that “model comparisons will be made based on statistical criteria, but other issues (e.g., theory, cost of obtaining variables) should usually be consulted before selecting a final model” (p. 397). Hosmer and Lemeshow (2000) also note that the researcher “should not be lured into accepting the variables suggested by a best subset strategy without considerable critical evaluation” (p. 132). Accordingly, I suggested a best model to predict the dropout of adult learners from an e-learning course, based on statistical and substantive grounds.

Chapter Summary

This chapter described the conceptual framework, conceptual model, instrument development, study sample, data collection, data preparation, and data analysis in order to conduct a study that determines which specific set of variables can best predict the dropout of adult learners from e-learning courses in the workplace. The survey instrument constructed for this study was designed to obtain information about learners’ motivation to participate in e-learning in the workplace, as well as their individual backgrounds. Through exploratory factor analyses of pilot and final studies, the evidence of validity and reliability of the instrument was obtained. Logistic regression was chosen for data analysis because of the nature of the data. This chapter also dealt with some assumptions and specific statistical techniques to answer the three research questions.

CHAPTER IV

FINDINGS

The purpose of this study was to determine which specific set of variables can best predict the dropout of adult learners from e-learning courses in the workplace. This chapter presents the results of the statistical analyses described in Chapter III. These findings are addressed in relation to each of the three research questions that structured the study. The research questions are as follows:

1. To what extent does a model consisting of individual background and motivational variables predict the dropout of adult learners from an e-learning course?
2. Which individual background and motivational variables have a substantive relationship to the dropout of adult learners from an e-learning course?
3. Which is the best model to predict the dropout of adult learners from an e-learning course?

The study findings related to each research question are described in the following sections.

Findings Related to Research Question 1

To answer Research Question 1, I performed the model chi-square test (Log-likelihood test of a model), Hosmer and Lemeshow's Goodness of Fit Test, and Nagelkerke's R-Square; calculated statistics of percentages correctly classified; and developed a plot of observed groups and predicted probabilities with SPSS 12.0.

The proposed logistic regression model had 14 predictor variables to predict the dropout of adult learners from an e-learning course. These predictors consisted of participants' individual background variables (i.e., Number of e-learning courses completed, Age, Gender, Educational level, Marital status, Number of learning hours for the course, Mandatory/voluntary attendance, and Hours worked per week) and motivational variables (i.e., Attention, Relevance, Confidence, and Feedback). Out of individual background predictors, Educational level and Mandatory/voluntary attendance variables had two level dummy variable codings, respectively.

Expressed in terms of the predictors used in the proposed logistic regression, the logistic regression equation is

log(p/1-p) = -3.070 + .083** · Number of e-learning courses completed -.013 · Age + 3.351** · Gender .126 · Educational level (1) -.624 · Educational level (2) -.418 · Marital status -.137 · Number of learning hours for the course + .230 · Mandatory/voluntary attendance (1) -.074 · Mandatory/voluntary attendance (2) + .032 · Hours worked per week + .160 · Relevance + .086 · Feedback -.051 · Confidence + .621* · Attention.

Note: * = significant at the .05 level; ** = significant at the .01 level; Educational level (1) = High school diploma or GED vs. Bachelor's degree or beyond; Educational level (2) = Associate or two-year degree vs. Bachelor's degree or beyond; Mandatory/voluntary attendance (1) = I had to take this e-learning course vs. I attended the e-learning course voluntarily; Mandatory/voluntary attendance (2) = It was mandatory to take a course, but I chose this course voluntarily vs. I attended the e-learning course voluntarily.

These estimates represent the relationship between the predictor and the criterion variables, where the criterion variable is on the logit scale. In other words, these estimates tell the amount of increase (or decrease) in the predicted log odds of Dropout = 1 that would be predicted by a 1 unit increase (or decrease) in the predictor, holding all other predictors constant.

As shown in Table 22, the model chi-square test of the full model (204.252) versus a model with intercept only (301.636) was statistically significant ($\Delta\chi^2_{(14, N = 258)} = 97.384$, $p <$ .001), indicating that the model with all predictors is significantly better than the initial model. Model chi-square is a likelihood ratio test that reflects the difference between error not knowing the predictors (initial chi-square) and error when the predictors are included in the model (deviance). The probability of obtaining the chi-square statistic ($p < .001$) given infers that at least one of the population coefficients differs from zero (or this is a well-fitting model), rejecting the null hypothesis that knowing the predictors makes no difference in predicting the criterion Dropout in logistic regression.

Table 22

Omnibus Tests of the Proposed Logistic Regression Model Coefficients

	χ^2	**df**	***p***
Model	97.384	14	.000

Table 23 shows Hosmer and Lemeshow's Goodness of Fit Test. The Hosmer and Lemeshow's fit test statistic ($\chi^2_{(8)} = 3.730$, $p > .05$) reveals that the proposed model fits well, failing to reject the null hypothesis that there is no difference between the observed and model-predicted values of the criterion. This implies that the model's estimates fit the data at an acceptable level.

Table 23

Hosmer and Lemeshow's Goodness of Fit Test for the Proposed Logistic Regression Model

χ^2	**df**	***p***
3.730	8	.881

Nagelkerke's R-Square (.456, in Table 24) reveals a moderately strong relationship between the criterion and its predictors. The statistics of percentages correctly classified (see Table 25) show that the proposed model correctly classified 50.0% of the completers (specificity) and 96.8% of the dropouts (sensitivity), for an overall accuracy rate of 84.1%.

Table 24

Model Summary for the Proposed Logistic Regression Model

-2 Log likelihood	**Cox & Snell R-Square**	**Nagelkerke R-Square**
204.252	.314	.456

Table 25

Classification Table of the Proposed Logistic Regression Model

	Predicted		
Observed	Completer	Dropout	Percentage Correct
Completer	35	35	50.0
Dropout	6	182	96.8
Overall Percentage			84.1

Note: The cut value is .50.

The plot of observed groups and predicted dropout probabilities that is an alternative way of assessing correct and incorrect predictions under logistic regression is shown in Figure 8. The X axis is the predicted probability from 0.0 to 1.0 of the criterion being classified "1." The Y axis is frequency, or the number of cases classified. Inside the plot are columns of observed 1's and 0's, which it here codes as 2's (the dropout) and 1's (the completer), with 1.25 cases per symbol.

```
      20 +                                                        2   +
         |                                                        2   |
         |                                                        2   |
F        |                                                        2   |
R     15 +                                                   2    2  2+
E        |                                                   2  2 2  2|
Q        |                                                 2 22 222  2|
U        |                                                22 22 222  2|
E     10 +                                               222 22 222 22+
N        |                                               222 222222222|
C        |                                           2 22222 222222222|
Y        |   2                                   2   2 22222 222222222|
       5 +   12 11                               22222222222 222222222+
         |   11 11   2                     2   2 21222222222 222222222|
         |  111 111 11    2     1  2       1  222112121211212122112222|
         |  1111111 11 1  1     12 11   1  122221111121111112111112122|
Predicted ---------------+--------------+--------------+---------------
  Prob:   0            .25            .5             .75             1
  Group:  111111111111111111111111111111222222222222222222222222222222
          Predicted Probability is of Membership for 2
          The Cut Value is .50
          Symbols: 1 – The completer
                   2 – The dropout
          Each Symbol Represents 1.25 Cases.
```

Figure 8. The plot of observed groups and predicted dropout probabilities for the proposed logistic regression model.

Findings Related to Research Question 2

In order to determine which predictor variables have a substantive relationship to the dropout of adult learners from an e-learning course, I presented the Wald statistic, the Bayesian Information Criterion (BIC), and the fully standardized coefficient using SPSS 12.0.

The Wald's test statistic provides information about which variables are statistically significant among the predictor variables included in the proposed logistic regression model at the .05 (or .01) level. I analyzed Wald's test statistics (Wald = $[\mathbf{B}/_{S.E.\boldsymbol{B}}]^2$) for the significance of individual regressors. These are commonly used to test hypotheses (H_0: $\beta_i = 0$ and H_1: $\beta_i \neq 0$) of individual logistic regression coefficients for each predictor.

Table 26 represents the logistic regression coefficient (B), standard error (S.E.), Wald test, odds ratio (Exp(B)), and confidence interval (C.I.) for each of the predictors. Employing a .05 criterion of statistical significance, Number of e-learning courses completed, Gender, and Attention variables had significant partial effects on Dropout predictability, indicating the coefficients of the predictors are significantly different from 0.

Table 26

Logit Coefficients and Wald Statistics of the Proposed Logistic Regression Model

Predictor	**B**	**S.E.**	**Wald (df)**	***p***	**Exp(B)**	**95.0% C.I. for EXP(B)**	
						Lower	Upper
Number of e-learning courses completed	.083	.025	11.140 (1)	.001**	1.086	1.035	1.140
Age	-.013	.035	.138 (1)	.710	.987	.922	1.057
Gender	3.351	.779	18.500 (1)	.000**	28.543	6.198	131.446
Educational level			1.801 (2)	.406			
Educational level (1)	.126	.445	.080 (1)	.777	1.134	.474	2.715
Educational level (2)	-.624	.591	1.113 (1)	.291	.536	.168	1.707
Marital status	-.418	.722	.335 (1)	.563	.658	.160	2.711
Number of learning hours for the course	-.137	.084	2.661 (1)	.103	.872	.740	1.028
Mandatory/voluntary attendance			.220 (2)	.896			
Mandatory/voluntary attendance (1)	.230	.611	.141 (1)	.707	1.258	.380	4.164
Mandatory/voluntary attendance (2)	-.074	.443	.028 (1)	.867	.928	.389	2.214
Hours worked per week	.032	.020	2.474 (1)	.116	1.032	.992	1.074
Relevance	.160	.211	.581 (1)	.446	1.174	.777	1.774
Feedback	.086	.225	.147 (1)	.702	1.090	.701	1.694
Confidence	-.051	.190	.072 (1)	.788	.950	.654	1.380
Attention	.621	.246	6.351 (1)	.012*	1.861	1.148	3.015
Constant	-3.070	1.579	3.778 (1)	.052	.046		

Note: B = unstandardized logit coefficients; S.E. = standard error; * = significant at the .05 level; ** = significant at the .01 level.

In order to obtain the BIC values (z^2 - ln$n$), I first obtained the natural log of the sample size. The natural log of the sample size (N = 258) used by the BIC equals 5.55 for this sample. Dividing the coefficients of the predictors by the standard errors gives the z ratio, and the squared z ratio equals the Wald statistic. Out of the predictors, only Gender, Number of e-learning courses completed, and Attention have BIC values greater than 0, while the remaining predictors fail to meet the BIC for significance. The BIC values for Gender, Number of e-learning courses completed, and Attention are 12.95, 5.59, and .80, respectively. Only the BIC value for Gender falls into the very strong range, while the BIC value for Number of e-learning courses completed falls into the moderate range and the BIC value for Attention falls into the weak range.

As mentioned in Chapter III, the fully standardized logistic regression coefficients ($\boldsymbol{B_{yx}*}$, in Table 27) can provide the real effects of predictors on the criterion as well as the relative ranks of the predictors in an equation.

Based on the fully standardized logistic regression coefficients ($B_{yx}*$), as with the BIC values, the variables of Gender, Number of e-learning courses completed, and Attention had relatively large effects on Dropout. Gender appeared to have the strongest effect (.40), followed by Number of e-learning courses completed (.36), and then Attention (.22). In other words, (1) a 1 standard deviation increase in Number of e-learning courses completed is associated with a .36 standard deviation increase in logit (Dropout), holding all other predictors constant, and (2) a 1 standard deviation increase in Attention is associated with a .22 standard deviation increase in logit (Dropout), holding all other predictors constant. For Gender, however, a 1 standard deviation increase is not as intuitively meaningful as the difference between males and females, as reflected in the unstandardized logistic regression. Changes in Age, Educational level (1) and

(2), Marital status, Number of learning hours for the course, Mandatory/voluntary attendance (1) and (2), Relevance, Feedback, and Confidence are associated with changes of less than one-tenth of a standard deviation in logit (Dropout).

Table 27

Fully Standardized Coefficients of the Predictors for the Proposed Model

Predictor	b_{yx}	S_x	R	$s_{logit(\hat{Y})}$	B_{yx}*
Number of e-learning courses completed	.083	13.090	.614	1.833	.36
Age	-.013	6.773	.614	1.833	-.03
Gender	3.351	.355	.614	1.833	.40
Educational level (1)	.126	.953	.614	1.833	.04
Educational level (2)	-.624	.456	.614	1.833	-.10
Marital status	-.418	.380	.614	1.833	-.05
Number of learning hours for the course	-.137	2.059	.614	1.833	-.09
Mandatory/voluntary attendance (1)	.230	.883	.614	1.833	.07
Mandatory/voluntary attendance (2)	-.074	.463	.614	1.833	-.01
Hours worked per week	.032	9.264	.614	1.833	.10
Relevance	.160	1.046	.614	1.833	.06
Feedback	.086	1.043	.614	1.833	.03
Confidence	-.051	1.117	.614	1.833	-.02
Attention	.621	1.071	.614	1.833	.22

Note. b_{yx} = the logistic regression coefficients; s_x = the standard deviation of X; R = the correlation between the predicted probabilities and the dummy criterion variable; $s_{logit(\hat{Y})}$ = the standard deviation of logit($\hat{Y}$).

In sum, based on the Wald statistic, the Bayesian Information Criterion (BIC), and the fully standardized coefficient, the Gender, Number of e-learning courses completed, and Attention predictor variables appeared to have a substantive relationship to the dropout of adult learners from an e-learning course.

Findings Related to Research Question 3

To find the best model, I used the likelihood score statistic, Nagelkerke's R-Square, and the Akaike's Information Criterion (AIC) as criteria. SAS 9.0 was used to obtain theses statistics.

Selecting the Best Model

Table 28 shows the best values of AIC for each predictor combination. As mentioned earlier, AIC is useful for comparing model fit in models nested. The AIC values will be smallest for a model that exhibits good fit with a small number of predictors. As shown in Table 28, the AIC value is smallest when a model contains five predictors. These values were calculated based on the suggestion of Shtatland, Barton, and Cain (2001) that the sequence of models start with the null model and end with the full model using the stepwise sequence (Note. This is different from the stepwise procedure for identifying the best set of predictors.) with SLENTRY (the significance level for entering) = 1 and SLSTAY (the significance level for stay) = 1 under SAS's PROC LOGISTIC.

Table 28

Best Values of AIC for Each Predictor Combination

M	1	2	3	4	5	6	7	8	9	10	11	12
AIC	239.629	227.363	220.530	219.890	219.770	220.939	223.382	225.005	226.644	228.538	230.477	234.252

Note. M = Number of predictors included in model; AIC = the values of AIC with the intercept and the predictors.

Table 29 presents the best values of likelihood score statistic and predictors for each predictor combination.

Table 30 presents the three best subset candidates selected based on the likelihood score statistic and the AIC values. The models represent the best models with 3, 4, 5, and 6 predictors, respectively. The reasons that I chose these models were (1) they had very small AIC values; (2) there were little differences in the likelihood score statistic value between the selected models and the model with the largest value (91.135); and (3) these models contained relatively important predictors, such as Gender (I3), Number of e-learning courses completed (I1), and Attention, as discussed in the previous section.

Table 29

Best Values of Likelihood Score Statistic for Each Predictor Combination

Number of predictor	Best score value	Predictor in model
1	73.437	I3
2	81.396	I1 I3
3	86.627	I1 I3 A
4	88.449	I1 I3 I8 A
5	89.817	I1 I3 I6 I8 A
6	90.340	I1 I2 I3 I6 I8 A
7	90.633	I1 I3 I5 I6 I8 R A
8	90.908	I1 I3 I4 I5 I6 I8 R A
9	91.101	I1 I2 I3 I4 I5 I6 I8 R A
10	91.119	I1 I2 I3 I4 I5 I6 I7 I8 R A
11	91.134	I1 I2 I3 I4 I5 I6 I7 I8 R F A
12	91.135	I1 I2 I3 I4 I5 I6 I7 I8 R F C A

Note. I1 = Number of e-learning courses completed; I2 = Age; I3 = Gender; I4 = Educational level; I5 = Marital status; I6 = Learning hours for the course per week; I7 = Mandatory/voluntary attendance; I8 = Hours worked per week; R = Relevance; F = Feedback; C = Confidence; A = Attention.

Table 30

Summary Statistics for Comparing Models in a Best Subset Logistic Regression in Terms of Likelihood Score Statistic, AIC, and Nagelkerke's R-Square

Model	Predictor in Model	Score	AIC	R^2
1	I1 I3 I6 I8 A	89.817	219.770	.442
2	I1 I3 I8 A	88.449	219.890	.434
3	I1 I3 A	86.627	220.530	.424
4	I1 I2 I3 I6 I8 A	90.340	220.939	.446

Note. Score = likelihood score statistic; R^2 = Nagelkerke's R-Square; AIC = Akaike's Information Criterion; I1 = Number of e-learning courses completed; I2 = Age; I3 = Gender; I6 = Number of learning hours for the course; I8 = Hours worked per week; A = Attention.

Out of the four best subset candidates, I selected Model 1 consisting of Number of e-learning courses completed, Gender, Learning hours for the course, Hours worked per week, and Attention as the best model since it has the smallest value of AIC and there are little differences in the likelihood score statistic and the Nagelkerke's R-Square values between Models 1 and 4.

In addition, the inclusion of the two predictors of Number of learning hours for the course and Hours worked per week, despite their not being statistically significant, is supported by Jun's (2004) study. His study, which was conducted in a context similar to that of the current study, identified these two variables as important predictors for discriminating between completers and noncompleters. In terms of model parsimoniousness, Model 3, consisting of all three statistically significant and substantive predictors (see *Findings Related to Research Question 2* above), can be selected as the best model. However, this model has a poor Hosmer and Lemeshow's fit test statistic ($\chi^2_{(8)} = 16.102$, $p < .05$), revealing that the model's estimates fit the data at a non-acceptable level.

The Best Model Selected

After choosing the best model, I conducted logistic analysis for the model using SPSS 12.0. As shown in Table 31, the model chi-square test of the full model (207.770) versus a model with intercept only (301.636) was statistically significant ($\Delta\chi^2_{(5, N = 258)} = 93.866$, $p < .001$), indicating the model with the five predictors is significantly better than the model with intercept only.

In Table 32, Hosmer and Lemeshow's Goodness of Fit test ($\chi^2_{(8)} = 4.956$, $p > .05$) reveals that the best model fits well, implying that the model's estimates fit the data at an acceptable level. There was a small decrease in Nagelkerke's R-Square (see Table 33) from .456 (the proposed model) to .442 (the best model), but it revealed a moderately strong relationship between the criterion and its predictors. The statistics of percentages correctly classified (see Table 34) show that the best model correctly classified 48.6% of the completers and 97.9% of the dropouts, for an overall accuracy rate of 84.5% for the model. Comparing this to the proposed model, the best model increased by 1.8% in classifying the dropout correctly, while the accuracy rate increased only by 0.4% overall.

Table 31

Omnibus Tests of the Best Logistic Regression Model Coefficients

	χ^2	**df**	***p***
Model	93.866	5	.000

Table 32

Hosmer and Lemeshow's Goodness of Fit Test for the Best Logistic Regression Model

χ^2	**df**	***p***
4.956	8	.762

Table 33

Model Summary for the Best Logistic Regression Model

-2 Log likelihood	**Cox & Snell R-Square**	**Nagelkerke R Square**
207.770	.305	.442

Table 34

Classification Table of the Best Logistic Regression Model

	Predicted		
Observed	Completer	Dropout	Percentage Correct
Completer	34	36	48.6
Dropout	4	184	97.9
Overall Percentage			84.5

Note. The cut value is .50.

The observed groups and predicted probabilities of dropout for the best logistic regression model are shown in Figure 9.

```
      16 +                                                     2      +
         |                                                     2      |
         |                                                2    2  2  2|
F        |                                                2 2  2 222 2|
R     12 +                                            2   2 2  2 222 2+
E        |                                            2   2 2 22 222 2|
Q        |                                          2 2   222 22 222 2|
U        |                                          2 2   222 222222 2|
E      8 +                                        2 2 2   222222222222+
N        |                                        2 2 222 222222222222|
C        |    2                                   2 2 222 222222222222|
Y        |    1                                   2 1 2222222222222222|
       4 +    1 11                               22 122222222212222222+
         |  111 1121                        2 2 2212122122122221222222|
         |  11111111 1 2                  1 22222212121122121221122222|
         |  1111111111 112 1     1   1  2 1122222112111111111111111222|
Predicted ---------------+--------------+--------------+---------------
  Prob:   0            .25            .5             .75             1
  Group:  111111111111111111111111111111222222222222222222222222222222

          Predicted Probability is of Membership for 2
          The Cut Value is .50
          Symbols: 1 – The completer
                   2 – The dropout
          Each Symbol Represents 1 Case.
```

Figure 9. The plot of observed groups and predicted probabilities of dropout for the best logistic regression model.

Table 35 represents the logistic regression coefficient (B), standard error (S.E.), Wald test, odds ratio (Exp(B)), and confidence interval (C.I.) for each of the predictors of the best logistic regression model. Employing a .05 criterion of statistical significance, the variables of Number of e-learning courses completed, Gender, and Attention had significant partial effects on Dropout predictability.

Table 35

Logit Coefficients and Wald Statistics of the Best Logistic Regression Model

Predictor	**B**	**S.E.**	**Wald (df)**	***p***	**Exp(B)**	**95.0% C.I. for EXP(B)**	
						Lower	Upper
Number of e-learning courses completed	.079	.023	12.020 (1)	.001**	1.083	1.035	1.132
Gender	2.982	.565	27.813 (1)	.000**	19.729	6.513	59.759
Number of learning hours for the course	-.120	.082	2.151 (1)	.142	.887	.756	1.041
Hours worked per week	.029	.019	2.232 (1)	.135	1.029	.991	1.069
Attention	.540	.191	8.004 (1)	.005*	1.717	1.181	2.497
Constant	-3.433	1.129	9.253 (1)	.002	.032		

Note. B = unstandardized logit coefficients; S.E. = standardized error; * = significant at the .05 level; ** = significant at the .01 level.

Table 36 presents the fully standardized logistic regression coefficients (B_{yx}*) of the predictors in the best model. Number of e-learning courses completed, Gender, and Attention have relatively large effects on Dropout. Gender and Number of e-learning courses completed (.35) appear to have the strongest effect (.35), followed by Attention (.19).

Table 36

Fully Standardized Coefficients of the Predictors for the Best Model

Predictor	$\boldsymbol{b_{yx}}$	$\boldsymbol{S_x}$	***R***	$s_{logit(\hat{Y})}$	$\boldsymbol{B_{yx}}$*
Number of e-learning courses completed	.079	13.090	.614	1.833	.35
Gender	2.982	.355	.614	1.833	.35
Number of learning hours for the course	-.120	2.059	.614	1.833	-.08
Hours worked per week	.029	9.264	.614	1.833	.09
Attention	.540	1.071	.614	1.833	.19

Note. b_{yx} = the logistic regression coefficients; s_x = the standard deviation of X; R = the correlation between the predicted probabilities and the dummy criterion variable; $s_{logit(\hat{Y})}$ = the standard deviation of logit($\hat{Y}$).

The interpretation of the odds ratio for each predictor is as follows:

- The odds ratio for Number of e-learning courses completed indicates that when holding all other predictors constant, each one e-learning course increase in Number of e-learning courses completed predicts an 8.3% increase in the odds of dropping out of an e-learning course.

- The odds ratio for Gender indicates that when holding all other predictors constant, a man is about 19.73 times more likely to drop out of an e-learning course than a woman.
- The odds ratio for Number of learning hours for the course indicates that when holding all other predictors constant, each one hour increase in Number of learning hours for the course predicts an 11.3% decrease in the odds of dropping out of an e-learning course.
- The odds ratio for Hours worked per week indicates that when holding all other predictors constant, each one hour increase in Hours worked per week predicts a 2.9% increase in the odds of dropping out of an e-learning course.
- The odds ratio for Attention indicates that when holding all other predictors constant, each one point increase (one standard deviation) in Attention predicts a 71.7% increase in the odds of dropout of an e-learning course. (Note. See Table 15. The five items developed for the Attention construct were negatively loaded on Factor IV, Attention, and transformed into the factor score of Attention. Hence, if a learner had a high factor score, then he or she had a low level of motivation in Attention.)

Chapter Summary

This chapter presented the results of the statistical analyses described in Chapter III. These findings are addressed in relation to each of the three research questions that structured the study. First, the overall assessment of the proposed model consisting of 14 individual background and motivational variables reveals that the logistic regression model is acceptable in predicting the dropout of adult learners from e-learning courses in the workplace, with a fair degree of accuracy. The statistics of percentages correctly classified show that the proposed model correctly classified 50.0% of the completers and 96.8% of the dropouts, for an 84.1% overall accuracy rate. Second, based on the Wald statistic, the Bayesian Information Criterion (BIC), and the fully standardized coefficient, the Gender, Number of e-learning courses completed, and Attention predictor variables appeared to have a substantive relationship to the dropout of adult learners from an e-learning course. Finally, a model with the 5 predictors of Number of e-learning courses completed, Gender, Learning hours for the course per week, Hours worked per week, and Attention was chosen as the best model in comparing the AIC values, the likelihood score statistic, and the Nagelkerke's R-Square values of the three suggested best models.

CHAPTER V

SUMMARY, DISCUSSION, IMPLICATIONS, AND SUGGESTIONS

The purpose of this chapter is to discuss the research findings presented in Chapter IV. This chapter is organized into five sections: study summary, discussion of the findings, implications for practice and research, suggestions for further research, and limitations of the study.

Study Summary

In this study data were collected from a sample of employees who took e-learning courses for improving job skills related to their work. The study concentrated on identifying variables to predict dropout of adult learners in e-learning environments. The purpose of this study was to determine which specific set of variables can best predict the dropout of adult learners from e-learning courses in the workplace. For this purpose, three research questions were developed:

1. To what extent does a model consisting of individual background and motivational variables predict the dropout of adult learners from an e-learning course?
2. Which individual background and motivational variables have a substantive relationship to the dropout of adult learners from an e-learning course?
3. Which is the best model to predict the dropout of adult learners from an e-learning course?

The framework for this study was derived from Boshier's (1973) congruency model, Rubenson and Hoghielm's (1978) expectancy-valence model of dropout, Bean and Metzner's (1985) model of nontraditional undergraduate student attrition, Keller's (1987) ARCS model, Billings' (1988) model for completion of correspondence courses, and Kember's (1995) open learning model.

A logistic regression model was proposed for this research. In constructing a model, I relied on the work of these eight authors and examined variables based on their relevance to an e-learning context. Variables included in the model for logistic regression were categorized into eight individual background variables (Number of e-learning courses completed, Age, Gender, Educational level, Marital status, Number of learning hours for the course, Mandatory/voluntary attendance, and Hours worked per week) and four kinds of motivational variables (Attention, Relevance, Confidence, and Feedback).

A survey instrument was developed to specifically address the three research questions. The survey instrument gathered from employees who took e-learning courses in the workplace information about their motivation to participate in an e-learning course and selected individual background variables. The development of the instrument involved the following phases: (1) clarification of the concept, (2) development and refinement of the item pool, (3) pre-pilot review of the pilot survey instrument, (4) addition of individual background items, (5) translation, and (6) pilot survey.

The sample used for this study was a non-random convenience sample of employees of Company A in South Korea. The participant pool consisted of 2112 participants who participated in 20-hour e-learning courses provided by Company A from July to December of 2004. A two-step process was used to distribute the survey instrument: (1) a cover letter and the survey instrument were e-mailed, and (2) four follow-up reminder e-mails with the above two items were sent out (once each week) to all potential candidates until the data collection phase ended.

Participants returned 259 usable surveys, and the data were entered into an SPSS database for the purpose of statistical analysis. In order to answer the three research questions, I conducted the following statistical analyses: reliability of the scale, frequencies, normtest macro test, correlation, exploratory factor analysis, and logistic regression.

Data analysis was conducted using SPSS 12.0 and SAS 9.0 statistical software packages. The statistical analysis provided the information necessary to answer the study's primary research questions. The primary results of the three research questions were:

(1) The overall assessment of the proposed logistic regression model consisting of individual background and motivation variables revealed that the model had a moderate association between the predictor variables and Dropout (Nagelkerke's R-Square, .456).

(2) Gender, Number of e-learning courses completed, and Attention predictor variables had a substantive relationship to the dropout of adult learners from an e-learning course (B_{yx}* = .40, 36, and .22, respectively).

(3) The logistic regression model consisting of Number of e-learning courses completed, Gender, Learning hours for the course per week, Hours worked per week, and Attention was chosen in terms of efficient predictability of dropout of adult learners. This model had a moderately strong relationship between the criterion and its predictors (Nagelkerke's R-Square, .442) and correctly classified 48.6% of the completers and 97.9% of the dropouts, for an overall accuracy rate of 84.5% for the model.

Conclusions and Discussion

Since there was no existing model developed specifically for the context in which I was working, in choosing predictor variables related to the dropout of adult learners from e-learning environments, I relied on several models related to the dropout of adult learners, as well as related literature in adult education, human resource development, and distance learning (discussed in Chapter III).

This study was not a direct search for the reasons or causes of adult learner dropout. Some variables, such as illness, family problems, unexpected responsibilities at work, or changes at work, might be the direct cause of adult learner dropout from e-learning courses in the workplace. Instead, this study sought to identify adult learner characteristics and aspects of the adult learner's learning environment that might have an effect on their dropout. The overall assessment of the model consisting of individual background and motivation variables reveals that the logistic regression model is acceptable for predicting dropout of adult learners from e-learning courses in the workplace with a fair degree of accuracy.

This section discusses the two primary conclusions related to the findings of the study. These conclusions are:

(1) Individual background predictors had much more influence than motivation predictors on the dropout of adult learners from e-learning courses in the workplace, and

(2) The model with the best subset of predictors for efficiently predicting which adult learners were most likely to drop out from e-learning courses consisted of individual background and motivation predictors.

The following discussion centers around these conclusions.

Findings Related to Conclusion (1)

As can be seen in Figure 10, which reveals the relative substantive relationship of each predictor in the model to Dropout in terms of the fully standardized coefficient, individual background predictors such as Gender and Number of e-learning courses completed had a more substantive relationship to the dropout of adult learners than did motivation variables. I discuss below the findings related to the first conclusion.

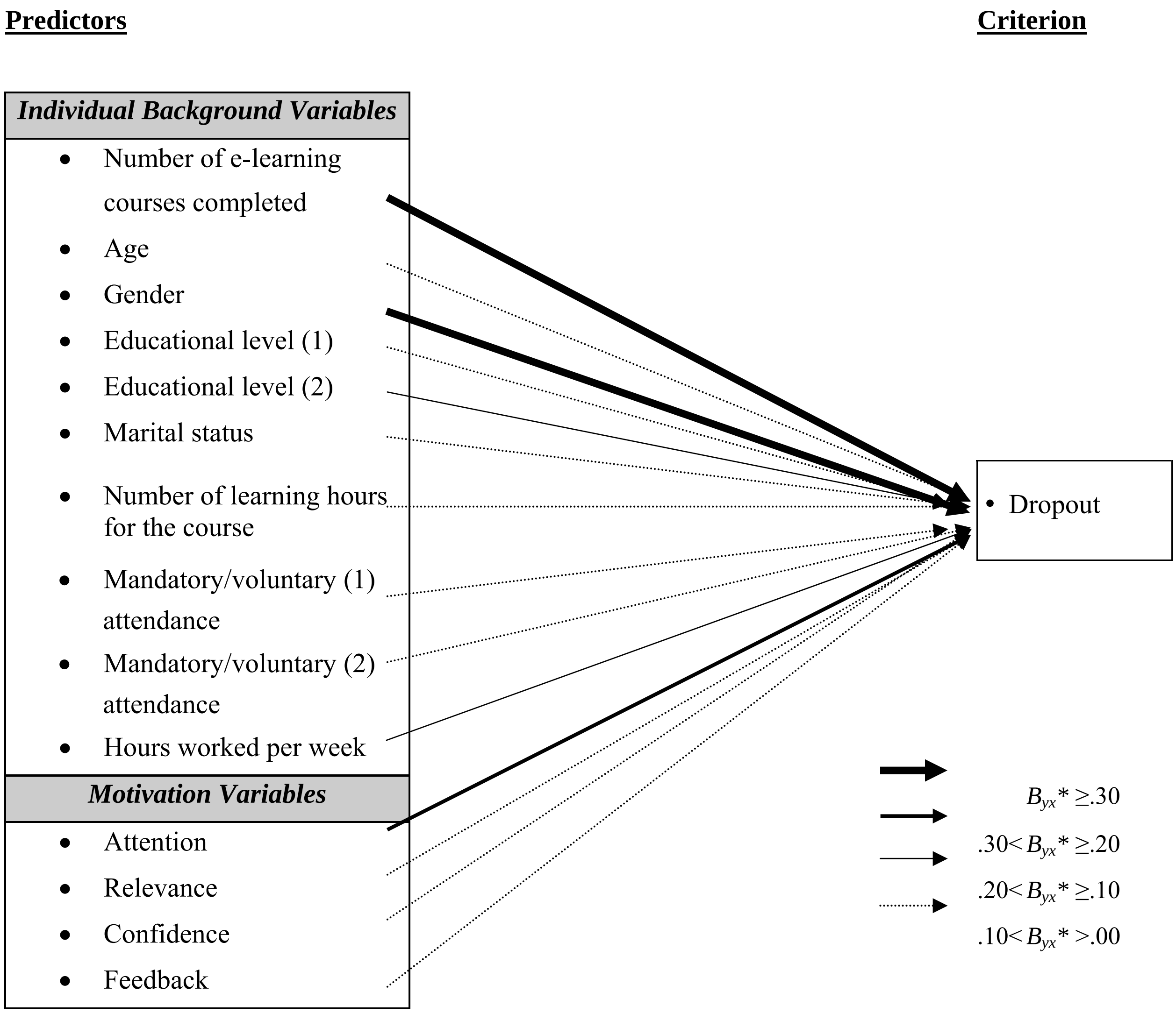

Figure 10. Relative substantive relationship of each predictor to Dropout.

Number of e-learning courses completed. Although the Number of e-learning courses completed predictor was identified as the second most substantive variable of the predictors in the model, this variable produced an unexpected result. This outcome may be caused by a participant's discovery that current course content is significantly similar to the content of a previous course he or she has taken. The odds ratio for Number of e-learning courses completed indicates that when holding all other predictors constant, each one e-learning course increase in

Number of e-learning courses completed predicts an 8.6% increase in the odds of dropping out from an e-learning course. In other words, the adult learner with more completed e-learning courses was more likely to drop out from e-learning courses than was a learner who had completed fewer e-learning courses. This finding is inconsistent with the study by Osborn (2001), conducted to identify at-risk students who enrolled in Web-based and video conferencing courses in a higher education setting. Osborn found that, compared to the completing students, at-risk students had not taken as many distance learning courses prior to participation in the study.

If we assume that the more e-learning courses an adult learner has completed leads to greater computer confidence, then the findings of this study are also contrary to the results of other studies (ASTD & The MASIE Center, 2001; Black, 1998; Frankola, 2001b; Horton, 2000; Osborn, 2001; Vrasidas & McIsaac, 1999). These studies assert that computer confidence is one of the major components that has an influence on the dropout or persistence of adult learners in e-learning and that at-risk learners have less computer confidence. The findings of the current study may have been influenced by two factors: (1) all the participants received enough technical support, or (2) they were already accustomed to today's technological environment. Accordingly, although computer confidence was not directly measured in the study, it is possible that computer confidence has nothing to do with adult learner dropout from e-learning courses in the workplace.

Age, educational level, and marital status. Although many studies of learner dropout used the Age, Educational level, and Marital status variables as entry characteristics, the findings of this study indicate that these predictors were not key predictors for discriminating between completers and noncompleters. These findings are consistent with the study by Osborn (2001), who found that these predictors had little effect on students' dropout. However, Fjortoft (1995) found that adult learners who were older were less likely to persist in a correspondence distance program.

Gender. Contrary to Osborn's (2001) finding that gender had little effect on Dropout, this study found that the Gender variable appeared to have the strongest effect on Dropout. The odds ratio for Gender indicates that when holding all other predictors constant, a man is about 28.54 times more likely than a woman to drop out from an e-learning course. In light of the characteristics of the sample for this study, women were younger (mean = 30.55) than men (mean = 37.83). In addition, while most men were married (91.8%), most women were non-married (71.1%). This fact implies that men had more job-related, social, or family responsibilities than did women. This may be one reason for men being more likely than women to drop out from an e-learning course. Another reason is that women could be more motivated. In Korean society, where the labor market has been slower than educational settings in achieving gender equality, women experience severe gender discrimination in getting a job, and those who do succeed in finding a job face formal and customary gender discrimination in their workplace regarding stable hiring, assignment to departments, training and education, promotion, and salary (Jang, 2002). These limited employment opportunities, the formal and informal gender discrimination, and unstable job position in the workplace may motivate women to complete the e-learning courses. By completing the e-learning courses they participated in, they may avoid unfavorable treatment that they might receive due to their dropout from the courses.

Number of learning hours for the course and hours worked per week. Although these variables were not statistical significant in terms of the Wald statistic, of the predictors in the proposed model, these predictors had moderate effects on Dropout. The odds ratio for Number of learning hours for the course indicates that when holding all other predictors constant, each one hour increase in Number of learning hours for the course predicts a 12.8% decrease in the odds of dropping out from an e-learning course. In addition, the odds ratio for Hours worked per week indicates that when holding all other predictors constant, each one hour increase in Hours worked per week predicts a 3.2% increase in the odds of dropping out from an e-learning course. In other words, those who have more hours of job-related duties are less likely to complete e-learning courses.

Farabaugh-Dorkins's (1991) study, conducted to understand why older students were frequently dropping out of a large public university in the Midwest, reveals that weekly study hours failed to contribute directly or indirectly to explaining attrition variance. Unlike the face-to-face learning setting, Number of learning hours for the course in the current study contributed moderately to explaining the dropout of adult learners from the e-learning environment. The more hours a learner studies, the more likely he or she is to complete the e-learning course.

Osborn's (2001) study shows that the at-risk students actually worked fewer hours per week. He notes that this may be caused by time management rather than absolute amount of time for the study. Contrary to the study by Osborn, the current study revealed that the Hours worked per week predictor had a moderate effect on Dropout.

Mandatory/voluntary attendance. If an employee's participation in an e-learning course is mandatory, we can expect this factor to have a substantive effect on course completion (ASTD & The MASIE Center, 2001). Contrary to the expectation, the Mandatory/voluntary attendance variable had little effect on the criterion of Dropout. In other words, whether or not the attendance of adult learners in e-learning was mandatory, this variable was not a key predictor for discriminating between completers and noncompleters. There are some possible reasons for the finding: (1) there were not any penalties for employees' dropout from e-learning courses, and (2) there were many opportunities to take the course again.

Motivation. Motivation is usually considered to be the most important variable in predicting dropout, as indicated in several models of dropout of adult learners (Bean & Metzner, 1985; Billings, 1988; Boshier, 1973; Kember, 1995; Rubenson & Hoghielm, 1978; Stahl & Pavel, 1992). In addition, many studies and e-learning experts also note that motivation is closely related to dropout of adult learners in e-learning contexts (ASTD & The MASIE Center, 2001; Broadbent, 2001; Black, 1998; Chyung, 2000, 2001a, 2001b; Chyung et al., 1998; Frankola, 2001b; Frontline Group, 2001; Gilroy, 2001; Greer, Hudson, & Paugh, 1998; Horton, 2000; Kember, 1995; Khan & Vega, 1997; Lim, 2001; Osborn, 2001; Shepherd, 2001; Vrasidas & McIsaac, 1999).

When the variable of motivation is used in studies of dropout of adult learners, it typically refers to satisfaction motivation. In this study, based on Keller's (1987) ARCS model, I developed a scale consisting of four subscales (Attention, Confidence, Relevance, and Feedback) because the study deals with a comprehensive motivation that is related to the dropout of adult learners.

Of the four motivation subscales, only Attention had a relatively substantive relationship to Dropout. This finding may reveal that the Attention variable is much more important than the other motivation predictors of Relevance, Confidence, and Feedback in e-learning settings. Attention was defined as characteristics or ability of the course to get and sustain the attention of the learner. The odds ratio for Attention indicates that when holding all other predictors constant, each one point increase (one standard deviation) in Attention predicts an 86.1% increase in the odds of dropout from an e-learning course. This finding is supported by Osborn's (2001) study.

Although he did not specify motivation itself, he found that lower motivation was a key predictor for discriminating between completers and noncompleters. Lee's (2005) study is also consistent with the finding of the current study. She identifies that "boredom of instructional materials" was recognized as one of critical obstacles in e-learning by adult learners in a cyber-university.

Findings Related to Conclusion (2)

The results of this study indicate that for this sample, a model with the best subset consisting of the four individual background predictors (i.e., Number of e-learning courses completed, Gender, Learning hours for the course per week, and Hours worked per week) and one motivation predictor (i.e., Attention) was most useful in predicting adult learners' dropout in terms of efficient predictability. Usually, the objective of testing and modifying several competing theories or prediction equations is to pare down a large group of variables to a subset that meets theoretical or predictive standards (King, 2003). Like the current study, if no models have been hypothesized in advance, the best subset logistic regression is available for identifying important predictors. According to Hosmer and Lemeshow (2000), "The subsets of predictors selected for *best* models depend on the criterion chosen for *best* " (p. 131). In this study, I considered efficiency for predicting adult learners' dropout as the predictor selecting criteria for best. For selecting the best subsets of predictors, I used statistical and substantive grounds discussed in Chapters III and IV.

Individual background variables are a starting point that affects dropout in a model of dropout of adult learners (Bean & Metzner, 1985; Billings, 1988; Boshier, 1973; Keller, 1987; Kember, 1995; Rubenson & Hoghielm, 1978; Stahl & Pavel, 1992) and many studies related to dropout in e-learning (Driscoll, 1988; Frankola, 2001b; Frontline Group, 2001; Jun, 2004; Osborn, 2001; Vrasidars & McIsaac, 1999). Since many studies of adult learner dropout conducted in the fields of adult education, distance learning, and HROD have had different backgrounds and samples, there were no consistent set of individual background variables that most affect adult learner dropout in any context. Accordingly, the matter of which variables should be included in the model depends on the specific situation of each study. In this study, Number of e-learning courses completed, Gender, Learning hours for the course per week, and Hours worked per week were considered to be important individual background predictors for discriminating between completers and noncompleters. One or more predictors out of the four individual background variables were commonly found as a critical discriminator in studies conducted by Bean and Metzner (1985), Kember (1995), Stahl & Pavel (1992), and Osborn (2001).

Motivation variables are considered to be among the most important dropout variables, as indicated in several models of dropout of adult learners (Bean & Metzner, 1985; Billings, 1988; Kember, 1995; Stahl & Pavel, 1992). As the most powerful variable that affects the adult learners' decision to dropout, the motivation predictor typically refers to learners' satisfaction with courses they have participated in. In the current study, of the four motivation variables, only Attention is included in the best subset model. Lee's (2005) study supports this result. In her study, Attention was an important variable, the lack of which was considered to be one of the critical obstacles in e-learning.

In summation, compared to the proposed model consisting of all 14 predictors, the model consisting of only five predictors (the four individual background predictors and one motivation predictor) was more efficient in predicting the dropout of adult learners from e-learning courses in the workplace. The study was undertaken to shed light on the characteristics of completers and noncompleters and also to select reasonable variables to assist e-learning designers or instructors in the early detection of at-risk adult learners. The results of this study suggest that we can effectively detect at-risk adult learners using only these five predictors.

Implications for Theory and Practice

This study has the potential for theoretical contributions to the field of adult education, particularly regarding e-learning in the workplace. First, the results of this study expand the knowledge base related to understanding the dropout of adult learners in e-learning programs. As shown in the literature review, the majority of studies of dropout have focused on traditional educational settings, such as face-to-face, classroom-based programs. This study provides adult and distance education scholars with empirical evidence delineating which predictors have a substantive relationship to the dropout of adult learners from e-learning courses in the workplace. The results of the study reveal that out of the variables included in the proposed model, the five predictors of Number of e-learning courses completed, Gender, Number of learning hours for the course, Hours worked per week, and Attention have a relatively substantive relationship to the dropout of adult learners from e-learning courses in the workplace.

Next, the results of this study contribute a theoretical framework that can be utilized to develop future empirical studies of dropout from e-learning courses. E-learning is becoming more popular because it allows training to be available on demand, to be delivered remotely, and to keep up with the rapid pace of economic change. The flexibility of time, place, low delivery cost, and program content that is provided via e-learning is very appealing to workers who are trying to improve their job performance or individual development, as well as to training managers who are trying to seek effective and efficient instructional delivery. Training in the workplace is performed to ensure maximum benefit to the stakeholders who have a stake in the training. Thus far, many studies related to e-learning have focused on such subjects as the comparisons among strategies for the success of e-learning, the satisfaction of adult learners in e-learning programs, and the return on investment (ROI) of e-learning programs. Although many studies related to e-learning have been conducted in the field of adult education or HRD, relatively little attention has been given to why adult learners drop out of e-learning courses in the workplace. As Zielinski (2000) mentioned, there is little broad-based quantitative research pointing to evidence of a widespread dropout problem for e-learning in the corporate world. This study could provide a useful theoretical framework for future studies of dropout from e-learning courses.

The study also provides practical contributions to the field of human resource and organization development, as well as adult education arenas. Specifically, the findings of this study have some implications for e-learning course designers, instructors, managers in the workplace, and those in adult education or higher education fields. By examining which specific set of variables can best predict adult learners' dropout from an e-learning course in the workplace, this study revealed implications regarding what can be done in order to prevent dropout or to reduce the dropout rate in e-learning programs.

In this study, the five predictor variables of Number of e-learning courses completed, Gender, Attention, Number of learning hours for the course, and Hours worked per week were critical variables in predicting the dropout of employees from e-learning courses in the workplace. Based on the findings, designers and managers of e-learning programs can develop a variety of strategies to prevent dropout of adult learners. Examples of these strategies are provided below:

- Number of e-learning courses completed: This study revealed that the adult learner with more completed e-learning courses was more likely to drop out from the e-learning course. Designers and managers of e-learning programs can use a variety of learning activities, such as small-group cooperative learning strategies and student support services (e.g., mentoring), in order to motivate learners to successfully complete e-learning courses. They can provide adult learners with an in-depth and supplementary differentiated curriculum for the same course.

- Gender: The findings of the study indicated that men were much more likely than women to drop out from an e-learning course. For improving men's e-learning course completion rate, e-learning designers and managers can propose a welfare policy, such as learning leave, or the participants' completion of the e-learning course can be reflected in their performance evaluations.
- Number of learning hours for the course and Hours worked per week: The study indicates that these two variables were also critical predictors in explaining the dropout of employees from e-learning courses. In order words, employees' dropout from e-learning courses may partly be explained by lack of time.
- Attention: This predictor was the only statistically significant and substantive one out of the four motivation variables. In order to increase the attention of participants in e-learning courses, e-learning designers can develop more interesting e-learning courses by using instructional strategies such as reflecting potential participants' needs about the course format of content in the courses, letting subject matter experts into the course development process to design interesting e-learning courses, and adopting advanced technologies to create appealing Web pages.

The results of the study indicate that the phenomenon of adult learner dropout from e-learning courses should be viewed from a multivariate framework. As noted earlier, many studies have pointed out that the phenomenon of adult learner dropout cannot be understood by considering one or two reasons. Accordingly, the efforts for reducing the dropout rate of adult learners in e-learning courses should be exerted from a macro approach, such as by providing them with student support services, as well as from a micro approach, such as by improving the quality of an e-learning course through instructional systems design. If the cause of adult learner dropout is attributed only to the individual level, it becomes difficult to find a solution for the dropout phenomenon. Employees' successful completion of e-learning courses has important implications for the company and for themselves because employees' successful learning experiences will contribute to the achievement of the goals of the organization.

The survey instrument developed for this study provides the designers and managers of e-learning programs with a tool that can be used to assess their own e-learning courses in terms of motivation, or Attention. Based on the results of the assessment, they can identify the strengths and weaknesses of the e-learning courses currently being offered. If a weakness of the e-learning course is found, an action plan can be developed that has the potential to improve the overall quality of the e-learning programs.

This study can provide a useful approach for developing an e-learning motivation scale itself. This scale can be referred to in developing another scale of motivation and can provide a helpful guideline to researchers who want to create similar scales and examine their psychometric properties.

Suggestions for Further Research

The purpose of this study was to determine which specific set of variables can best predict the dropout of adult learners from e-learning courses in the workplace. This study has provided some answers to the research questions that guided this investigation of a very specific environment. This section suggests a number of possibilities for future research on this topic that were not covered in this study.

First, this study was conducted in a specific organization in South Korea. Additional studies can be conducted in international locations to compare whether or not the findings of this study hold consistency. These comparative studies can provide some implications in terms of geographical location, social contexts, and cultural differences.

Second, this study used logistic regression to answer the research questions. Hence, the findings of this study dealt with only simple relationships between the predictors and the criterion. A future study might examine the relationships among the predictors, as well as the criterion variable of Dropout, using path analysis or structural equation models. These statistical methods can be helpful in accounting for the complexity inherent in analyzing learner dropout. Of course, the relationships among the predictor variables in the model for path analysis or structural equation modeling should be based on the models of dropout and an extensive literature review of empirical findings, or on existing conceptual models of dropout that need to be tested.

Finally, this study presented the interpretation of the odds ratio for each predictor. There is a need for further empirical research for a better understanding of the results through qualitative research. For instance, further research could address the following questions: “Why are men more likely than women to drop out from an e-learning course?” or “Why are adult learners with more completed e-learning courses more likely than those learners with fewer completed e-learning courses to drop out from an e-learning course?” The use of interviews, focus groups, and observations may help provide better answers to such *why* questions.

Limitations of the Study

This study employed convenience, non-random sampling. Specifically, the survey was administered to a convenience sample of employees who took a one-month, 20-hour e-learning course provided from February to April of 2004 in one company in South Korea. It can be difficult to draw conclusions about a population based on information derived from a sample, because convenience sampling does not produce a representative sample of the population. In other words, the findings from convenience sampling may produce a fit to the sample data, but may produce a model that has nothing to do with the population. Therefore, further study with larger, representative samples is suggested to extend these results to the entire employee population who took e-learning courses for improving job skills related to their work in South Korea.

Another limitation is that the survey response rate was very low (12.26%). I chose the e-mail survey as a data collection method for its superiority over postal surveys in terms of response speed and cost efficiency. However, this low response rate can induce the effects of non-response error, reflecting an inordinate percentage of a particular demographic portion of the sample.

The third limitation is the limited number of predictor variables. The predictor variables employed in this study were selected based on a review of the literature. However, there could be many variables not included in the study because I studied only a finite number of predictors. According to Garson (2003), "If relevant variables are omitted, the common variance they share with included variables may be wrongly attributed to those variables, or the error term may be inflated" (¶ 73).

The final limitation is the survey instrument used in this study. The researcher developed a survey instrument to obtain motivational perceptions related to the dropout of adult learners from e-learning courses in the workplace and their individual background information. Specifically, the motivation scale for this study was based on Keller's (1987) ARCS model, which is a well-known motivational design model applying motivational principles to instructional design. Although I followed rigorous procedures in order to develop a well-designed survey instrument, an extracted four-factor solution consisting of Attention, Confidence, Relevance, and Feedback only captures about 57% of the variance in the items. This indicates that the measures are not very strong.

For replicated studies using the survey instrument developed by the researcher, the three following suggestions are recommended. First, a cross-validation process needs to be conducted through a confirmatory factor analysis with a large enough sample. Second, since the survey was developed in English and then translated into Korean based on only a committee approach method, other translation methods such as *back translation*, *bilingual technique*, or *pilot testing* may be needed to see if the translation is correct. Finally, the survey instrument needs to be refined through several replicated pilot studies.

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APPENDICES

APPENDIX A

AN EXPLORATORY FACTOR ANALYSIS FOR THE PILOT STUDY

Items for the Pilot Study

v01. I enjoyed working on such a well-designed course
v02. The quality of the course was sufficient to keep my attention
v03. I felt uncertain that I understood the course objectives
v04. The course variety held my attention
v05. I was unsatisfied with the course content
v06. The course materials were too difficult to understand
v07. The topics of the course were irrelevant to my interests
v08. This course stimulated my curiosity
v09. I got enough feedback to know how well I was doing
v10. I felt the web-pages of the course were unappealing
v11. The course content was applicable to my personal interests
v12. The organization of the course made me enthusiastic
v13. I felt confident I could learn each lesson
v14. The examples used in the course were relevant to my interests
v15. I was unsure about my ability to pass the test(s) in the course
v16. This course was unsuccessful in meeting my learning needs
v17. The way the course was organized helped me to gain confidence
v18. I was unsatisfied with course learning activities
v19. This course provided helpful feedback
v20. The way the information was arranged on the web-pages helped keep my attention
v21. I felt confident I would do well in the course
v22. This course was irrelevant to my present career opportunities
v23. Whenever I needed technical support, this course provided help
v24. The course content was too abstract to keep my attention
v25. The course format bored me
v26. The course content was inapplicable to my job
v27. The examples used in the course were relevant to my current job
v28. Whether or not I succeeded in the course was up to me
v29. The topics of the course were unimportant to me
v30. The course content was applicable to my future career opportunities
v31. I felt this course was irrelevant to my goals
v32. The topics of the course were irrelevant to my job performance
v33. This course provided unmanageable assignments that are too advanced
v34. The examples used in the course were irrelevant to my future professional goals

An Exploratory Factor Analysis for the Pilot Study

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.880
Bartlett's Test of Sphericity	Approx. Chi-Square	1832.440
	df	231
	Sig.	.000

Communalities

	Initial	Extraction
v32r	.610	.627
v27r	.584	.463
v34r	.460	.453
v22r	.473	.437
v26r	.680	.580
v30r	.570	.552
v29r	.565	.530
v31r	.518	.466
v06c	.502	.592
v15c	.386	.428
v33c	.365	.442
v03c	.337	.366
v21c	.461	.446
v13c	.380	.391
v02a	.461	.470
v08a	.421	.471
v25a	.420	.367
v24a	.583	.647
v10a	.266	.232
v19s	.315	.449
v09s	.384	.434
v23s	.287	.229

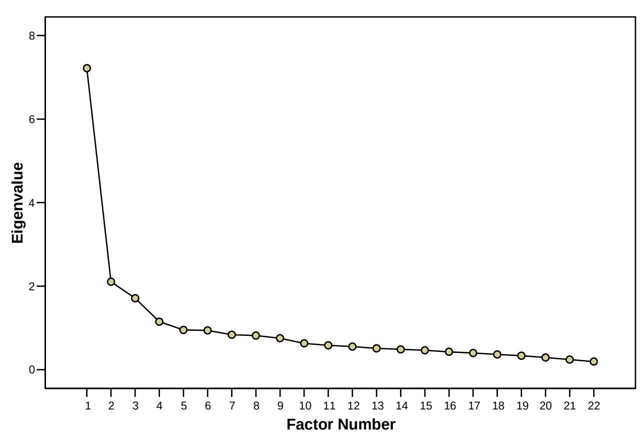
Extraction Method: Principal Axis Factoring.

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings(a)
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	7.218	32.811	32.811	6.702	30.466	30.466	5.812
2	2.108	9.581	42.391	1.585	7.204	37.670	3.892
3	1.712	7.783	50.174	1.157	5.259	42.929	2.673
4	1.151	5.231	55.405	.626	2.846	45.776	3.257
5	.953	4.334	59.739				
6	.940	4.272	64.011				
7	.837	3.805	67.816				
8	.818	3.718	71.534				
9	.755	3.432	74.966				
10	.633	2.875	77.841				
11	.586	2.664	80.505				
12	.556	2.525	83.030				
13	.512	2.329	85.359				
14	.488	2.216	87.575				
15	.466	2.120	89.695				
16	.430	1.953	91.648				
17	.401	1.824	93.473				
18	.365	1.661	95.133				
19	.336	1.528	96.662				
20	.294	1.336	97.997				
21	.245	1.112	99.109				
22	.196	.891	100.000				

Extraction Method: Principal Axis Factoring.
a When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

Scree Plot



Factor Matrix(a)

	Factor			
	1	2	3	4
v32r	.660	-.303	-.297	.101
v27r	.568	-.348	-.099	.095
v34r	.560	-.261	-.215	.158
v22r	.584	-.272	-.147	.018
v26r	.730	-.172	-.108	-.073
v30r	.702	-.235	-.027	-.057
v29r	.694	-.212	-.054	-.005
v31r	.642	-.227	-.041	-.022
v06c	.426	.582	-.240	-.119
v15c	.430	.364	-.265	.202
v33c	.391	.295	-.429	.137
v03c	.442	.403	-.015	-.084
v21c	.556	.359	.016	.083
v13c	.518	.332	.071	.086
v02a	.592	.016	.303	-.167
v08a	.553	-.151	.334	-.175
v25a	.535	.095	.226	-.142
v24a	.703	.128	.010	-.368
v10a	.422	.111	.197	-.058
v19s	.343	.032	.440	.370
v09s	.432	.092	.347	.345
v23s	.397	.130	.223	.067

Extraction Method: Principal Axis Factoring.
a 4 factors extracted. 10 iterations required.

Pattern Matrix(a)

	Factor			
	1	2	3	4
v32r	.844	.032	-.130	-.092
v27r	.726	-.133	-.047	.035
v34r	.700	.007	-.160	.012
v22r	.692	-.031	.012	-.051
v26r	.676	.090	.158	-.055
v30r	.674	-.018	.173	.006
v29r	.661	.016	.110	.032
v31r	.635	-.021	.121	.016
v06c	-.136	.810	.130	-.113
v15c	.073	.612	-.205	.099
v33c	.195	.609	-.241	-.104
v03c	-.077	.532	.201	.063
v21c	.017	.509	.079	.240
v13c	-.011	.446	.094	.274
v24a	.330	.319	.518	-.162
v08a	.322	-.151	.445	.180
v02a	.210	.041	.443	.199
v25a	.141	.139	.375	.164
v10a	.068	.137	.357	.196
v19s	-.040	-.072	-.050	.722
v09s	.009	.057	-.049	.652
v23s	.020	.139	.147	.322

Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalization.
a Rotation converged in 13 iterations.

Structure Matrix

	Factor			
	1	2	3	4
v32r	.774	.350	.115	.258
v27r	.668	.192	.168	.311
v34r	.656	.285	.072	.275
v22r	.659	.267	.208	.263
v26r	.742	.415	.377	.345
v30r	.725	.329	.389	.378
v29r	.718	.350	.339	.384
v31r	.672	.299	.327	.349
v06c	.217	.746	.243	.124
v15c	.327	.624	.008	.243
v33c	.342	.604	-.067	.082
v03c	.255	.567	.332	.269
v21c	.381	.611	.303	.435
v13c	.345	.549	.306	.443
v02a	.463	.307	.598	.479
v08a	.481	.160	.581	.453
v25a	.400	.346	.518	.416
v24a	.566	.546	.642	.288
v10a	.303	.292	.388	.369
v19s	.244	.121	.196	.662
v09s	.319	.251	.218	.655
v23s	.278	.283	.311	.430

Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalization.

Factor Correlation Matrix

Factor	1	2	3	4
1	1.000	.449	.323	.461
2	.449	1.000	.248	.310
3	.323	.248	1.000	.384
4	.461	.310	.384	1.000

Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalization.

APPENDIX B

SURVEY INSTRUMENT COVER LETTER

UNDERSTANDING DROPOUT OF ADULT LEARNERS IN E-LEARNING

Dear Participant:

We are currently involved in a study entitled, "Understanding Dropout of Adult Learners in E-learning," to determine whether a specific set of variables could be used to predict an adult learner's dropout in a work-related e-learning course. The study is being conducted by Ju Sung Jun, a doctoral student from the Department of Adult Education at The University of Georgia, under the guidance of Dr. Ronald M. Cervero, Professor of Adult Education (1-706-542-2214).

We are asking you to please volunteer a few minutes of your time to fill out the attached questionnaire. Your participation in this study is strictly voluntary. We do not foresee this study causing you any harm or discomfort. However, should you be uncomfortable about completing the questionnaire, simply stop doing this. You can skip any questions you feel uncomfortable answering.

The results of this participation will be confidential, and we will protect your identity in every way possible. When we publish our findings, we will report our findings based on groups, not on individuals. Internet communications are insecure and there is a limit to the confidentiality that can be guaranteed due to the technology itself. However, once the completed survey is received by the investigator standard confidentiality procedures will be employed.

If you have any questions about this research, please contact Ju Sung Jun via telephone number 1-706-543-3472, or Dr. Ronald M. Cervero via telephone number 1-706-542-2214. The Department's mailing address is the Department of Adult Education, 412 River's Crossing, The University of Georgia, Athens, Georgia 30602, U.S.A

Sincerely,

Ju Sung Jun	Ronald M. Cervero
jnet@uga.edu	rcervero@coe.uga.edu
Doctoral Student	Major Professor

Thank you for your help with this important research.

For questions or problems about your rights please call or write: Chris A. Joseph, Ph.D., Human Subjects Office, University of Georgia, 612 Boyd Graduate Studies Research Center, Athens, Georgia 30602-7411, U.S.A; Telephone 1-706-542-3199; E-Mail Address IRB@uga.edu.

[Korean Version of the Cover Letter]

이러닝(E-learning) 학습과정 참여자의 중도탈락에 관한 연구

안녕하세요?

저는 조지아 대학교 박사과정에 재학중인 전주성입니다. 저는 지도교수인 Ronald M. Cervero (1-706 542-2214) 교수의 지도하에, 직무와 관련된 이러링(E-learning) 학습과정에 참여한 성인학습자들을 대상으로 어떤 변인들이 이들 성인학습자들의 중도탈락을 효과적으로 예측할 수 있는지에 관한 연구를 수행하고 있습니다.

설문지에 대한 응답 여부는 전적으로 귀하의 자유 의지에 달려있습니다. 부디 바쁘시더라도 솔직하고 성의있게 대답해 주시기를 부탁드립니다. 설문지는 귀하의 감정을 상하게 하거나 혹은 어떤 불편함을 초래할 내용이 전혀 없습니다. 만일 설문지 응답 도중 이런 점이 발견되시면 언제라도 응답을 멈추실 수 있습니다.

귀하께서 응답해 주신 내용은 본 연구이외의 목적으로는 절대로 사용되지 않을 것입니다. 이 연구의 결과를 발표할 때에도 저희는 일체 귀하의 신분을 확인할 수 있는 어떤 단서도 밝히지 않을 것을 약속드립니다. 인터넷을 통한 커뮤니게이션이 귀하의 응답에 대한 정보유출 가능성이 있으나 연구자는 정보 유출을 막기위한 노력을 게을리 하지 않겠습니다.

귀하께서 이 연구에 관해 의문이나 질문이 있으시면 언제든지 전주성 (전화: 1-706-543-3472) 혹은 Ronald M. Cervero 교수 (전화: 1-706-542-2214) 에게 문의하실 수 있습니다. 학과 주소는 The Department of Adult Education, 412 River’s Crossing, The University of Georgia, Athens, Georgia 30602, U.S.A 입니다.

전주성
jnet@uga.edu
박사후보생

Ronald M. Cervero
rcervero@coe.uga.edu
지도교수

중요한 연구에 참여해 주셔서 진심으로 감사드립니다.

연구 참여자로서의 귀하의 권리에 관해 질문이나 문제가 있으시면 Chris A. Joseph 박사께 문의하여 주세요. 주소: Human Subjects Office, The University of Georgia, 612 Boyd Graduate Studies Research Center, Athens, Georgia 30602-7411; 전화 1-706-542-6514; 이메일: IRB@uga.edu.

APPENDIX C

SURVEY INSTRUMENT

E-LEARNING MOTIVATION QUESTIONNAIRE

INSTRUCTIONS: As you complete the survey, please base your responses exclusively on one ***e-learning course*** you took. If you have an e-learning course that you did not complete, please use that e-learning course for your answers. Mark the ***one*** number that indicates the extent to which you agree with the following statements using the scale below.

1 = Strongly Disagree(SD), 2 = Disagree(D), 3 = Neutral(N), 4 = Agree(A), 5 = Strongly Agree(SA)

♠ Name of the e-learning course you took: ( )

♠ Did you complete the e-learning course? ❑ YES ❑ NO

Section I: Motivation

To what extent do you agree with each statement?	*SD*	*D*	*N*	*A*	*SA*
1. I received constructive feedback on assignments and (or) tests	*1*	*2*	*3*	*4*	*5*
2. This course stimulated my curiosity	*1*	*2*	*3*	*4*	*5*
3. I was unsure about my ability to pass the test(s) in the course	*1*	*2*	*3*	*4*	*5*
4. I felt uncertain that I understood the course objectives	*1*	*2*	*3*	*4*	*5*
5. The course content was applicable to my future career opportunities	*1*	*2*	*3*	*4*	*5*
6. The quality of the course was sufficient to keep my attention	*1*	*2*	*3*	*4*	*5*
7. I got enough feedback to know how well I was doing	*1*	*2*	*3*	*4*	*5*
8. The topics of the course were irrelevant to my job performance	*1*	*2*	*3*	*4*	*5*
9. The instructor provided timely feedback	*1*	*2*	*3*	*4*	*5*
10. The instructor responded quickly to my inquiries	*1*	*2*	*3*	*4*	*5*
11. This course was irrelevant to my present career opportunities	*1*	*2*	*3*	*4*	*5*
12. This course provided regular feedback	*1*	*2*	*3*	*4*	*5*
13. I felt the web-pages of the course were unappealing	*1*	*2*	*3*	*4*	*5*
14. I felt confident I could learn each lesson	*1*	*2*	*3*	*4*	*5*
15. This course provided helpful feedback	*1*	*2*	*3*	*4*	*5*

To what extent do you agree with each statement?	*SD*	*D*	*N*	*A*	*SA*
16. The course content was too abstract to keep my attention	*1*	*2*	*3*	*4*	*5*
17. The topics of the course were unimportant to me	*1*	*2*	*3*	*4*	*5*
18. The examples used in the course were relevant to my current job	*1*	*2*	*3*	*4*	*5*
19. Whenever I needed technical support, this course provided help	*1*	*2*	*3*	*4*	*5*
20. I felt this course was irrelevant to my goals	*1*	*2*	*3*	*4*	*5*
21. The course format bored me	*1*	*2*	*3*	*4*	*5*
22. The course materials were too difficult to understand	*1*	*2*	*3*	*4*	*5*
23. The examples used in the course were irrelevant to my future professional goals	*1*	*2*	*3*	*4*	*5*
24. This course provided unmanageable assignments that are too advanced	*1*	*2*	*3*	*4*	*5*
25. The course content was inapplicable to my job	*1*	*2*	*3*	*4*	*5*
26. I felt confident I would do well in the course	*1*	*2*	*3*	*4*	*5*
27. Other students in the course provided helpful feedback	*1*	*2*	*3*	*4*	*5*

Section II: Background Information

---

1. How many e-learning courses have you ever taken? (   )

2. In what year were you born? (   )

3. What is your gender? ❑ Male ❑ Female

4. What is your highest educational degree?

   ❑ High school diploma or GED

   ❑ Associate or two-year degree

   ❑ Bachelor's degree

   ❑ Graduate degree

5. What is your present marital status? ❑ Married ❑ Single

6. How many hours per week did you study for the e-learning course? (   ) hrs

7. Why did you take the e-learning course?

   ❑ I had to take this e-learning course

   ❑ It was mandatory to take a course, but I chose this course voluntarily

   ❑ I attended the e-learning course voluntarily

8. How many hours per week did you work? (   ) hrs

I appreciate your help with this important research!

[Korean Version of the Survey Instrument]

이러닝 (E-learning) 학습동기 설문지

※ 설문지에 응답하실 때는 귀하가 과거에 수강하신 하나의 이러닝 학습과정에 근거해 응답하여 주십시오. (수강하신 학습과정 가운데 혹시 끝까지 마치지 못한 과정이 있다면 그것을 선택해 설문에 응답해 주세요. **없으시면** 수료한 과정 중 하나를 선택해 주세요) 귀하의 경험에 비추어 볼 때, 다음의 진술들이 귀하가 느끼고 있었던 생각과 일치하는 정도에 따라 "전혀 그렇지 않다 (1)"부터 "정말 그렇다 (5)" 사이의 적절한 지점(숫자)을 응답 난에 적어 주십시오.

1 = 전혀 그렇지 않다, 2 =대체로 그렇지 않다, 3 = 그저 그렇다, 4 = 대체로 그렇다, 5 = 정말 그렇다

※ 이러닝 학습과정 이름 (   ) ※ 몇 시간짜리 과정입니까? (   ) 시간

Section I: 동기

귀하는 어느 정도 아래의 진술에 동의하십니까?	전혀 그렇지 않다				정말 그렇다	응답
1. 지도강사(과정담당자)로부터 과제나 시험 결과에 대해 유익한 피드백을 받는다.	1	2	3	4	5	
2. 이 학습과정은 나의 지적 호기심을 자극한다.	1	2	3	4	5	
3. 학습기간 중 실시하는 평가(과제)를 잘 마칠 자신이 없다.	1	2	3	4	5	
4. 학습과정의 학습목표들을 잘 이해하고 있는지 자신이 없다.	1	2	3	4	5	
5. 학습과정의 학습내용들을 앞으로 내가 갖게 될 직업(직무)에 적용할 수 있을 것 같다 .	1	2	3	4	5	
6. 학습과정의 질이 나의 관심을 충분히 끌고 있다.	1	2	3	4	5	
7. 내가 얼마나 잘하고 있는지에 관해 지도강사(과정담당자)로부터 충분한 피드백을 받고 있다.	1	2	3	4	5	
8. 학습과정의 학습주제들이 나의 현재 직무 수행에 도움이 되지 않는다.	1	2	3	4	5	
9. 지도강사(과정담당자)는 시기적절한 피드백을 제공해 준다.	1	2	3	4	5	
10. 지도강사(과정담당자)는 질문 또는 요구에 재빨리 응답하여 준다.	1	2	3	4	5	
11. 이 학습과정은 나의 현재의 경력 개발과 관련이 없다.	1	2	3	4	5	
12. 나는 정기적으로 나의 학습진척 상황에 대해 피드백을 받는다.	1	2	3	4	5	
13. 학습과정의 웹페이지 디자인이 나의 관심을 끌기에 부족하다.	1	2	3	4	5	
14. 학습과정의 각 (학습)단위들을 충분히 학습할 수 있다고 생각한다.	1	2	3	4	5	
15. 지도강사(과정담당자)는 유익한 피드백을 제공하여 준다.	1	2	3	4	5	
16. 학습과정의 학습내용이 너무 추상적이어서 나의 관심을 끌지 못한다.	1	2	3	4	5	
17. 학습과정의 각 학습주제들이 나에게 중요하지 않다.	1	2	3	4	5	
18. 학습과정에서 제시하고 있는 사례들은 나의 현재 직무와 관련이 없다.	1	2	3	4	5	

19. 이러닝 학습과정을 수강하는데 따른 컴퓨터 조작 등의 기술적인 문제와 관련해서 언제든 도움을 받을 수 있다.	*1*	*2*	*3*	*4*	*5*
20. 이 학습과정은 내가 기대했던 수강 목적과 관계가 없다.	*1*	*2*	*3*	*4*	*5*
21. 학습과정의 구성이 지루하다.	*1*	*2*	*3*	*4*	*5*
22. 학습과정에서 이용되는 자료들이 이해하기가 너무 어렵다.	*1*	*2*	*3*	*4*	*5*
23. 학습과정에서 제시하고 있는 사례들은 나의 미래 직업 목표와 관련성이 없다.	*1*	*2*	*3*	*4*	*5*
24. 이 학습과정은 내 지식 수준에서는 해결하기 힘든 평가문제(과제)를 제시한다.	*1*	*2*	*3*	*4*	*5*
25. 학습과정의 학습내용을 나의 직무에 적용하기 어려울 것 같다.	*1*	*2*	*3*	*4*	*5*
26. 학습과정을 성공적으로 마칠 수 있을 것 같은 자신감이 든다.	*1*	*2*	*3*	*4*	*5*
27. 함께 수강하는 수강자들로부터 유익한 피드백을 받는다.	*1*	*2*	*3*	*4*	*5*

Section II: 개인배경

1. 그 동안 몇 강좌 정도의 직무 관련 이러닝 학습과정을 수강하셨습니까? (　　　　) 강좌
2. 귀하의 연령은? (　　　) 세
3. 귀하의 성별은? (　　) 남 (　　) 여
4. 귀하의 교육수준은?
   (　　) 고등학교 졸업 (　　) 전문대학 졸업 (　　) 4년제 대학 졸업 (　　) 대학원 졸업
5. 귀하의 결혼 여부는? (　　) 기혼 (　　) 미혼
6. 귀하는 **설문에 응답하신 이러링 학습과정**에 **한 주** 평균 몇 시간 정도를 투자하셨습니까?
   (　　　) 시간
7. 귀하가 설문에 응답하신 본 이러닝 학습과정은?
   (　　) 사내 규정에 의해 의무적으로 수강했다.
   (　　) 사내 규정에 의해 의무적으로 수강했지만, 이 학습과정은 내가 선택했다.
   (　　) 이 학습과정을 본인의 필요에 의해 자발적으로선택했다.
   (　　) 기타 이유 (　　　　　　　　　　　　　　　　　　)
8. 귀하는 (직장 내 회식 등의 비공식 일정 등을 포함해) **한 주**에 평균 몇 시간 정도를 근무하시나요?
   (　　　) 시간
9. 이 응답하신 과정을 수료하셨습니까? 수료함 (　　) 수료하지 못함 (　　)

참여해 주셔서 진심으로 감사 드립니다.