T.C.
THE REPUBLIC OF TURKEY
BAHCESEHIR UNIVERSITY

ANALYSIS OF UBIQUITOUS LEARNING ENVIRONMENT OUTCOMES WITH PARTIAL LEAST SQUARES AND STRUCTURAL EQUATION MODELING

Ph.D. Thesis

AHMET YÜCEL

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ÖZET

ÇEVRELEYEN ÖĞRENME ORTAMI ÇIKTILARININ KISMİ EN KÜÇÜK KARELER

VE YAPISAL EŞİTLİK MODELİ İLE ANALİZİ

Ahmet Yücel

Bilgisayar Mühendisliği Doktora Programı

Tez Danışmanı: Yrd.Doç.Dr. Dilek KARAHOCA

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Bu çalışmanın amacı, üniversite öğrencileri arasında kullanılan çevreleyen öğrenme ortamının teknoloji kabul düzeyini araştırmaktır. Araştırmacılar, öğrencilerin bireysel bakış açıları hakkında birçok bilgiyi toplayarak, daha uygun çevreleyen öğrenme ortamları veya sistemleri geliştirebilirler. Bu doktora tez çalışmasında, Park'ın Teknoloji Kabul Modeline, Bilgisayar Tabanlı İletişim ölçeği eklenerek, çevreleyen öğrenme ortamının, üniversite öğrencileri arasındaki teknoloji kabul düzeyi incelenmiştir. Bu çalışmanın örnek kitlesini, Bahçeşehir Üniversitesi Mühendislik Fakültesine kayıtlı öğrencilerden; Java Programlama, Mühendislik Etiği, Veri Analizi derslerine kayıtlı, farklı bölümlerden rasgele ve heterojen olarak seçilen 356 öğrenci oluşturmaktadır. Ayrıca, çalışmaya katılan öğrencilerin Bilgi Teknolojileri dersinden de başarılı olması aranmıştır. Bu çalışmanın katılımcıları, Moodle tabanlı uzaktan öğrenme platformunu kullanan ve e-öğrenme kültürüne sahip öğrencilerdir. Çalışmada veri toplama teknikleri, yapılandırılmamış tartışma, örnekleme, yapılandırılmış öğrenci müzakereleri ve uyarlanmış ölçekler (TAM, CMC) kullanılmıştır. Toplanan veriler, veri doğrulama çalışmasına tabi olmuştur. Kısmi en küçük kareler yöntemi ve yapısal eşitlik modeli ile göstergeler arasındaki ilişkiler tespit edilmiştir. Çalışmada PLS-SEM yöntemi kullanılmış ve modelin göstergeleri için doğrusal regrasyon ağırlıkları hesaplanmıştır.

Anahtar Kelimeler: Kısmi En Küçük Kareler Yapısal Eşitlik Modeli, Bilgisayar Tabanlı İletişim, Teknoloji Kabul Modeli, Çevreleyen Öğrenme Ortamı

ABSTRACT

ANALYSIS OF UBIQUITOUS LEARNING ENVIRONMENT OUTCOMES WITH PARTIAL LEAST SQUARES AND STRUCTURAL EQUATION MODELING

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Computer Engineering Doctoral Programme

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This study aims to investigate the level of technology acceptance for ubiquitous learning among the university students. Ubiquitous learning environment can design more suitable based on the student's learning motivation. In this study, Park's TAM has extended by adding Computer-Based Communication (CMC) scale to investigate students' technology acceptance in the ubiquitous learning environment. 356 students were randomly and heterogeneously selected in different departments of Engineering Faculty of Bahcesehir University (BAU), who registered to the courses of Java Programming, Engineering Ethics, Data Structures. Students who participated in this study have e-learning culture in technology-supported platform which is called Moodle. Also they are successful in Introduction to Information Technologies course as well. With the Data Gathering Techniques, we have examined an observation, unstructured discussion, sampling, student interviews (structured interviews) and adapted scales (TAM and CMC). Collected data has been processed in data validation study. Partial Least Squares Structural Equation Modeling (PLS-SEM) has been used to identifying relationships between indicators. PLS-SEM was used and linear regression weights were computed for indicators of the model.

Keywords: Partial Least Squares Structural Equation Modeling, Computer-Based Communication, Technology Acceptance Model, Ubiquitous Learning Environment.

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ABBREVIATIONS

A	: Attitude
ADDIE	: Analysis Design Development Implementation Evaluation
AIC	: Akaike's Information Criterion
BAU	: Bahcesehir University
BI	: Behavioral Intention
CAIC	: Consistent Akaike's Information Criterion
CFA	: Confirmatory Factor Analysis
CFI	: Comparative Fit Index
CMC	: Computer-Based Communication
CWAM	: Course Website Acceptance Model
ECVI	: Expected Cross Validation Index
EFA	: Exploratory Factor Analysis
EmoSitu	: Emotional Situations
GFI	: Goodness of Fit Index
IFI	: Incremental Fit Index
IQ	: Information Quality
ISQ	: Information Systems Quality
IT	: Information Technology
LM	: Lagrange Multpliyer
LR	: Learning Relevance
MesCont	: Message Contens
MesInt	: Message Interaction
MOOSE	: Orianted Object Multiuser Environment
NFI	: Normed Fit Index
NNFI	: Non Normed Fit Index
PBC	: Perceived Behavioral Control
PEU	: Perceived Ease of Use

PGFI	: Parsimony Goodness of Fit Index
PLS	: Partial Least Square
PNFI	: Parsimony Normed Fit Index
PU	: Perceived Usefulness
RMR	: Root Mean Square Residual
RMSEA	: Root Mean Square Error of Approximation
SA	: System Accessibility
Sec	: Security
Sem	: Semantics
SEM	: Structural Equation Model
SML	: Self-Management of Learning
SN	: Subjective Norm
TAM	: Technology Acceptance Model
TPB	: Theory of Planned Behavior
TRA	: Theory of Reasoned Action
ULE	: Ubiquitous Learning Environment
ULSE	: Ubiquitous Learning Self Efficacy

1. INTRODUCTION

Main motivation of the thesis is to create a model to identify technology acceptance levels of university students in ubiquitous learning by using the Partial Least Squares Structural Equation Modeling (PLS-SEM). Technology Acceptance Model (TAM) and Computer-Mediated Communication (CMC) scales were used to collect data about students' perspective in ubiquitous learning environment. 356 students were randomly and heterogeneously selected in different departments of Engineering Faculty of Bahcesehir University (BAU), who registered to the courses of Java Programming, Engineering Ethics, Data Structures. Students who participated in this study have e-learning culture in technology-supported platform which is called Moodle. Also they were successful in Introduction to Information Technologies course as well. We have examined an observation, unstructured discussion, sampling, student interviews (structured interviews) and adapted scales (TAM and CMC). Collected data has been processed in data validation study. Partial Least Squares Structural Equation Modeling (PLS-SEM) has been demonstrated to identifying relationships between indicators. By help of the PLS-SEM, linear regression weights were computed for indicators of the model.

This PhD thesis has 8 different sections to identify the motivation, background of the study, material and methods of the research, and statistical analysis of the model creation steps. In the first chapter ubiquitous learning and its details were given to underline the motivation and the problem. General concepts related to the Ubiquitous Learning Environment also was presented in this section. The second chapter covered the history of Structural Equation Models and Path analysis modeling. In the third chapter Confirmatory Factor Analysis (CFA) and Exploratory Factor Analysis (EFA) were compared and the evaluation of the model and structure of covariance model were discussed. In the fourth chapter, Structural Equation with latent variable is explained. In the fifth chapter, students' acceptance of u-learning was evaluted by using Technology Acceptance Model (TAM) and Computer-Mediated Communication (CMC) surveys. In the sixth chapter, comparative future perceptions of ubiquitous learning devices for learning have been presented. Results were discussed in the seventh part of the thesis. At the last part, conclusion is given based on the results and discussion of the study.

The sub chapters cover ubiquitous learning (UL) and computing (UC), UL characteristics and theoretical framework in detail.

1.1. UBIQUITOUS LEARNING

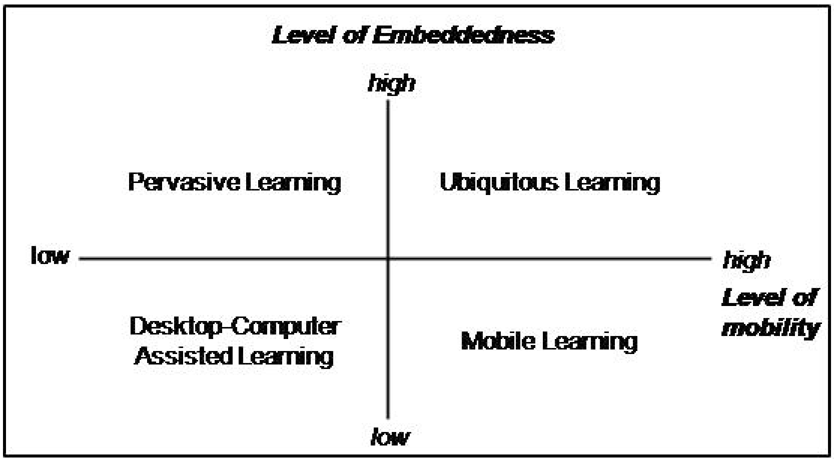
Ubiquitous Learning (u-learning) paradigm comes after the the electronic learning (e-learning), and mobile learning (m-learning) by supporting the contex awareness. (Yahya, et al., 2010). U-learning environment includes continuous learning and supporting learners by a set of training materials wich related with the individual needs (Ogata & Yano, 2004). U-learning occurs in home, workplace, library, museum, and daily interactions with other lernars through active engagement. It covers triggering sensing, hearing, touching, feeling and tasting for learning.

1.2. UBIQUITOUS COMPUTING

Ubiquitous computing has different small and embedded computers, cell phone, IoTs, smart cards, and handheld devices to support learners at anytime and anywhere (Sakamura & Koshizuka, 2005).

The information and communication technologies (ICTs) help and support students that can create connection to the ulearning environment in aynytime and anywhere without encountering any limitations (Ogata & Yano, 2004).

Figure 1.1 Classification of learning environments



Source: Ogata and Yano, 2004

Learning environments can be classified by embeddedness of the computing power with pervasive to u-learning and situtation of mobility is organized as desktop computer assisted learning to m-learning.

U-learning enforces u-computing based frameworks, such as, high level of embeddeness with high level of mobility.

U-learning covers different characteristics when compared with convential learning and e-learning.

1.3. THE PROPOSED CHARACTERISTICS OF U-LEARNING

Information is permanent, accessible, interactive, and context related in u-learning (Yahya, et al., 2010).

- Permanency: learner can remove the information unless remove it.
- Accessibility: learner can access the information in any time and anywhere.
- Immediacy: learner can reach information straight off
- Interactivity: learner can interact with others powerfully.
- Context-awareness: The learning environment can help learners for real situation to provide adequate information for the learners

1.4. ACCEPTANCE OF E-LEARNING AND U-LEARNING FROM LEARNER PERSPECTIVE

Nowadays, u-learning environment supports learners with different performance behavior in the personal application of educational technology. Demographic factors of learners in u-learning environment affected by certain cultural attitudes format. (Hara, 2000) indicates online learning has acceptance of new technlogies to support student-centered learning design. A similar study has been done in (Mun & Hwang, 2003). The learned technology focuses on the importance of determination on adoption.

Different learning communities in u-learning environment have also positive effects on organizational factors and behavioral performance in the use of technology achievement. Thus, researchers have to study on technology acceptance methodologies' indicators, such as perceived easy of use, perceived usefulness, attitude towards, and intention to use of ulearning.

In literature, mostly used model was technology acceptance model (TAM) (Davis Jr, 1986). TAM estimates the intention to use of information technology based on the user attitues and behavior (Legris, et al., 2003). TAM has external variables such as influence belief, attitude, and intention to use. TAM covers two different cognitive beliefs, perceived usefulness and perceived ease of use. TAM also proposes that external factors affect intention and actual use through mediated effects on perceived usefulness and perceived ease of use. TAM has extended versions such as TAM2 that tries to explain perceived usefulness and usage intentions including social influence (Venkatesh & Davis., 2000).

TAM has been used to modeling e-learning usage by the way of technology adoption. (Selim, 2003). He considered that TAM has to be used for the adoption of web-based learning. He proposed course website acceptance model (CWAM) and structural equation modeling has been used to explain the relationships in CWAM.

In the u-learning environment external factors are highly effective in success of learning and adoption in information systems. Different type of e-learning in the perspective of work affects the perception of the user intention information system (Saadé, et al., 2007).

1.5. AN OVERVIEW OF THE U-LEARNING ENVIRONMENT IN THEORETICAL FRAMEWORK

U-learning Environments lead to the construction of new training activities by being adapted to the educational context of different models and theories with reference to the adoption of new teaching technologies. In U-learning approach, different approaches in the implementation of new learning technologies have attracted notice based on the studies on Diffusion of Innovations Theory (Theory of Reasoned Action) (Van Raaij & Schepers, 2008)., (Venkatesh, et al., 2003). In terms of U-learning platforms, our point of view on Diffusion of Innovations Theory is how to activate the new technology with the communication process in social systems. Diffusion of Innovations Theory has been analyzed for four parameters: Innovation, communication channels, time and social system (Rogers, 2003). Innovation's perceived features are defined in the u-learning environment as one innovation is comprehended better than the other.

Diffusion of Innovations Theory states the complexity when it has been perceived that it is difficult to use innovation in the ubiquitous learning environments. Its congruity absorbs the relevant value, expectation and gravity force of the learning subjects which exist in the u-learning environment. From this point of view, basic approach which is embraced by the technology acceptance model is associated with the channel of communication in the learning environment and sensing point on the social system.

In the learning social systems, learners' sensing point of complication, congruity and relative utility is also related to the utility sense they expect from the system. Utility sense and acceptance of innovation is going to be mentioned beneath the TAM model. Farther developed and unified TAM is going to transform into performance expectation output. Thus, it is going to be possible to associate the learners' beliefs regarding to difficulty or easiness of the use of a new learning object in the u-learning environment with the effort they make.

The theory of planned behavior (TPB) is a generally connected anticipation esteem model of mentality conduct connections which has met with some level of achievement in foreseeing an assortment of practices (Ajzen, 1991). Theory of Reasoned Action (TRA) is a socio-psychology theory based on behavior theory (Ajzen & Fishbein., 1975). Perceived Behavioral Control (Towler & Shepherd., 1991) added measures of PBC and habit to the TRA, and found that habit had an independent effect on intention, while PBC did not. Similarly, (Godin, et al., 1993) found that habit was the most important predictor of exercising behavior, over and above all TPB variables.

Table 1.1Theories and models that are based upon the dissemination, acceptance and assimilation of innovations in terms of educational context

Theory/Model	Single Model/Theory	Combined	Sum
Technology Acceptance Model	18	7	25
Diffusion of Innovations Theory	5	4	9
The Unified Model of Use and Acceptance of Technology	2	2	4
Theory of Reasoned Action	1	2	3
Theory of Planned Behavior	1	2	3

Source: Godin et al. (1993)

1.6. DESIGING THE LEARNING ACTIVITIES IN U-LEARNING

Learning from surrounding feeder system for determining the activity of learning strategies in the awareness of the media will be effective for the mobile learners and it is very important for processing their personal information. Learning the strategies followed in the learning model that will improve the environment awareness is guidance on how the real world. Learners from real-world data collected with the help of sensors portfolio can be managed personal profile. Experiential information is provided by the course the learner will receive from the real world. Mobile devices also support real-world objects to make observations on behalf of students benefiting from the instant question and answer mechanism.

Learner’s data collected from real-world continuesly by the wireless communication technologies. The data collected are reported shortcomings in the areas of learning for learners are identified. The areas that lack of information is structured by the interplay of relationships learned again and teaches. Creating groups of learner common data studies performed in the real world and new issues are discussed. These strategies are shaped by these models.

Table 1.2 Twelve models for conducting context-aware u-learning activities

ID and Name of the Model	U-learning Strategies and Examples
ULS1 Learning in the real world with online guidance	The understudies learn in this present reality and are guided by the framework, in light of the individual profile, portfolio and genuine information gathered by the sensors. E.g., for the understudy who takes a science course, insights are given consequently in view of his or her genuine activities amid the analysis method.
ULS2 Learning in the real world with online support	The understudies learn in this present reality, and support is consequently given by the framework in light of the individual profile, portfolio and genuine information gathered by the sensors. E.g., for the understudy who is figuring out how to recognize the sorts of plants on grounds, significant data concerning the elements of every kind of plant is given naturally in light of his or her area and the plants around him or her.
ULS3 Online test based on real-world object observations	The understudy is requested that answer questions introduced on the screen of the cell phone by watching this present reality objects. E.g., "What is the kind of tree situated before you?"
ULS4 Real object observation	The understudy is requested that discover the protest in this present reality, in view of the question exhibited in the cell phone. E.g., "Watch the plants around you and discover the plant that is most like the one appeared on the screen."
ULS5 Collect data in the real world via observations	The understudies are requested that gather information by watching objects in this present reality, and exchange the information to the server by means of remote correspondences. E.g., "Watch the plants here and exchange the information (counting the photographs you take and your own particular

	portrayals of the elements of every plant) to the server."
ULS6 Collect data in the real world via sensors	The understudies are requested that gather information by detecting objects in this present reality, and report what they have found. E.g., "Discover three distinct examples of water, and report any contaminant found by utilizing the sensors."
ULS7 Identification of a real-world object	Understudies are requested that answer the inquiries concerning the ID of this present reality objects. E.g., "What is the name of the creepy crawly appeared by the educator?"
ULS8 Observations of the learning environment	Understudies are requested that answer the inquiries concerning the perception of the learning environment around them. E.g., "Watch the school cultivate, and transfer the names of the majority of the bugs you find."
ULS9 Problem-solving via experiments	Take care of issues by outlining tests in this present reality and discovering insights on the Internet E.g., "Consider the inflatable given by the educator; plan an examination to discover the relationship between the payload mass and the height of the inflatable."
ULS10 Real world observation with online data searching	The understudies are requested that watch this present reality protests and discover arrangements by getting to the system. E.g., "Watch the working before you; find nitty gritty information about it on the web."
ULS11 Cooperative data collecting	A gathering of understudies is asked to agreeably gather information in this present reality, and talk about their discoveries with others by means of cell phones. E.g., "Agreeably draw a guide of the school by measuring every territory, and incorporate the gathered information."
ULS12 Cooperative problem solving	The understudies are asked to agreeably take care of issues in this present reality by examining through cell phones. E.g., "Seek every side of the school and discover the proof that can

	be utilized to decide the level of air contamination."

Source: (Hwang, et al., 2010)

As given in Table 1.2, students can be applied to u-learning for the different motivations. For example, there is a difference between ULS1 and ULS2 which ULS1 supports a structure and ULS2 yields online help to learners when they needs (Hwang, et al., 2009).

1.7. COMPARING M-LEARNING AND U-LEARNING

The dimension of environment awareness of m-learning system includes accessing the database through a learning portfolio to querying personal information and the real-world environment where the information can be learned. Learner also can access to services on the system by using materials' to access m-learning. It is possible access to the ubiquitous environment learners in the learning environment with personalized service. Learners continue through registration systems in online learning behavior on on the size of the portfolio content. World behavior and accessing real information of learners in the u-learning environment is realized with recording system.

- **Personalized support:**

Learner profile on m-learning systems is associated with the attitude of the records of online learning behavior while personal behavior in u-learning learning system relates to learning behavior in the real world.

- **Seemless learning future:**

Due to the action of the learning activity in m-learning system which is configured as a process, learning services continues to serve in the u-learning environment from one location without being connected. Awareness in the u-learning environment providing with adaptive service, the learning process is managed taking into account the different information they receive from the environment of the learners with different mobile devices. Learning functions within the different mobile devices are kept active in their ubiquitous learning environment.

- **Computer Mediated Communication (CMC):**

In this thesis study, text-based learning is taken on the basis of CMC will be discussed e-mail-based discussion, computer conferencing environments, communication in web-based environments, person communication channels leading to the person or group of persons. Interface design in the digital environment in the CIM approach and transmission speed of the message affect to use CMC. In other words, transparent detected of technology to be perceptible constitutes the structural lines of CMC. The use of CMC is part of the learning process at real-time communication environment in one to one conversations and discussions. Especially in professional training with sustainability the structuring of the communication structure is important to support by structurant structures in Orianted Object Multiuser Environment (MOOSE).

CMC means that the structure of the educational process unchanged that it is essential paragmatik presentation of information and communication tools of the information in the process of transmission from person to person and from person to group. (Romiszowski, 1995) defined CMC is not only a tool, but it is also the environment of technology. CMC is the social engineering.

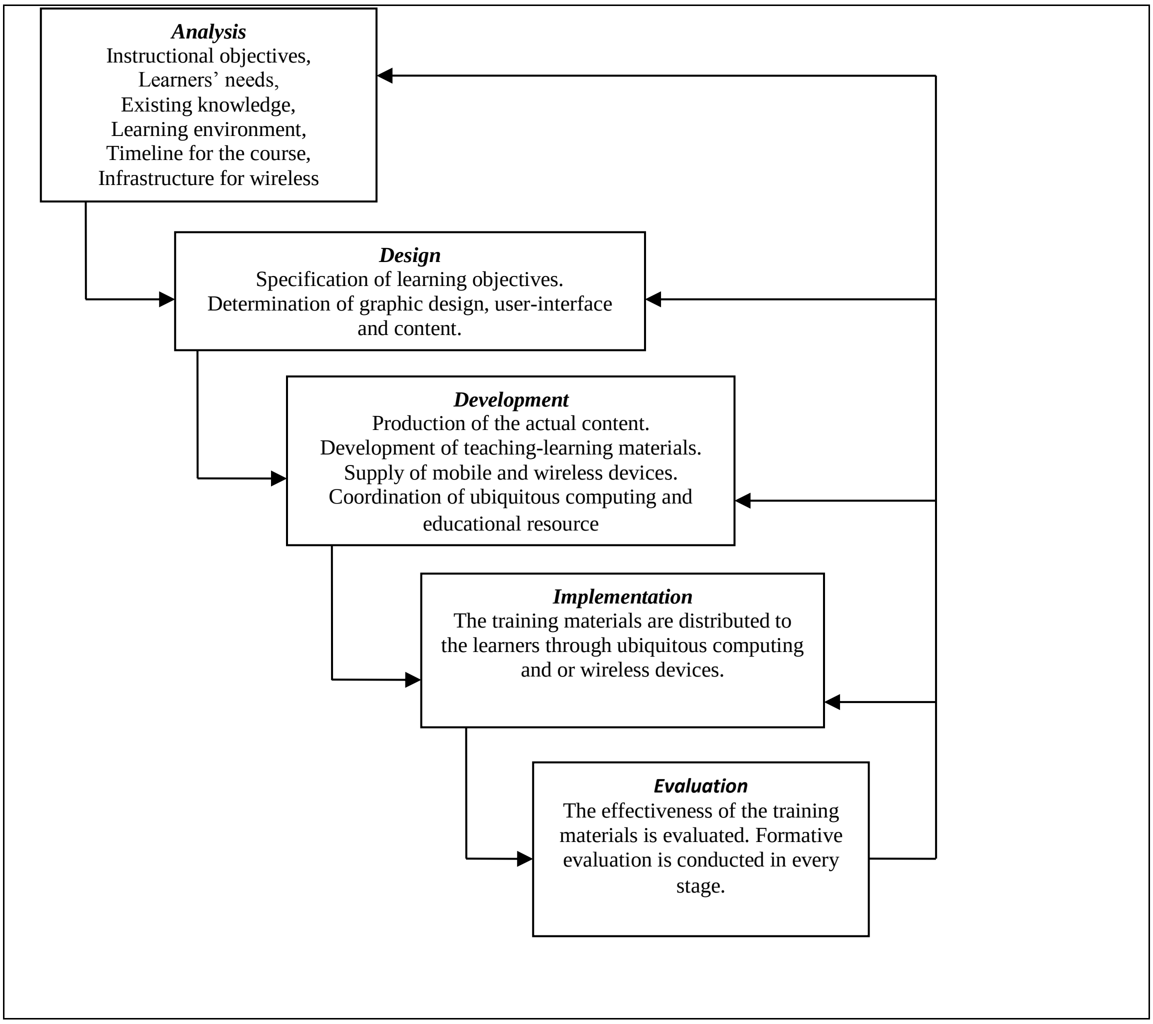
1.7.1 ADDIE Model for U-Learning

New generation learning technologies is evident as interaction, access, continuity and compliance in terms of instructional design with its characteristics. Instructional design is close to the ADDIE model at the instructional software design. ADDIE model consists of five phases.

- Analysis: This phase covers analyzing and identifying of learning problem, instructional objectives, learners' needs, existing knowledge, learning environment, delivery options, and the schedule for the course. Also, ICTs for creating connection and providing web-based services in u-learning environment (Laroussi & Derycke, 2004).
- Design: The design phase starts with identifying the learning objectives and other basic things such as visual design, human computer interface and content design.

- Development: The course content and materials are developed and the mobile learning infrastructure is prepared. Also, ubiquitous computing and educational resources are aggregated and coordinated as a single environment
- Implementation: The plan is implemented. Platforms' training materials are shared with learners through ubiquitous computing environment.
- Evaluation: The sutitability of the training materials is evaluated as formative and summative way. Formative evaluation has to be done in every phase of the instructional design model.

Figure 1.2. An instructional design model in ubiquitous learning



Source: (Laroussi & Derycke, 2004)

ADDIE model can be blended with instructional design and specific alternative for ubiquitous learning environments. Pedagogical sense of learning scenarios was surrounded from person to person, group of persons, and a person from the group by a communication network in ubiquitous learning environments. In this sense, pedagogical scenarios convert learning to self motivated position with different communication points. As a result ubiquitous learning environment with pedagogical content reveals a common learning structure.

- **Self Management Learning:**

The self-management of learning (SML) means that "individual can engage in self learning" (Wang, et al., 2009) . SML includes these two concepts for learning; individual self-discipline and the learning autonomy. Self-directed and self regulated constitutes the essence of independent learning activities (Balapumi & Aitken, 2012).

1.8. RELATED LITERATURE

U-learning is a mobile learning way to learning different content, from anywhere and anytime. The ubiquitous learning environment covers more context data than e-learning (Zhao, et al., 2010).

Ubiquitous learning supports following advantages:

a) Teacher-student interaction is not limited with classroom, and teacher is not only one resource for information gathering.
b) Students supported to become lifelong learners.
c) Creates interaction with content and prepares the environment in "free of stress" mode.
d) Makes students informed for "real life."

Education has experienced real changes as of late, with the advancement of computerized data exchange, stockpiling and specialized strategies having a huge impact. This advancement has been taken into consideration to access new revolutionary e-learning and m-learning environments. Internet and mobile devices take place to support self learning in life learning mode. By this way, Ubiquitous Learning (u-learning) is rising with the idea of ubiquitous computing (Jones & Jo, 2004). In u-learning, learners have chance to choose and investigate her needs to develop herselves by self motivated and designed different contents.

The best advantages of applying the hypothesises of affordances in the Ubiquitous Learning Environment are acquiring self-reflection aptitudes, peer input, and in addition creating psychological abilities for arranging and checking understudy advance. The theory of affordance further recommends that learners' recognitions might be transformed into the esteem that articles offer to the people. There are likewise sure purposes of crossing point between the movement hypothesis and affordances as they both share the essential thought that observation is connected with activity (Alsheail, 2010).

(Chu, et al., 2010) builts up a study to explore understudies' slants in constructivist association careful widespread learning circumstances. A constructivist connection mindful pervasive learning (u-learning) situations review (CULES) was created, comprising of eight scales including usability, congruity, pertinence, versatile substance, different sources auspicious direction, understudy arrangement and request learning.

In another study, (Loiacono, et al., 2013) again developed a survey to investigate the blind or low-visioned people’s need when they are using web sites. The aim is to answer that developing a behavioral web site is effective and satisfactory through the needs of visually disabled people. They developed a TAM, and analyzed the collected data through this model. Their TAM is developed through the model of (Davis, 1989). They applied the survey to selected diabled people, some of them blind, some of them have %70-80 low vision. Also they give a task to these people, like buying something from amazon.com. at the end of the task and survey, they tried to analyze their hypothesis. As a result, they told that one of most used TAM is not enough to satisfy the needs of visionally disabled people. The modified model is more effective in scales of ease of use and reliability.

As we mentioned before, TAM is one of the most popular technic to explore new technological changes’ effect. Through this perspective, (Iqbal & Zeeshan, 2015) tried to develop a TAM and made a survey through this model. They tried to analyse the students’ readiness for using m-learning technics and tools. They selected a sample of students from private sector universities in a growing country. They developed 5 hypotheses, which include the main scales as perceived ease of use, perceived usefulness. They collected 244 valid responses to their survey. According to their analyses of collected data, students’ physicological mood, strongly affect the use of m-learning models. Especially this effect can be seen on perceived ease of use and perceived usefulness of m-learning.

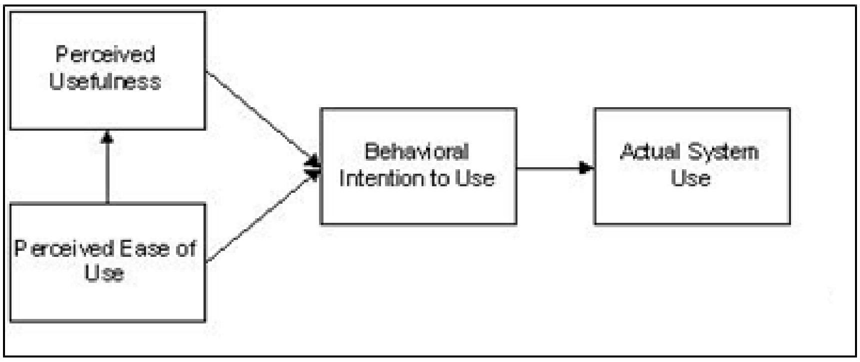
There are a lot of technics of education, as we said technology usage is one of this technics which is often used in last years. As an example of technological technic are developed applications. (Van De Bogart & Wichadee, 2015) tried to examine how undergraduated students accepted LINE application for using it in class room related activities. These activities are like submitting homeworks, downloading materials via LINE app. Also they tried to see the factors that might affect the stundents' intention to use the app. They developed a questionnaire from TAM and utilized some activities based on app. At the end of study they defined some important relationships between TAM parameters that possibily affect the use of app and also intention of students to use the app. Throguh this study, there is positive relationship between intention to use and perceived usefulness while perceived ease of use and received usefulness is positively related. Also this study showed, TAM can be employed as as useful theoretical framework tu understand and explore users' intention in use of new technologies in education.

In a context-aware u-learning environment, learning systems may sense students learning behaviours help of context-aware (sensor) technology. By this way, students can be directed to detect or activate real-world objects with personalized support (Hwang, et al., 2010). Context-aware u-learning integrates wireless, mobile and context-awareness technologies and detects the situation of learners to support them by directives (Chu, et al., 2010). New innovations in ICT have enabled the m-learning and u-learning approaches, which places students in an environment that syndicates real-world and digital world learning resources. Nowadays education has been revolutinized, by the help significant developments in ICT. This advancement has considered access to worldwide interchanges and the quantity of assets accessible to today's understudies at all levels of tutoring. After the underlying effect of PCs and their applications in instruction, the presentation of e-learning and m-learning typified the steady changes that were happening in training. The adaptation of ubiquitous computing in education supports u-learning (Carmona, et al., 2009). As indicated by advancements in innovation have defeat the imperatives on learning space, a failure to suitably abuse the innovation may make it an impediment to learning (Wang & Wu, 2011). At the point when incorporating the applicable data to build up a u-learning environment, it is in this manner important to consider to personalization prerequisites of the learner to guarantee that the innovation accomplishes its expected result. In spite of the fact that u-learning situation have pulled in the consideration of specialists in the fields of software engineering and instruction, the criteria of building up a completely utilitarian u-learning environment is still indistinct (G.J., et al., 2008).

TAM is a variation of the Theory of Reasoned Action (TRA) to the field of IS. TAM suggests that perceived usefulness and perceived ease of use to control a person's aim to use a system with aim to use aiding as a facilitator of system use. Perceived usefulness has directly impacts on perceived ease of use. Research studies show that TAM can be shortened by eliminating the attitude construct (Venkatesh, et al., 2003).

Endeavors to augment TAM have for the most part adopted one of three strategies: by presenting variables from related models, by presenting extra or option conviction components, and by looking at forerunners and mediators of perceived ease of use and perceived usefulness (Wixom & Todd, 2005).

Figure 1.3. TAM Model



Source: Davis et.al.(1989)

The Technology Acceptance Model (TAM) progresses the TRA by hypothesizing that perceived usefulness (PU) and perceived ease of use (PEU) are key determinants that unavoidably prompt to the genuine utilization of a specific innovation or framework.

Perceived usefulness is characterized as "how much an individual trusts that utilizing a specific framework would improve his productivity ". Perceived ease of use is is characterized as "the degree an individual trusts that utilizing a specific framework would be free of exertion" (Davis, 1989), (Lin, et al., 2011).

The TAM indicates that both perceived usefulness (PU) and perceived ease of use (PEU) are independent constructs to control user' attitudes (A) concerning behavioral intention (BI).

The rapid advancement of technology, the technology and the social events associated with science requires that the relationship between these events more understandable. İnstead of latent variables abstract concepts used in the study can be explained by their own indicator variable. Researchers are examining the connections between events, have used statistical analysis methods such as Factor Analysis, multivariate regression analysis and path analysis. In recent years, explanation and modeling of these concepts detailed and more correctly is performed with the help of structural equation modeling (SEM) which is called multivariate statistical analysis. The most important feature that distinguishes it from other analyzes, structural equation model is confirmatory rather than explanatory. The main feature of the structural equation model that separates from path analysis, Factor analysis and multivariate regression analysis is to analyze simultaneously both measurement and the function estimated between events. Structural Equation Modeling is analysing method including cause and effect relationship between the direct and indirect effects of the event in Concepts and predictions made for this event, the analysis of the margin of error in the result of the measurement.

2. PATH ANALYSIS

Structural Equation Modeling is a statistical approach which based on (Correlation) relationship between measurable and unmeasurable variables with the cause and effect. Development of structural equation modeling was initiated with the development to be used in genetic studies of path analysis. Sewall Wright first began to publish their work in 1918 on the path analysis, after literally known in 1921; he maturated path analysis and has set basic rules. Wright revealed three aspects of the path analysis: 1) Path diagram 2) Equality related variance and correlations 3) Separation of effects (Bollen, 1989). Using the path a set of diagrams Wright has proposed the rules for the writing of equality of correlations for model parameter that contains variable. This proposition is the second aspect of the path analysis. The third aspect of the path analysis is the separation of total effect between any two variables in the direct and indirect effects that the total effect is related to.

Models are used to bring solutions to real events, determine the relationship between these events and to predict events. These models are used to test the reliability of the actual event. The structural equation model has a structure which is difficult to solve even if events can easily test allows you to see relations difference between variant (Gong, et al., 2004).

Structural equation modeling is a popular statistical analysis in recent years. This method is used in many sectors that investigator optimally captures the true with this model. The relationship between many variables with structural equation model is the difference between other used models can be examined.

Structural equation modeling, the second generation of data analysis as a technique (Bagozzi & Fornell, 1982) deal with a systematic and comprehensive way the first generation such as regression compared with statistical techniques, complex research problems with modeling the relationship between the number of dependent and independent variables in a single process (Anderson & Gerbing, 1988). For many reasons structural equation modeling method is used such as the test is successful especially in complex models take into account measurement errors. If we examine the model for the network of relationships in the recommended new arrangements made at a time of much analysis, regulating mediation and (moderation) to facilitate impact analysis, made at a time of much analysis that take into account measurement errors, Many theories for the testing and development of new model is a method used in the process.

2.1 PATH ANALYSIS

Structural equation modeling is a statistical analysis of multivariate analysis contains the logic of the path analysis in its infrastructure. In both analyzes, the assumptions of the model used, the causal between variables and / or with no causal relationship shown above the path diagrams. In addition, even though both models due to the fact that they do not have to occure similar purpose or skill to prove causality "causal model" can be found under the heading (Kelloway, 1995).

If there is a similarity or commitment in terms of changes in the exchange of two distribution units examined, it is said that there is a relationship between the distributions of events to which they relate (Kaygısız, et al., 2005). Examined relationship between two variables is often a cause and result relationship (Çömlekçi, 1998). This relationship between the variables related to work on general topics is examined in two groups as a linear and non-linear relationship. If there is a relationship between the variables the degree of this the functional form tries to identify (Bal, et al., 2000). Two or more of the work done to be shown by mathematical relationships between variables and studies reveal the nature of the relationship is the subject of regression analysis. For the relationship between two or more variables can be shown by mathematical operations and the studies reveal the nature of the relationship is the subject of regression analysis. İnvestigation of the direction and degree of the relationship between variables is the subject of correlation analysis (Kaygısız, et al., 2005).

One of the reasons other variables as a result of this reason are taken; correlation coefficient is a measure of the extent to that these can be effective on each other. However the correlation coefficient is not sufficient to determine exactly in this sense of the relationship between two variables. Due to a third variable correlation between these two variables may be great. Therefore the correlation between two variables, it may need to calculate while other variables steady state. Correlation coefficients calculated in this way is called the Partial Correlation Coefficient. However, the correlation coefficient and the partial correlation coefficients do not provide a cause-effect relationship we have dealt with the relationship between of the variables in the form.

In multiple regression analysis, the direct impact of each independent variable on the dependent variable is concerned. However, in some cases, as direct relationship between the independent variables and the dependent variables can be the existence of indirect relationship. In this case classical regression analysis and correlation analysis is insufficient (Bal, et al., 2000).

In this case that the correlation analysis and regression analysis of inadequate "Path Analysis" has led to the emergence of so-called statistical techniques. The aim of path analysis is to estimate the significance and magnitude of the causal relationships between variables groups. Under the assumptions taken into account in the multiple regression analysis, when analyzing a dependent variable over all the arguments, all the dependent variables in the path analysis were used to analyze each argument that can be made through multiple regression analysis (Kaygısız, et al., 2005).

Determining the model in Path analysis exogenous variables in the model analysis is done by determining the direction of effects on endogenous variables. Correlations between the variables in the model should be calculated to determine the path coefficient. Calculated path coefficients indicate based on a unit change in exogenous variables on the amount of change expected endogenous variables. Path coefficients are called standardized regression coefficients (Loehlin, 2004).

(Wright, 1934) if it can be represented by a state diagram of the path, The correlation between any two variables of path diagram showed that two points can be expressed as the sum of the components connecting path (Loehlin, 2004). This Path component must comply with the following three rules (Şimşek, 2007):

1. No Cycle: a path can not pass more than once from the same variable,
2. After you go forward not back there: After going a path forward on an arrow can not go back again but it is necessary you can go back before path going forward.
3. . It can be up to a curved arrow own path: Only one path leading to a curve arrow may contain (variable correlated pair).

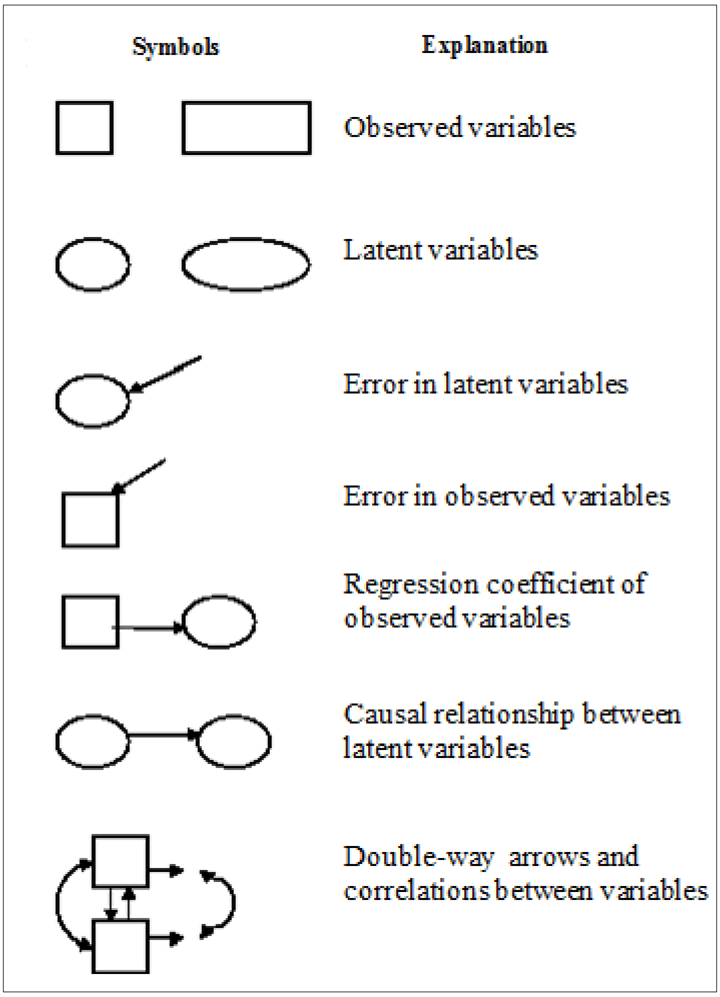
There are similar assumptions as multiple regressions in path analysis (Şimşek, 2007):

- The relationship between the variables is linear.
- There is no interaction effect.
- Error terms are uncorrelated with internal variables.
- There should not be higher multiple linear connection between exogenous variables.
- Models should not be missing identification, in other words the number of equations must be equal or greater than the number of unknown parameters.
- Models must be consecutive so it must be a one-way flow of causality.
- There should not be determined error in model.
- Correlations that will be used as input must be compatible with the scale of the data: for two interval-scale variable is Pearson Correlation, For ordered two variable-sized is polychoric correlation, for two dichotomous variable is Tetrachoric correlation, one sequential range to another scale-sized two variables are Polyserial correlation and one is a range other two dichotomous variables correlation should be used Biserial.
- Measurement error should not be.

Relationships between the variables that are in the cause-effect relationship with each other are illustrated by the path diagrams. Path diagram are representation of the manner of a simultaneous system of equations and extension of multiple regression analysis. One of the advantages of the path diagram is that can be drawn a picture of the supposed relationship. Image for many researchers, relationship reveals more clear and understandable manner of the equation. (Hair & al., 1998).

Path diagram is a visual expression of system simultaneous equations. (Bollen, 1989). Path diagram contains all information related to the system of equality. The main symbols are used to draw the path diagram is shown in Fig. 2.1 (Yılmaz & Çelik, 2009), (Şimşek, 2007).

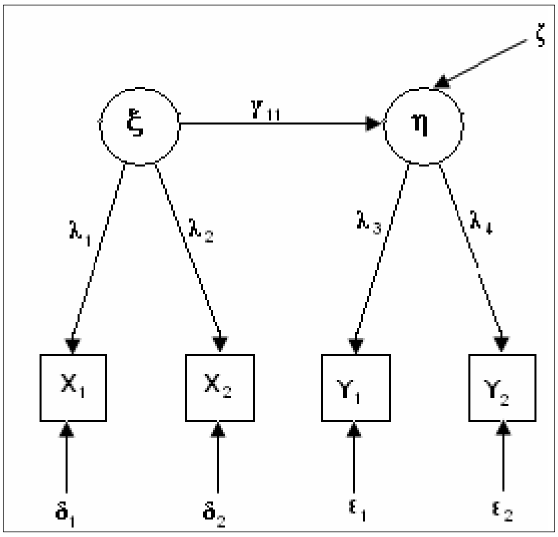
Figure 2.1. The main symbols are used to draw the path diagram



Source:Yılmaz Çelik (2009)

Two-headed curved arrow represents the association between the two variables. For various reasons variables may be in associated. This relationship may be due to both variable depends on a third variable or may be due to be determined in a causal relationship.

Figure 2.2 An example of a path diagram



Source: Bollen, 1989:34.

The following path diagram in Fig. 2.2 is equivalent to the simultaneous equations.((Bollen, 1989) (Yılmaz & Çelik, 2009) (Şimşek, 2007)):

$$\begin{aligned} &\eta = \gamma_{11}\xi + \zeta \\ &x_1 = \lambda_1\xi + \delta_1 \qquad y_1 = \lambda_3\eta + \varepsilon_1 \\ &x_2 = \lambda_2\xi + \delta_2 \qquad y_2 = \lambda_4\eta + \varepsilon_2 \end{aligned} \tag{2.1}$$

COV(ξ,δ_i), COV(ξ,ζ), COV(δ_i,ε_j), COV(ε_j, ε_{j+1}),COV(ε_j, ζ), COV(ξ, ε_j) and COV($\delta_{i,}$ δ_{i+1}) are equal to zero.

2.2 STRUCTURAL MODEL AND MEASUREMENT MODEL

Structural equation modeling includes in its different levels of analysis:

- Structural model showing the relationship between Latent independent (exogenous) variables and dependent latent variables (endogenous);
- Measurement model (exogenous) showing the relationship between the Observed independent variables and latent independent variables (exogenous);

- Dependent (endogenous) measurement model showing the relationship between a dependent latent variable and observed dependent variable (endogenous) is defined as the measurement model.

Privatization of dependent and independent measurement models in structural equation modeling reveals the factor structure of each of the dependent and independent set of observed variables. In other words, based on the models of each measurement is a confirmatory factor analysis in subsequent sections which will be described in detail.

Variable or variables observed indicators of a latent variable contain random or systematic measurement errors, whereas latent variables do not include error. Each of these variables is all hidden variables or hypothetical variables that corresponded to a hypothetical concept. Structural model of independent latent dependent variable shows the effect of latent variables.

A latent variable model covers structural equations that summarize in twos the relationship between all latent variables. In this sense, the parametric expansion of the structural model

$$\eta = B\eta + \Gamma\xi + \varsigma \quad \textbf{(2.2)}$$

It is written in the form (Bollen, 1989) (Tabachnick, 1996). The assumptions made for this model are listed in the following format:

Dependent, independent latent variables and the expected value of the model error is zero.

$$E(\eta) = 0 \quad \textbf{(2.3)}$$

$$E(\xi) = 0 \quad \textbf{(2.4)}$$

$$E(\varsigma) = 0 \quad \textbf{(2.5)}$$

- There is no cohesion between the errors and independent latent variables.

$$Cov(\xi, \varsigma) = 0 \quad \textbf{(2.6)}$$

– Covariance matrix for the model should be singular. (I - B) is not singular. In addition, the term iζ error in the i'th structural equation's are assumed to be uncorrelated and homeskedas. The notations and defines used in the structural model are given in Table 2.1.

Table 2.1 Impressions used in structural model

The structural model for the latent variables

$\eta = B\eta + \Gamma\xi + \varsigma$

Assumptions

$E(\eta) = 0$

$E(\xi) = 0$

$E(\varsigma) = 0$

$(I - B)$) is not singular.

$Cov(\xi, \varsigma) = 0$

Notation	Name	Size	Description
η	Eta	$m\times 1$	Latent endogenous variables
ξ	Ksi	$n\times 1$	Latent exogenous variables
ζ	Zeta	$m\times 1$	Latent errors in equality
B	Beta	$m\times m$	The coefficient matrix of latent endogenous variables
Γ	Gamma	$m\times n$	The coefficient matrix of latent exogenous variables
Φ	Phi	$n\times n$	$E(\xi\xi')$ covariance matrix
Ψ	Psi	$m\times m$	$E(\zeta\zeta')$ covariance matrix

Source: Bollen (1989)

Measuring model is the structural equation model representing the connection between latent and observed variables. These equations are non-deterministic character, it is stochastic character.

Expansion of the independent measurement model is:

$$= \Lambda \xi + \delta x x \quad \textbf{(2.7)}$$

Expansion of the size-dependent models while it was configuration is:

$$= \Lambda \eta + \varepsilon y y \quad \textbf{(2.8)}$$

as it is written (Long, 1983). Both measurement model assumptions and notation and definitions used are given in Table2.2 (Hair & al., 1998).

Table 2.2. Impressions Used in Measurement Model

Structural equation model for measuring

$$x = \Lambda_x \xi + \delta$$

$$y = \Lambda_y \eta + \varepsilon$$

Hypothesises

$$E(\eta) = 0$$
$$E(\xi) = 0$$
$$E(\varepsilon) = 0$$
$$E(\delta) = 0$$

$$Cov(\xi, \varepsilon) = 0, Cov(\eta, \varepsilon) = 0, Cov(\delta, \varepsilon) = 0$$
$$Cov(\xi, \delta) = 0, Cov(\eta, \delta) = 0$$

Notation	Name	Dimension	Definition
y	-	px1	observed indicators of η
x	-	qx1	observed indicators of ξ
€	Epsilon	px1	measurement error of y
δ	Delta	qx1	measurement error of x
Λ_y	Lambda y	pxm	coefficients conjunctive y with η
λ_x	lambda x	qxn	coefficients conjunctive x with ξ
Θ€	Theta-Epsilon	pxp	E(€€^{1}) covariance matrix
Θ_δ	Theta-Delta	qxq	E(δδ^1) covariance matrix

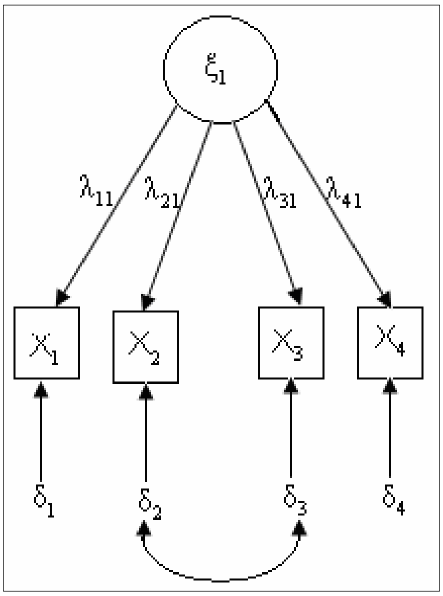
Source: Bollen (1989)

Measuring the variables in the model, as in latent variable models are deviations from the average. Latent variables observed variables over which the regression coefficients λ i 's are expected to express the amount of change observed in the case of a unit change in the variable latent variables.

2.3 COVARIANCE AND CORRELATION SEPARATION

Path analysis provides written as a function of the covariance and correlation between the two variables in the model parameters. Simple model in Figure 2.3 in the four indicator variables (x1, ..., x4) with a single latent variable (ξ) is shown. There is no correlation between δ_2 and other measurement error than 3 δ. All measuring errors (δ_i 's) to be uncorrelated with ξ_1 and for all $E(\delta_i)= 0$ it is assumed to be I. E (Bollen, 1989).

Figure 2.3 Path Diagram of Latent variables with four indicator variables



Source: Bollen, 1989:35.

If we separate COV(x1,x4)

$$
\begin{aligned}
COV(x_1, x_4) &= COV\left(\lambda_{11}\xi_1 + \delta_1, \lambda_{41}\xi_1 + \delta_4\right) \\
&= \lambda_{11}\lambda_{41}\phi_{11}
\end{aligned} \qquad \textbf{(2.9)}
$$

It will be the right side of equations consists of equations described in path diagrams for x1 and x4. Here It appears to be a function of the variance of the latent variables and x1 and x4 of COV(x1 , x4) the effect on the ξ.

For more sophisticated models would be appropriate to use matrix algebra.

Including x = Λxξ +δ the covariance matrix of x is the expected value of xx'.

$$
\begin{aligned}
xx' &= \left(\Lambda_x\xi + \delta\right)\left(\Lambda_x\xi + \delta\right)' \\
&= \left(\Lambda_x\xi + \delta\right)\left(\xi'\Lambda_x' + \delta'\right) \\
&= \Lambda_x\xi\xi'\Lambda_x' + \Lambda_x\xi\delta' + \delta\xi'\Lambda_x' + \delta\delta'
\end{aligned} \qquad \textbf{(2.10)}
$$

$$
\begin{aligned}
E(xx') &= E\left(\Lambda_x\xi\xi'\Lambda_x' + \Lambda_x\xi\delta' + \delta\xi'\Lambda_x' + \delta\delta'\right) \\
&= \Lambda_x E\left(\xi\xi'\right)\Lambda_x' + \Lambda_x E\left(\xi\delta'\right) + E\left(\delta\xi'\right)\Lambda_x' + E\left(\delta\delta'\right) \\
\Sigma &= \Lambda_x\Phi\Lambda_x' + \Theta_\delta
\end{aligned} \qquad \textbf{(2.11)}
$$

Thus, the covariance matrix of x element is isolated from Σ, Λx, Φ, Θs elements. Covariances can be separated in a similar manner for all variables in this connection. Separation is important because it sows associated parameters with covariance and that caused them to different parameter values of different covariance (Bollen, 1989). Impact of separation of path analysis approach is the most powerful part in accordance with the basic principles and other analysis (Maruyama, 1997).

2.4 THE SEPARATION OF CAUSAL AND NON-CAUSAL COMPONENTS WITH RELATIONSHIPS BETWEEN VARIABLES

The effect of one variable on another variable, direct impact, indirect effects, counterfeit effect and effects that can not be analyzed is divided into four part. The sum of the direct and indirect effects can be considered as part due to the causality resulting correlation between two variables. Some of the non-causal correlation between the two variables indicated by U and cause variables can not analyze the effect resulting from the correlated variables and denoted by S is indicated by the total impact from common effects of false (Şimşek, 2007).

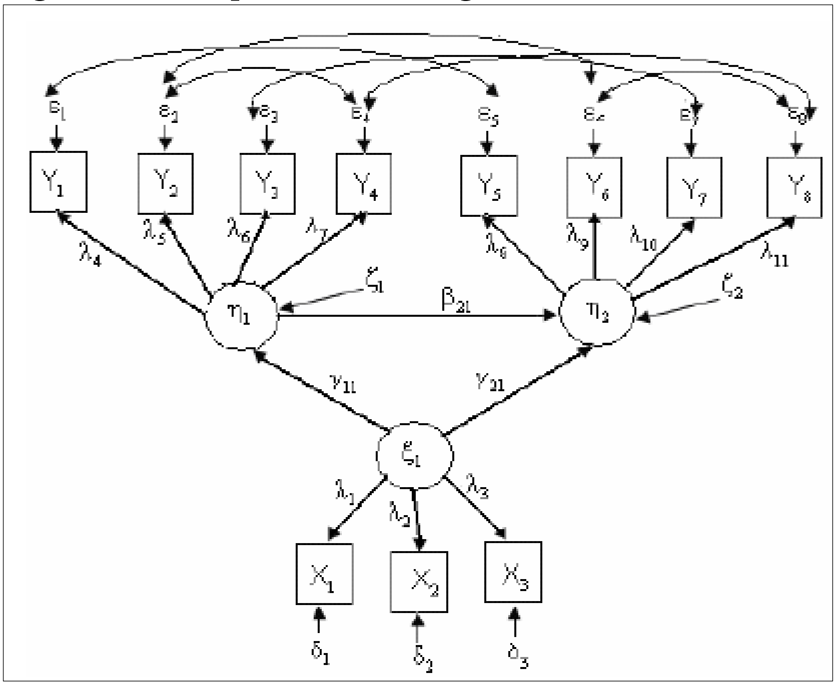
Direct effect is defined as a variable without interference from any path variable in the model effect on other variables (Maruyama, 1997). Direct effects path in the model was estimated by Ordinary Least Squares method.

The indirect effect of a variable consists of a variable together with the entry at least. Adding the path to the path diagram for indirect effects loss of degrees of freedom is not in question (Byrne, 2013).

Separation of Influence is always specific model discussed. If a system of equations is changed by adding or subtracting variable, the direct and indirect modified total effects variable will change (Rogosa, 1993).

Unobservable latent variable models used for measurement model of the direct, indirect and total effects of structural equation models are demonstrated using the example of the path diagram in Figure 2.4.

Figure 2.4 Example of a Path Diagram



Source: Bollen, 1989: 37

3. CONFIRMATORY FACTOR ANALYSIS

3.1. THE DIFFERENCE BETWEEN EXPLORATORY AND CONFIRMATORY FACTOR ANALYSIS

In his 1904 article Spearman utilized this system to figure out if a general knowledge component underlies singular execution on tests. His objective was to clarify the relationship between various observed variables as far as a latent variable. It was helpful for the multifactor. The goal is clarify covariance between numerous observed variables through the agency of generally couple of latent variables (Bollen, 1989).

Factor analysis is used for data reduction and removes duplication from a set of correlated variables, to define the meaning of factors. Factors are shaped that are generally independent of each other. There are two types of variables: latent variables that are not directly measured and observed variables that are used to define latent variables. Factor analysis gets a small set of variables from a large set of variables. There are two types of factor analysis: Exploratory and comfirmatory. It is exploratory when researcher could find number and type of latent variables in a sensible model. After reasonable model is decided, other sample data are used to comfirm the model. Confirmatory factor analysis is utilized to test particular hypothesis about the structure or the number of dimensions fundamental variables (Reyna, 2016).

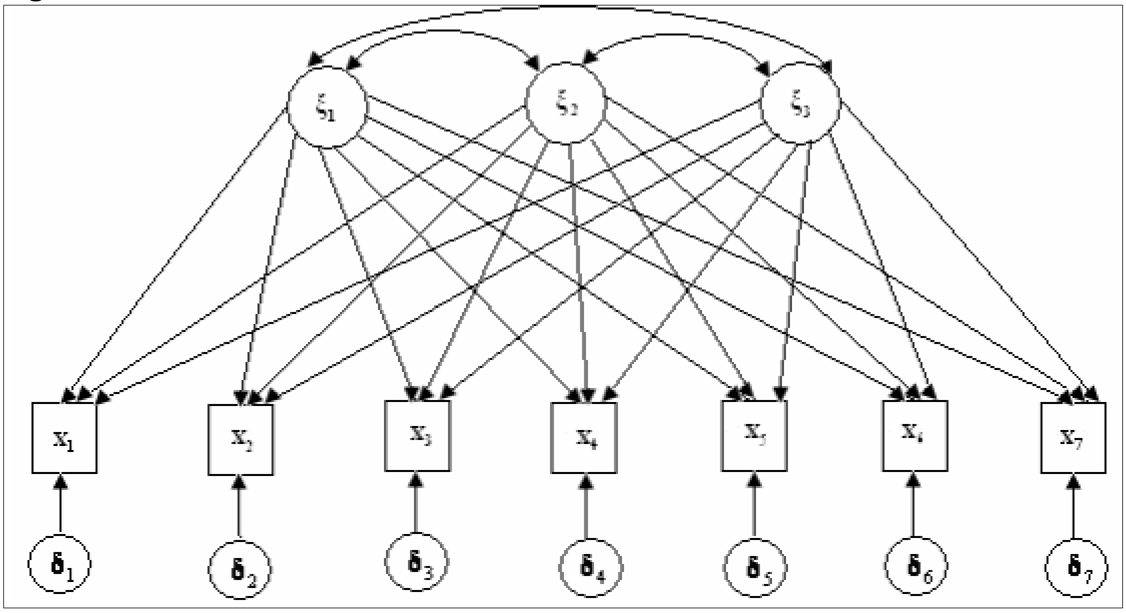
Exploratory Factor Analysis

- Is a variable reduction procedure which recognizes the quantity of latent variables and the basic element structure of an arrangement of variables
- Hypothesizes a fundamental construct, a variable not measured specifically
- Estimates elements which impact reactions on observed variables
- Allows you to depict and recognize the quantity of latent factors
- Includes remarkable elements, blunder because of lack of quality in estimation
- Traditionally has been utilized to investigate the conceivable fundamental factor structure of an set of measured variables without forcing any biased structure on the result (Suhr, 2006).

Assumptions underlying EFA are

- Interval or ratio level of measurement
- Random sampling
- Relationship between observed variables is linear
- A normal distribution (each observed variable)
- A bivariate normal distribution (each pair of observed variables)
- Multivariate normality

Figure 3.1 Three Factor Model for the Seven Observed Variables



Source: Şimşek,2007

Latent variables are represented by ξ_1, ξ_2 and ξ_3. There are seven correlated latent variables which are x1, x2, …, x7 and depend on latent variables in Figure 3.1.

3.2. DETERMINATION OF CONFIRMATORY FACTOR MODEL

Number of common factors, number of observed variables, variances and covariances among common factors, relationship among unique factors and observed variables and variance and covariances among unique factors should be known for determination of confirmatory factor model (Long, 1983).

In EFA, the normal component model is utilized to speak to observed measured variables (MVs) as elements of model parameters and latent variables (LVs). The model for raw data is characterized as below: (Preacher & al., 2013).

$$x = \lambda\xi + \delta \quad \textbf{(3.1)}$$

where x is a p x 1 vector containing data from a typical individual on p variables, Λ is a p x m matrix of factor loadings relating the p variables to m factors, ξ is an mx1 vector of latent variables, and δ is a p x 1 vector of person-specific scores on unique factors. The δ are assumed to be mutually uncorrelated and uncorrelated with ξ. The covariance structure implied Equation (3.2) is as follows:

$$\Sigma = \Lambda\, \phi\, \Lambda' + \Psi \quad \textbf{(3.2)}$$

Σ : p x p population covariance matrix

ϕ : Symmetric matrix of factor variances and covariances.

Ψ : Diagonal matrix of unique factor variances. These parameters are estimated using information in observed data.

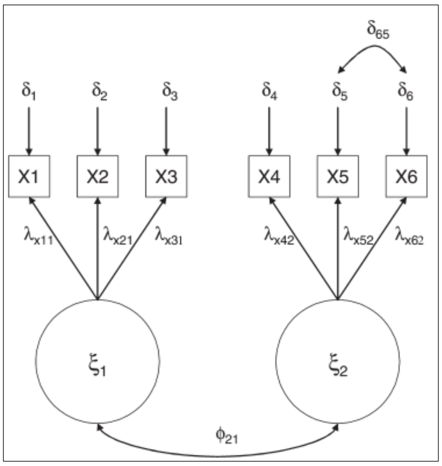
$$\delta = s + e \quad \textbf{(3.3)}$$

s represents the specific variance related with each variable. e is remaining random component in x. Since both segments are errors in x as for measuring ξ and both are uncorrelated with δ and with each other. x is called as a random errors of measurement (Bollen, 1989).

A latent variable must have no less than one arrow driving into it from another latent variable, now and again alluded to as an endogenous latent variable. Any latent variable that does not have a arrow prompting it in SEM is known as exogenous latent variables. If no arrows lead to a latent variable from another latent variable in the SEM, then it is a latent independent variable and are gauged by observed dependent variables denoted by X. If an arrow leads to a latent vairable from another variabler in SEM, it is a latent dependent variable and are measured by observed dependent variable denoted by Y (Schumacker & Lomax, 2004).

Figure 3.2 and Figure 3.3 present the LISREL documentation for the parameters and matrices of a CFA solution for latent X and Y details (Brown, 2006).

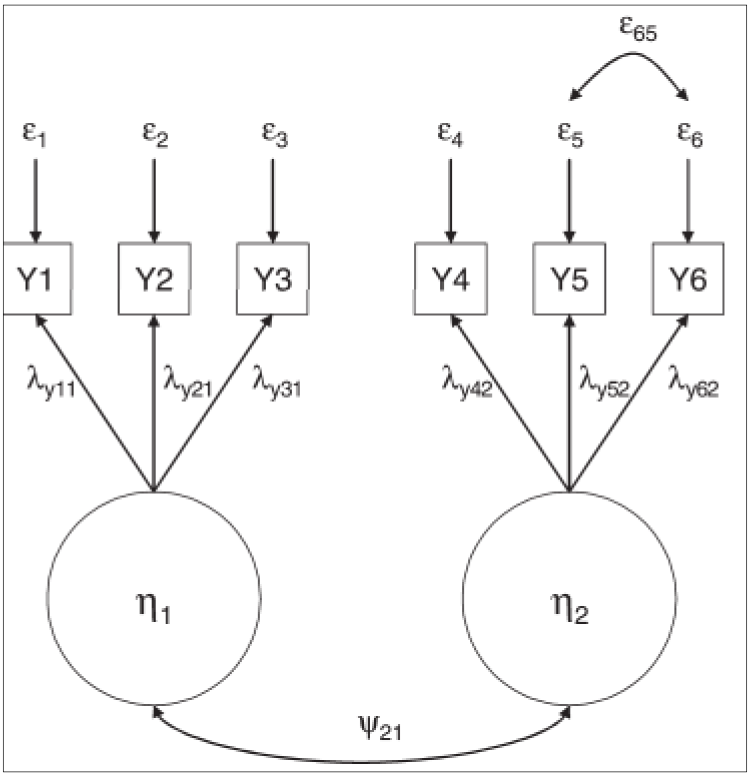
Figure 3.2. Latent X notation for a two-factor CFA model with one error covariance. Factor variances, factor means, and indicator intercepts are not depicted in the path diagram.



Name	Parameter	Matrix	Type	Description
Lambda-X	λx	Λx	Regression	Factor loadings
Theta delta	δ	Θ δ	Variance–covariance	Error variances and covariances
Phi	φ	Φ	Variance–covariance	Factor variances and covariances
Tau-X	τx		Mean vector	Indicator intercepts
Kappa	κ		Mean vector	Latent means
Xi (Ksi)	ξ		Vector	Names of exogenous variables

Source: Brown, 2006:55

Figure 3.3 Latent Y notation for a two-factor CFA model with one error covariance. Factor variances, factor means, and indicator intercepts are not depicted in the path diagram



Name	Parameter	Matrix	Type	Description
Lambda-X	λy	Λy	Regression	Factor loadings
Theta delta	ε	Θε	Variance–covariance	Error variances and covariances
Phi	ψ	Ψ	Variance–covariance	Factor variances and covariances
Tau-Y	τy		Mean vector	Indicator intercepts
Alpha	α		Mean vector	Latent means
Eta	η		Vector	Names of endogenous variables

Source: Brown, 2006:55

The one-way arrows (→) from the parameters to the indicators describe impacts of the latent measurements onto the observed measures, the particular regression coefficients are the lambdas. One-way arrows bind the thetas to the observed variables (e.g., X1–

X6) these bolts don't show regressive paths. Curved, bidirectional arrows are utilized to symbolize covariances; in Figures 3.3 and 3.4.

3.3. COVARIANCE STRUCTURE OF THE CONFIRMATORY FACTOR MODEL

Covariance matrix of x as a function of $\boldsymbol{\theta}$ (Bollen, 1989):

$$\begin{aligned}\Sigma(\theta) &= E(xx') \\ &= E\left[(\Lambda_x\xi+\delta)(\xi'\Lambda_x'+\delta')\right] \\ &= \Lambda_x E(\xi\xi')\Lambda_x' + \Theta_\delta \\ &= \Lambda_x \Phi \Lambda_x' + \Theta_\delta\end{aligned} \qquad \textbf{(3.4)}$$

$\boldsymbol{\phi}$ is the covariance matrix of latent factors and $\boldsymbol{\Theta_\delta}$ is the covariance matrix for the errors of measurement $\boldsymbol{\delta}$.

The dependent variable in the regression and factor analysis were seen, the arguments can not be observed in the factor model. Therefore, model parameters can not be predicted directly. Tehy can be predicted by regressing on dependent X and independent ξ variables. In confirmatory factor model, latent variables can not be estimated directly, examining the covariance structure between observed variables on the right side of the equation is a useful method. Variables included in this condition are thought to be higher than the normal component.

The variance and covariance of symmetric matrix Σ, can be estimated directly using sample data. Before estimating the other unknown parameters, it must be known whether it is possible to obtain a single estimate of the parameters.

3.3.1. t-rule

For the basis of this rule, Eq.3.5 should be examined:

$$\Sigma(\theta) = \Lambda_x \Phi \Lambda_x' + \Theta_\xi \qquad \textbf{(3.5)}$$

Λ_x matrix is qxn. Φ has $\frac{1}{2}$ (n) (n+1) nonredundant parameters. Θ_s has $\frac{1}{2}$ (q) (q+1) unique parameters. For the system to be solved, it is necessary to ensure the condition of the number of independent parameters in Eq.3.6 (Bollen, 1989):

$$t \leq \frac{1}{2}(q)(q+1) \quad \textbf{(3.6)}$$

The positions of the fixed parameter for carrying out the test on model and it presented their hypothesis that the predetermined value should be known.

3.3.2. Rule of three indicators

The sufficient condition for a one-factor model tanımlılıg load indicator for the presence of at least three non-zero and δ Θ's also is a diagonal matrix. A model which is very indicative of the three is called over defined. Three indicators are not enough, but the rules are a necessary condition for definiteness (Bollen, 1989).

3.3.3. Rule of two indicators

Two indicators ξ rule 's condition is an adequate alternative to models that have more than one. Three - such as the indicative guidelines, Θ_δ 's are assumed to be diagonal. Each latent variable is the same size. Each latent variable is the case under these circumstances is sufficient to define because it has two indicators. When two latent variables to be considered a simple structure, for this model δ Θ are diagonal matrix. Λ x and Φ matrices in Eq.3.7;

$$\Lambda_x = \begin{bmatrix} 1 & 0 \\ \lambda_{21} & 0 \\ 0 & 1 \\ 0 & \lambda_{42} \end{bmatrix}, \qquad \Phi = \begin{bmatrix} \phi_{11} & \\ \phi_{21} & \phi_{22} \end{bmatrix} \quad \textbf{(3.7)}$$

One is the complex factor for each monitored variable; the first condition has been achieved. As long as there is no one in the zero elements in φ, the second condition is true. It concluded that these two conditions are defined for achieving the given model. Two - display rule, Σ's written as a function of defined parameters creates a sufficient condition for identification by any unknown parameters (Bollen, 1989).

4. STRUCTURAL EQUATION MODELING WITH LATENT VARIABLES

Structural equation modeling multivariate models observed by measuring the path models are formed as a result of taking part in the same model. These models both observed variables of the measurement model revealed their relationship with the advantages offered by the latent variables both latent variable models embody the path of the advantages of revealing their relationship with each other. The first component of the structural equation model is a structural model with latent variable models or any other expression. This model,

$$\eta = B\eta + \Gamma\xi \tag{4.1}$$

form is shown. Model η, $m \times 1$ vector of latent variables,

ξ shows $n \times 1$ vector of random variables exogenous latent B and Γ and $m \times m$ and $m \times n$-dimensional coefficient matrix respectively. Model $E(\zeta) = 0$ and $COV(\zeta, \xi) = 0$ is assumed.

The second component of the structural equation model is the measurement model is expressed by equation (Muthén, 2002).

$$y = \Lambda\eta + \varepsilon \tag{4.2}$$

$$x = \Lambda\xi + \delta \tag{4.3}$$

Models vector y and x variables are observed. Λy and Λx are coefficient matrix showing the effects on respectively y on η and x on ξ. ε and δ indicate the measurement error and is assumed to be uncorrelated with each other. Also $E(\varepsilon) = E(\delta) = 0$ hypothesis is maintained.

For $\eta = B\eta + \Gamma\xi$ equation, when $\Lambda y=Im$, $\Lambda X=In$, $\Theta\delta=0$, $\Theta\varepsilon=0$, the equation becomes $y = By + \Gamma x + \zeta$ formation.

4.1. IDENTIFICATION OF LATENT VARIABLES IN STRUCTURAL EQUATION MODELS

Definiteness unknown parameters in the covariance matrix, means can be solved in terms of the parameters are known to be defined. θ's Σ each element's must be addressed according to one or more known elements. It is shown that covariance structure $\Sigma=\Sigma(\theta)$ implies $\frac{1}{2}(p+q)(p+q+1)$ nonredundant equations of the form $\sigma ij=\sigma ij(\theta)(i\leq j)$, where σij is the ij element of Σ and $\sigma ij(\theta)$ is the ij element of $\Sigma(\theta)$ (Bollen, 1989).

4.1.1. t-rule

t - rule is necessary for definiteness but insufficient rule. Under this rule the number of independent and unconstrained parameters in θ, i.e. t, must be smaller than the non-redundant number of elements in Σ (Bollen, 1989).

$$t < \frac{1}{2}(p+q)(p+q+1) \qquad \textbf{(4.4)}$$

4.1.2. Two step rule

Two-step rule is a two-step process. The first step in bringing the DFA approach to model definiteness research is done. Original x and y variables for x variable, the original ξ and η is considered as ξ. The second step is the observed variable is considered to be identifiable and latent variables before the said format of the observed variable structural equation modeling analysis is performed. The general model may be defined for both stages, it must be provided of description (Bollen, 1989).

4.1.3. Multiple indicators multiple causes rule

Some special case of general models includes observed variables which are Multiple Indicators and Multiple Causes (MIMIC) of a single latent variable (Bollen, 1989).

$$\eta 1 = \Gamma x + \zeta_1 \quad \textbf{(4.5)}$$

$$y = \Lambda y \eta_1 + \varepsilon \quad \textbf{(4.6)}$$

$$x = \xi \quad \textbf{(4.7)}$$

x is a perfect measure of ξ. η 1 is latent variable and straightforwardly influenced by x, it is shown by y. If $p \geq 2$ and $q \geq 1$, it means that condition is sufficient for identification.

4.2. THE ESTIMATION OF LATENT VARIABLE STRUCTURAL EQUATION MODEL

For general structural equation models or latent variable structural equation modeling, EB, GEKK, AEKK and other estimation methods may be used which are previously mentioned. According to this method, fitting functions to be used in order to obtain prediction function is given below (Bollen, 1989):

$$F_{EB} = \log\left|\Sigma(\theta)\right| + tr\left(S\Sigma^{-1}(\theta)\right) - \log\left|S\right| - (p+q) \quad \textbf{(4.8)}$$

$$F_{GEKK} = \left(\frac{1}{2}\right) tr\left\{\left(S - \Sigma(\theta)\right)W^{-1}\right\}^2 \quad \textbf{(4.9)}$$

$$F_{EKK} = \left(\frac{1}{2}\right) tr\left[\left(S - \Sigma(\theta)\right)^2\right] \quad \textbf{(4.10)}$$

Each of these functions is minimized regarding θ.

4.3. STANDARDIZED AND UNSTANDARDIZED COEFFICIENTS

An investigation of the covariance matrix of observed variables prompts unstandardized coefficients that rely on the units in which the variables are scaled. Ordinarily these units are subjective. It can be hard to analyze the impacts of two or more variables on the same dependent variable when they have diverse units of estimation. Standardized coefficient can be helpful in surveying relative impacts of various explanatory variables.

$$\hat{\lambda}_{ij}^{s} = \hat{\lambda}_{ij}\left(\frac{\hat{\sigma}_{jj}}{\hat{\sigma}_{ii}}\right)^{1/2} \quad \textbf{(4.11)}$$

$$\hat{\beta}_{ij}^{s} = \hat{\beta}_{ij}\left(\frac{\hat{\sigma}_{jj}}{\hat{\sigma}_{ii}}\right)^{1/2} \quad \textbf{(4.12)}$$

$$\hat{\gamma}_{ij}^{s} = \hat{\gamma}_{ij}\left(\frac{\hat{\sigma}_{jj}}{\hat{\sigma}_{ii}}\right)^{1/2} \quad \textbf{(4.13)}$$

s: a standardized coefficient.

i: dependent varaible.

j: independent variable.

$\hat{\sigma}_{ii}$ and $\hat{\sigma}_{jj}$: the model-predicted variances of the ith and jth variables.

The institutionalized coefficient is the normal movement in standard deviation units of the dependent variables that is because of a one standard deviation shift in the independent variable when alternate variables are held steady.

It is conceivable to evaluate the general model with capture terms for the estimation and latent variable equations and to appraise latent variable means.

$$\eta = \alpha + B\eta + \Gamma\xi + \zeta \quad \textbf{(4.14)}$$

$$y = \upsilon_y + \Lambda_y\eta + \varepsilon \quad \textbf{(4.15)}$$

$$x = \upsilon_{x} + \Lambda\Lambda_x\xi + \delta \quad \textbf{(4.16)}$$

The means of exogenous variables (ξ) are in a $n \times 1$ vector, κ. The expected values of the latent endogenous variables are:

$$E(\eta) = E\left[(I-B)^{-1}(\alpha + \Gamma\xi + \zeta)\right] = (I-B)^{-1}(\alpha + \Gamma\kappa) \quad \textbf{(4.17)}$$

The mean vectors of x and y:

$$E(\mathrm{x}) = \upsilon_x + \Lambda_x\kappa \quad \textbf{(4.18)}$$

$$E(\mathrm{y}) = \upsilon_y + \Lambda_y(I-B)^{-1}(\alpha + \Gamma\kappa) \quad \textbf{(4.19)}$$

In this case, the mean of η depends on function of parameters inκ, Β, Γ ve α. So also the mean of y is controlled by these matrices and in addition by υy, Λx and κ.

4.4. TOTAL, DIRECT AND INDIRECT EFFECTS

All out impacts are characterized in two ways. The primary sets them equivalent to a total of forces of coefficient matrix. Alternate allots intending to aggregate impacts by utilizing reduced-form coefficients. Both definitions lead to the same results. I display the "infinite sum" definition and allude the peruser to (Alwin & Hauser, 1975), (Graff & Schmidt, 1982), and (Bollen, 1989) for the reduced-form definition. The total effects on η on η or Tηη :

$$T_{\eta\eta} = \sum_{k=1}^{\infty} B^k \tag{4.20}$$

Tηη is only defined if the infinite sum converges to a matrix with finite elements.

Table 4.1 sums up the decay of impacts for the general SEM with observed variables:

Table 4.1 Direct, Indirect and Total Effects

	Effects on:		
Effects of ξ	η	y	x
Direct Effect	Γ	0	Λ_x
Indirect Effect	$(I-B)^{-1}\Gamma-\Gamma$	$\Lambda_y(I-B)^{-1}\Gamma$	0
Total Effect	$(I-B)^{-1}\Gamma$	$\Lambda_y(I-B)^{-1}\Gamma$	Λ_X
Effects of η			
Direct Effect	B	Λ_y	0
Indirect Effect	$(I-B)^{-1}-I-B$	$\Lambda_y(I-B)^{-1}-\Lambda_y$	0
Total Effect	$(I-B)^{-1}-I$	$\Lambda_y(I-B)^{-1}$	0

Source: Bollen(1989)

Comments in SEM analysis, it is assumed that the observed latent and continuous variables were considered. However, due to constraints on measurement tools, the parameters observed are not always normally distributed. Ordinal scale, especially Likert scales, it is one of the most widely used type of scale in Social Sciences, many approaches have been proposed for AF with such variable and most of this feed is also implemented in the proposed approach (Muthén, 2002).

SEM ready software to measure levels of intermittent - rate and provides an analysis of the hybrid model that uses ordinal variables. Different methodologies which likewise utilize just first and second request minutes is that utilized as a part of PRELIS/LISREL and depicted by (Jöreskog, 1990) (Jöreskog & Sörbom, 1994) and that utilized as a part of MPLUS and portrayed by (Muthén, 1984)and (Muthén & Satorra, 1995) in love general setting. These are three-stage methods taking into account hidden normally distributed variables. In the initial step, the edges are assessed from the univariate edges of the observed variables. In the second step, the polychoric relationships are evaluated from the bivariate edges of the observed variables forgiven thresholds. In the third step, the element model is assessed from the polychoric correlations by weighted slightest squares utilizing a weight matrix which is the converse of an evaluation of the asymptotic covariance matrix of the polychoric correlations.The asymptotic covariance matrix is frequently temperamental in little specimens, especially if there are zero or little frequencies in the bivariate edges. By difference, the UBN approach evaluates the limits and the variable loadings in one single stride from the univariate and bivariate edges without the utilization of a weight matrix (Jöreskog & Moustaki, 2001).

4.5. STRUCTURAL EQUATION MODELING WITH VARIABLE ROW

After estimating the parameters of structural equation model, it is passed to evaluation stage that compliance with the covariance matrix derived from the model and the covariance matrix of sampling. In SEM, unlike other models for the evaluation of multivariate methods, there is no generally accepted hypothesis testing or criteria and in SEM there are numerous tests developed and measure not replace each other. These tests and criteria "general model tests and criteria" and "component compatibility criteria" can be grouped under two headings. The first set of criteria are used to evaluate the whole model, the second group of criteria have examined the significance of the model parameters in reliability and structural components in the measuring components individually and in detail. The criteria used for general alignment of the model are separated from each other according to the usage purpose. For example, while some is used to verify the model only some of these criteria used in the evaluation of various models that can be supported by theory. A third type of criteria contained in this group is the criteria used to create the model (Jöreskog & Sörbom, 1994) (Şimşek, 2007). It helps in finding the optimal statistical model data.

4.6. EVALUATION MODELS WITH COMPLIANCE CRITERIA

4.6.1. Compliance criteria for the general model

Criteria that have been developed to assess the overall fit of the model is a hierarchical structure. The goodness of fit of the model benchmarks case covers the extent that the case also for model validation. Criteria for comparison in the case of both models include model creation model validation criteria used in both cases. Components for each model discussed adaptation measures should be examined (Şimşek, 2007).

4.6.1.1. A Chi-Square (χ^2) Test

This test is obtained by multiplying compliance value between examples of covariance matrix and estimated covariance matrix for the model with the number obtained by multiplying the data used minus one. The results are calculated as χ 2 distribution. B, Γ, Λy, Λx, Φ, Ψ, Θε, Θδfixed, unconstrained and constrained parameters are valid. (N-1)FML or (N-1) FGLS provide $\chi 2$ estimators for testing H0:Σ=Σ(θ). Since H0 is equivalent to the hypothesis that Σ-Σ(θ)=0. In the prediction methods EB and GEKK:

$$\log L(\theta) = -\frac{n-1}{2}\left\{\log\left|\Sigma(\theta)\right| + tr\left[S\Sigma^{-1}(\theta)\right]\right\} \tag{4.21}$$

Maximum of logarithmic functions in the case where the null hypothesis is shown below:

$$\log L_0 = -\frac{n-1}{2}\left\{\log\left|\hat{\Sigma}\right| + tr\left[\hat{\Sigma}^{-1}S\right]\right\} \tag{4.22}$$

H1 in case of the alternative hypothesis is correct is in below:

$$\log L_1 = -\frac{n-1}{2}\left\{\log\left|S\right| + (p+q)\right\} \tag{4.23}$$

In case the maximum obtained H0 hypothesis is true, if multiplied by the maximum and ratio -2 obtained if the alternative hypothesis is not true test statistic is obtained:

$$c = (n-1)F\left(S, \Sigma\left(\hat{\theta}\right)\right) = (n-1)\hat{F} \tag{4.24}$$

If model is valid and defined, its degrees of freedom are:

$$d = \left(\frac{1}{2}\right)(p+q)(p+q+1) - t \tag{4.25}$$

If the χ 2 test sample is large enough and data fully meet the basic assumptions of multivariate statistics it gives an accurate measurement. The degree of freedom (SD) is an important criterion in the χ 2 test. Where in SD is bigger, SD tends to be give an meaningful results in χ 2, therefore, in some cases, the rate of SD to χ 2 to be used as a measure of adaptation capability. 1, 3 and lower rates is considered to be good compliance, 1 / 5a until the ratio is considered to be sufficient compliance. Sample size is affected by the convergence criteria. The sample was too small to be decentralized if asymptotic chi-square distribution results because of disruption can lead to Type II error. Again, the sample size is greater, however, if the variable deviate from the central square distribution also arises Type II error. In case of multivariate normality of the observed variables χ 2 test statistic for alternative calculation methods have been developed. The most commonly used Satorra - it is called Correction (Bollen, 1989) (Hair & al., 1998) (Şimşek, 2007).

4.6.1.2. Confidence Interval for Non Centrality Parameter (NCP)

In $\Sigma \neq \Sigma(\theta)$ situation, with d degrees of freedom and

$$\lambda = nF\left[\Sigma_0, \Sigma(\theta_0)\right] \tag{4.26}$$

being a decentralized central to conform to the parameters of the χ 2 distribution. λ is a value of the main mass's estimator:

$\lambda\hat{}$ = NCP(prediction) = Max{(c − d),0}and 90% confidence interval (4.27)

$$G\left(c|\lambda_A, d\right) = 0.95 \tag{4.28}$$

$$G\left(c \middle| \lambda_0, d\right) = 0.95 \qquad \textbf{(4.29)}$$

It is obtained from the solution of linear equations for λ_Λ and λu.

r subscript shows Mr more restricted model, and u subscript shows a less constrained Mu.

$$\Delta LR = \Delta\chi^2 = (n-1)(F_r - F_u) = c_r - c_u = \chi_r^2 - \chi_u^2 \qquad \textbf{(4.30)}$$

LM test is almost distributed χ 2 with d=dr-du degrees of freedom.

In case of rejection of $H_0 : \Sigma = \Sigma_r(\theta)$ or $\Sigma\text{-}\Sigma_r(\theta) = 0$ hypothesis, it could be said that limited model is deduced to be correct.

4.6.1.3. Lagrange Multpliyer (LM) Test

LM test comparing the fit of the model to fit the limited models less constrained only needs a limited model estimation. To test the validity of the restrictions, the test statistic is used (Bollen, 1989).

$$LM = \left[s\left(\hat{\theta}_r\right)\right]' \left[I^{-1}\left(\hat{\theta}_r\right)\right] \left[s\left(\hat{\theta}_r\right)\right] \qquad \textbf{(4.31)}$$

LM test is distributed χ 2 with d=dr-du degrees of freedom.

4.6.1.4. Wald Test

Wald test decides the degree to which $\hat{\theta}_u$ leaves from the limitations forced by the settled model:

$$W = \left[r\left(\hat{\theta}_u\right)\right]' \left\{ \left[\frac{\partial r\left(\hat{\theta}_u\right)}{\partial \hat{\theta}_u}\right]' \left[a\operatorname{cov}\left(\hat{\theta}_u\right)\right] \left[\frac{\partial r\left(\hat{\theta}_u\right)}{\partial \hat{\theta}_u}\right] \right\}^{-1} \left[r\left(\hat{\theta}_u\right)\right] \qquad \textbf{(4.32)}$$

It is distributed with degrees of freedom r and the limited model provided that the accurate asymptotically χ 2 (Bollen, 1989).

4.6.1.5. Akaike's Information Criterion(AIC)

AIC measurement exposes a result that logarithmic similarity based on the available data, the prediction of the data, which will occur in the future showing that similarity of logarithmic's estimated systematic errors.

$$AIC=(-2)(\text{logaritmic similarity}) + 2(\text{number of parameters}) \quad \textbf{(4.33)}$$

AIC's adapted version for SEM is shown below:

$$AIC(H_0) = (-2)\max \ln L(H_0) + 2q_0 \quad \textbf{(4.34)}$$

Where in q0, indicates the number of unknown parameters under the validity of hypothesis H_0:Σ=Σ(θ). AIC measures are calculated after estimated alternative models and AIC is assumed to be the correct model data to the model with the lowest (Akaike, 1987).

4.6.1.6. Consistent Akaike's Information Criterion(CAIC)

AIC similar logic (Merlin, 1987) into the sample units available in developed but the penalty area by Caicun criterion function is defined as follows:

$$CAIC = c + (1 + \ln n)t \quad \textbf{(4.35)}$$

The data model with the smallest value in Caicun alternative models are considered to be the model that best reflects (Şimşek, 2007).

4.6.1.7. Expected Cross Validation Index(ECVI)

One of the main mass of the same sample taken independently nc+1 and SV covariance matrix including V validity example, obtained using the calibration samples and the $\hat{\Sigma}_c$ covariance matrix of the difference between SV and validity example is called cross validation index (Şimşek, 2007):

$$CVI = F\left(S_V, \hat{\Sigma}_C\right) \quad \textbf{(4.36)}$$

When the calibration sample is kept constant, and calculating the effective sample CVI 's conditional expected value including $p^{*}=(p+q)(p+q+1)/2$:

$$E_V(CVI) = E_V\left\{F\left(S_V, \hat{\Sigma}_C\right)\middle|\hat{\Sigma}_C\right\} \approx F\left(\Sigma_0, \hat{\Sigma}_C\right) + n_V^{-1}p^{*} \tag{4.37}$$

The process calibration for example, the validity of the original sample, the validity of the sample can be dealt with as an example of repeated calibration. Because an estimated value of ECVI, 90% confidence interval for the ECV, ECV forecast models are used in conjunction with the comparison. ECV prediction model with the smallest AIC as the most appropriate model is selected.

$$(c_A, c_U) = \left(\frac{\left(\hat{\lambda}_A + p^{*} + t\right)}{n}; \frac{\left(\hat{\lambda}_U + p^{*} + t\right)}{n}\right) \tag{4.38}$$

4.6.1.8. Root Mean Square Residual

RM, is a measure of the average difference between data and reconstructed variance / covariance matrix, taken into account by the model reflects the average amount of variance and covariance. If the index is lower, it means the better the compliance model data. RMR to be close to zero indicates good compliance. Marginally acceptable level is 0.08.

The square root of the mean square error proposed by (Jöreskog & Sörbom, 1986)can be used as a measure of model fit (Bollen, 1989).

$$RMR = \left[2\sum_{i=1}^{p+q}\sum_{j=1}^{i}\frac{\left(s_{ij} - \hat{\sigma}_{ij}\right)^2}{(p+q)(p+q+1)}\right]^{1/2} \tag{4.39}$$

4.6.1.9. Standardized Root Mean Square Residual

It is a measure of the scale of the dependent variable in RMR in Eq. 4.39. Standardized for this drawback the invention proposes RM is calculated as follows (Bollen, 1989):

$$SRMR = \left[2\sum_{i=1}^{p+q}\sum_{j=1}^{i} \frac{\left(s_{ij}-\hat{\sigma}_{ij}\right) \Big/ \left[\left(\hat{\sigma}_{ii}\hat{\sigma}_{jj}+\hat{\sigma}_{ij}\right)/n\right]^{1/2}}{(p+q)(p+q+1)} \right]^{1/2}$$

(4.40)

4.6.1.10. Absolute Goodness of Fit Index

It was developed to reduce the depence of $c=(n-1)\hat{F}$ to n. GFI shows that the model measures what percentage of the sample in the variance-covariance matrix and the sample variance explained by the model is accepted. This certainty in these indexes is similar to the maintenance and regression adjusted coefficient of determination. Goodness of Fit Index and Adjusted Goodness of Fit Index are:

$$GFI = 1 - \frac{F\left[S,\Sigma\left(\hat{\theta}\right)\right]}{F\left[S,\Sigma\left(\theta\right)\right]}$$

(4.41)

$$AGFI = 1 - \frac{k(k+1)}{2d}(1-GFI)$$

(4.42)

Both dimensions must be in the range of zero and one. Including 0.90 threshold value, GFI and agfı the value close to 1 is a sign that adapt well to model data. However, experience, and other indicators showed relatively poor compliance with a model could have a major GFI more than 0.90. A small difference between GFI and AGFA, the model shows that with good compliance, but that little difference incommunicable which is sufficient as a criterion (Hair & al., 1998).

4.6.1.11. Root Mean Square Error of Approximation (RMSEA)

To find the level proposed is proximity to the covariance matrix of the estimates obtained from the sample covariance matrix for the model is calculated as follows.

$$RMSEA = \sqrt{\max\left[\frac{F(S,\Sigma(\theta))}{sd} - \frac{1}{N-1}, 0\right]}$$

(4.43)

A lower value indicates a better fit to the data model. This index value of less than 0.05 is a good fit; it shows the best fit when you get close to a value of between 0.05 and 0.08. According (Kelloway, 1995) RMSEA has a particular importance by providing both ease of interpretation and confidence interval estimates both in terms of providing independent sample size. As the model takes into account the degree of freedom is not affected by the complexity of the model. As well as this statistic in terms of gaining confidence intervals helps to make better decisions.

4.6.1.12. Normed Fit Index(NFI)

In independence model which is mentioned here, for example, confirmatory factor analysis, the absence of the factors underlying the observed variables so the covariance of observed variables (correlations) is shaped to be zero.

$$NFI = \frac{F_b - F_m}{F_b} = 1 - \frac{F_m}{F_b} = \frac{\chi_b^2 - \chi_m^2}{\chi_b^2} \tag{4.44}$$

Here it demonstrates the value and the estimated value of F_b, χ_b^2 show the value of the compliance function for the base model and the estimated value of χ 2. Fm and Fb had a maximum and thus enabling the NFI remains in the range [0, 1]. A value close to getting poor compliance, while taking a value close to 1 indicates good compliance threshold to be 0.90 ((Hair & al., 1998). If NFI take a value close to 0 indicates poor compliance, if it is taking a value close to 1 indicates good compliance threshold to be 0.90.

4.6.1.13. Parsimony Normed Fit Index (PNFI)

PNF obtained by rearrangement of degree of freedom of NFI. Theoretically [0,1] is not required to be in the range of values close to 1 indicate good (Hair & al., 1998).

$$PNFI = \left(\frac{sd_m}{sd_b}\right)\left(1 - \frac{F_m}{F_b}\right) \tag{4.45}$$

4.6.1.14. Incremental Fit Index(IFI)

The sample size for the evaluation of goodness of fit models as well as degrees of freedom is also an index that takes into account is calculated as follows:

$$IFI = \frac{F_b - F_m}{F_b - [sd_m/(n-1)]} = \frac{\chi_b^2 - \chi_m^2}{\chi_b^2 - sd_m} \tag{4.46}$$

IFI's theoretically [even 0,1] in the range is not necessary, in order to be accepted as 0.90 threshold values close to 1 represents the best fit.

4.6.1.15. NonNormed Fit Index(NNFI)

Non Nomed Fit index ([0.1] can not be converted to the range) is calculated like:

$$NNFI = \frac{F_b / sd_b - F_m / sd_m}{F_b / sd_b - [1/(n-1)]} = \frac{\chi_b^2 / sd_b - \chi_m^2 / sd_m}{\left(\chi_b^2 / sd_b\right) - 1} \tag{4.47}$$

This index is a value of 1 if the case full compliance with the provision of FEED assumptions. For NNF [0, 1] There is no requirement in the range. Including 0.90 threshold values close to 1 indicate good compliance (Şimşek, 2007).

4.6.1.16. Comparative Fit Index (CFI)

CFU is based on the parameter of χ^2 goodness of fit test not to be the center of statistics. Comparative fit index compare the compliance function for customized models with the compliance function obtained with derived from other based model.

$$\ell_b = T_b - sd_b = \chi_b^2 - sd_b \tag{4.48}$$

$$\ell_m = T_m - sd_m = \chi_m^2 - sd_m \tag{4.49}$$

In this situation CFI can be calculated as:

$$CFI = 1 - \frac{\ell_i}{\ell_j}$$
$$\ell_i = \max(\ell_m, 0) \qquad \ell_j = \max(\ell_b, \ell_m, 0) \tag{4.50}$$

CFI compares the covariance matrix produced by the independent model with the covariance matrix which is produced by the proposed SEM model. It gives a value reflecting the ratio between "0" to "1”. Values closer to 1 the model is considered to give a better fit and values above 0.90 are considered good fit.

4.6.1.17. Parsimony Goodness of Fit Index (PGFI):

PGFI is shown below:

$$PGFI = \left(2 \frac{sd_m}{k(k+1)} \right) GFI \tag{4. 51}$$

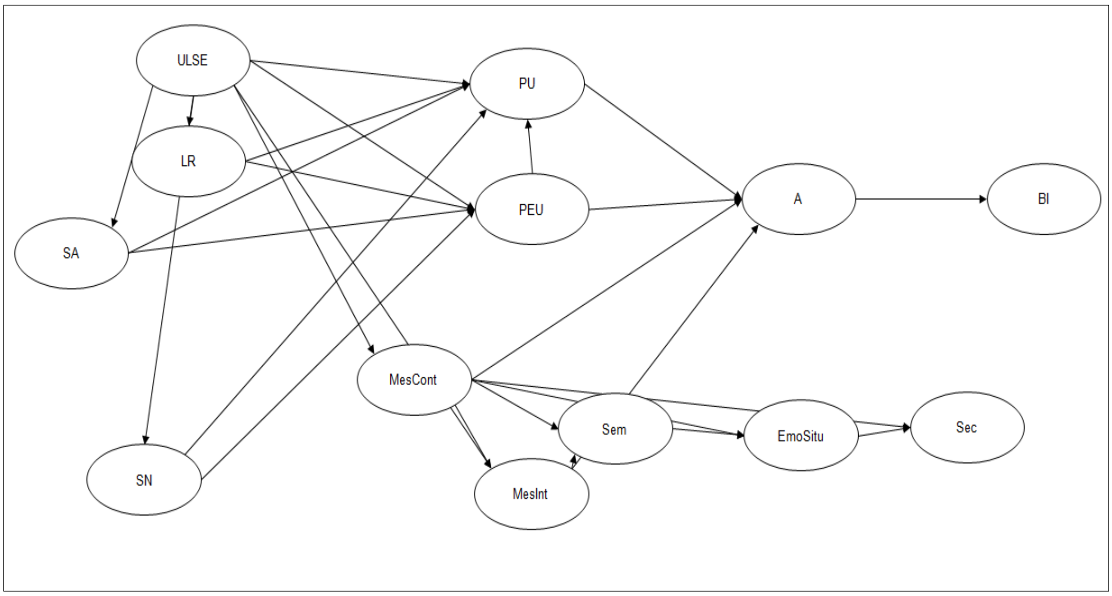
Here shows the number of observed variables. GFI as in [0, 1] is in the range shows good alignment of values close to 1.

5. MEASUREMENT OF TECHNOLOGY ACCEPTANCE FOR UBIQUITOUS LEARNING AMONG THE UNIVERSITY STUDENTS

5.1. STUDENT'S ACCEPTANCE TO U-LEARNING ENVIRONMENT

The data for this research was obtained by a questionnaire which was distributed to students whose have taken Java Programming, Engineering Ethics, Data Structure, Management Information Systems, and Introduction to Information Technology Management Services, Human Computer Interaction, and Health Informatics courses with the technology-assisted learning platform Moodle in Bahcesehir University. The questionnaire is consisting of two parts. One part includes survey of the Technology Acceptance Model (TAM) and the other part of includes survey of Computer-Mediated Communication (CMC).

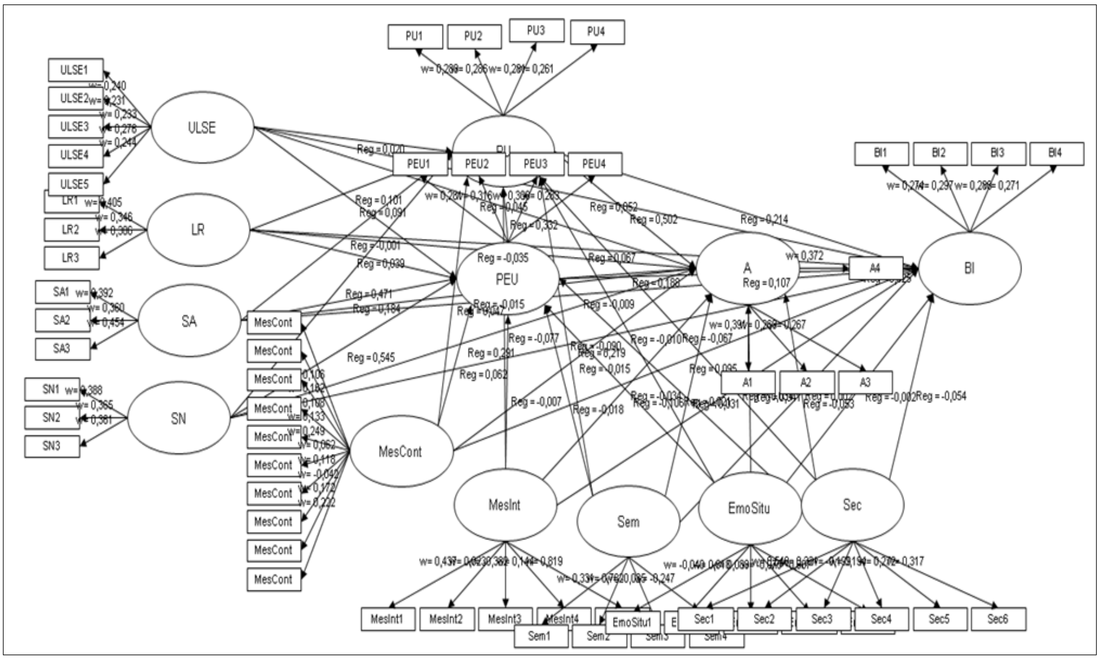
Figure 5.1 PLSPM Result Graph



Source: Created by Ahmet Yücel

Using both of them, we have measured the behavioural intentions of students regarding the Ubiquitous Learning Environment. The questions are twelve indicator variables of the fifty six independent variables shown in Figure 5.1 and Figure 5.2.

Figure 5.2 Structural model of the factors influencing the level of technology acceptance for ubiquitous learning among the university students



Source: Created by Ahmet Yücel

5.1.1. Participation rates of students who answer the questionnaires

The questionnaires were asked to Bahcesehir University students with a Likert scale of 1 to 5 as given in Table 5.1 and Table 5.2. 356 students were randomly and heterogeneously selected in different departments of Engineering Faculty and Health Sciences Faculty in Bahcesehir University (BAU) whose have already taking the one of the lectures such as Java programming, Engineering Ethics, Data Structure, Management Information Systems, Information Technology Management Services, Introduction to Human Computer Interaction, and Health Informatics in Moodle enviornment.

Table 5.1 Independent latent variables of Technology Acceptance Model (TAM) questionnaires

Latent Variables (LV)	Item Code	Description of Measurement Item (indicators)
Ubiquitous Learning Self-Efficiency (ULSE)	ULSE1	I have the necessary skills for ubiquitous learning
	ULSE2	I have confidence in using mobile devices for ubiquitous learning
	ULSE3	I have confidence in using computer for ubiquitous learning

	ULSE4	I understand computer's terminology when using a computer for ubiquitous learning
	ULSE5	I understand mobile device's terminology when using a mobile device for ubiquitous learning
Learning Relevance (LR)	LR1	Ubiquitous learning with mobile devices is necessary for my major study
	LR2	Ubiquitous learning with mobile devices is helpful for my major study
	LR3	Ubiquitous learning with mobile devices can help me to find a job in the future
System Accessibility (SA)	SA1	I can easily access information for ubiquitous learning
	SA2	Different mobile devices have a good compatibility with ubiquitous learning
	SA3	It is easy to access online resource for ubiquitous learning
Subjective Norm (SN)	SN1	Ubiquitous learning is significant for university students
	SN2	Ubiquitous learning is a social necessity
	SN3	I need to experience ubiquitous learning for my future job
Behavioural Intention (BI)	BI1	I have intention to perform ubiquitous learning
	BI2	I am going to positively utilize ubiquitous learning
	BI3	I will be a power user in ubiquitous learning
Attitude (A)	A1	Studying through ubiquitous learning is a good idea
	A2	I prefer using mobile devices over computers for ubiquitous learning
	A3	I prefer using computers over mobile devices for ubiquitous learning
	A4	I am positive toward ubiquitous learning
Perceived Usefulness (PU)	PU1	Ubiquitous learning would improve my learning performance
	PU2	Ubiquitous learning is a faster way of learning
	PU3	Ubiquitous learning is an easier way of learning
	PU4	Ubiquitous learning can lead to a deeper learning
Perceived Easy of Use (PEU)	PEU1	It is easy to download learning contents with mobile devices
	PEU2	It is easy to use menu of mobile devices software
	PEU3	It is easy to use ubiquitous learning contents with a mobile device
	PEU4	It is easy to use ubiquitous learning contents with a computer

Source: Created by Ahmet Yücel

Table 5.2 Independent latent variables of Computer-Mediated Communication (CMC) questionnaires (Response options 1–5; 1=strongly disagree to 5=strongly agree)

Latent Variables (LV)	Item Code	Description of measurement item (indicators)
Message Contents (MesCont)	MesCont1	CMC messages are social forms of communication
	MesCont2	CMC messages are an informal and casual way to communicate
	MesCont3	CMC messages convey feeling and emotion
	MesCont4	CMC messages are impersonal (do not have qualities or characteristics
	MesCont5	CMC is not confidential enough to use to communicate personal and/or sensitive information
	MesCont6	CMC is a sensitive means of communicating with others
	MesCont7	Using CMC to communicate with others is pleasant.
	MesCont8	I am comfortable participating, if I am familiar with the topics
	MesCont9	I am uncomfortable participating, if I am not familiar with the topics
	MesCont10	What is the likelihood that someone might obtain personal information about you from the messages you send and/or receive?
Message Interaction (MesInt)	MesInt1	The replies to my CMC messages are immediate
	MesInt2	Users of CMC are normally responsive to messages
	MesInt3	I am comfortable communicating with a person who is familiar to me
	MesInt4	I am comfortable communicating with a person who is not familiar to me
	MesInt5	What is your professional RELATIONSHIP to other participants with whom you communicate?
Semantics (Sem)	Sem1	The language people use to express themselves in online communication is stimulating
	Sem2	It is difficult to express what I want to communicate through CMC
	Sem3	The language used to express oneself in online communication is meaningful
	Sem4	The language used to express oneself in online communication is easily understood
Emotional Situations (EmoSitu)	EmoSitu1	What is the likelihood that a computer system operator might read and/or re-post messages sent to or from you?
	EmoSitu2	What is the likelihood that someone else might read and/or re-post messages sent to or from you?
	EmoSitu3	What is the likelihood that you might accidentally send message(s) to someone other than the intended recipients(s)?

	EmoSitu4	Do you know of any instance where someone has been personally or professionally embarrassed because of their online activities?
	EmoSitu5	Which of the following statements most closely reflects how you feel about the possibility of you even being personally or professionally embarrassed through your online participation?
Security (Sec)	Sec1	How PRIVATE are your messages on CMC?
	Sec2	How IMPORTANT is privacy of a CMC?
	Sec3	How SECURE/SECRET is your online participation
	Sec4	How RISKY is it to share personal and sensitive topics online?
	Sec5	If you are able to use online messages anonymously, how CONCERNED are you that your identity will be traced?

Source: Created by Ahmet Yücel

5.1.1.1. Data Analysis

Data collected from students were analyzed statistically. Confirmatory factor analysis and exploratory factor analysis were used. New factor arrangements which were obtained from exploratory factor analysis, were examined with Partial Least Squares Structural Equation Modeling (PLS-SEM) and the relationship between the dependent and independent variables were investigated.

The general method of investigation included structural equation modeling (SEM), which joins both measured and latent variables and can speak to all the while the estimated interrelationships between multiple variables, with a specific end goal to test the general model's fit to the data.

Confirmatory factor analysis was applied to the scale with XLSTAT software. The average variance explained by the compliance criteria is examined with factor loadings, cross loadings, reliability and validity of results. By using SPSS 17 software, varimax rotation method is applied to the exploratory factor analysis.

6. COMPARATIVE FUTURE PERCEPTIONS OF UBIQUITOUS LEARNING DEVICES FOR LEARNING

As indicated by the Chronbach alpha values, the best variable is the PU variable which is 0.92 as given in Table 6.1. BI, MesCont and the other variables' effects are observed also moderately high. Dillion Goldstien's Rho values are about 0.90 so reliability values of model is adequate and variables are impressed the model that means these variables can be included by the model.

Table 6.1 Composite reliability

Latent variable	Dimensions	Cronbach's alpha	D.G. rho (PCA)
ULSE	5	0,874879956	0,909083416
LR	3	0,853313897	0,910953555
SA	3	0,770639259	0,867565237
SN	3	0,879255177	0,925502875
MesCont	10	0,918549989	0,932509664
MesInt	5	0,768445727	0,845192288
Sem	4	0,673901137	0,804602689
EmoSitu	5		
Sec	6		
PEU	4	0,860875957	0,907680699
PU	4	0,920976709	0,944163597
A	4		
BI	4	0,907232475	0,934984188

Source: Created by Ahmet Yücel

Depending on the confirmatory factor analysis model by removing material that could adversely affect the Cronbach's alpha value was between 0.62-0.92. This shows that the stronger the relationship obtained as a result of the model.

Table 6.2 Goodness of fit index (1)

	GoF	GoF (Bootstrap)	Standard error	Critical ratio (CR)
Absolute	0.626	0.629	0.022	28.778
Relative	0.912	0.896	0.022	41.126
Outer model	0.948	0.948	0.021	45.484
Inner model	0.962	0.945	0.007	134.216

Source: Created by Ahmet Yücel

When a model fix index GoF (goodness of fit) is pointed out moderately consistent with 0.626, standard errors and critical ratio value mark is quite a good fit (Table 6.2). The relative GoF value is very high which is equal to 0.912. The standard error of convergence 0 value and CR value greater than 2 indicates that the model is consistent.

Table 6.3 Discriminant validity (Squared correlations < AVE) (Dimension 1)

Variable	Mean Communalities (AVE)
ULSE	0,666
LR	0,773
SA	0,685
SN	0,805
MesCont	0,560
MesInt	0,279
Sem	0,388

EmoSitu	0,246
Sec	0,297
PEU	0,713
PU	0,809
A	0,579
BI	0,782

Source: Created by Ahmet Yücel

Average Variance Extracted (AVE) is a criterion of convergent validity (Fornell and Larcker, 1981) and if its value is equal to 0.50, that means the latent variable can explain more than 50% of variance of its metrics in Table 6.3 (Gotz et al., 2009). The AVE value of ULSE, LR, SA, SN, MesCont, PEU, PU, A and BI exceed the 0.50 and indicate convergent validity for all constructs.

Table 6.4 Cross Loadings

	ULSE	LR	SA	SN	MesCont	MesInt	Sem	EmoSitu	Sec	PU	PEU	A	BI
ULSE1	0.792												
ULSE2	0.826												
ULSE3	0.797												
ULSE4	0.828												
ULSE5	0.839												
LR1		0.899											
LR2		0.865											
LR3		0.873											
SA1			0.852										
SA2			0.777										
SA3			0.852										
SN1				0.900									
SN2				0.899									
SN3				0.894									
MesCont1					0.767								
MesCont2					0.833								
MesCont3					0.799								
MesCont4					0.803								
MesCont5					0.848								

MesCont6	0.733								
MesCont7	0.721								
MesCont8	0.543								
MesCont9	0.732								
MesCont10	0.655								
MesInt1		0.573							
MesInt2		0.389							
MesInt3		0.103							
MesInt4		0.319							
MesInt5		0.896							
Sem1			0.722						
Sem2			0.945						
Sem3			0.343						
Sem4			-0.136						
EmoSitu1				0.395					
EmoSitu2				0.797					
EmoSitu3				0.380					
EmoSitu4				-0.037					
EmoSitu5				-0.542					
Sec1					0.802				
Sec2					0.695				
Sec3					0.114				
Sec4					0.451				
Sec5					0.493				
Sec6					0.442				
PU1						0.874			
PU2						0.914			
PU3						0.924			
PU4						0.885			
PEU1							0.857		
PEU2							0.907		
PEU3							0.900		
PEU4							0.695		
A1								0.906	
A2								0.575	
A3								0.604	
A4								0.895	
BI1									0.868
BI2									0.900
BI3									0.880
BI4									0.890

Source: Created by Ahmet Yücel

The generated PLS-SEM measurement model is seem to be compatible variables with latent variables cross loading as listed in Table 6.4. The most important factor in cross-loading is high load values of the respective measurement variable (≥0.70) that associated with the possession and related latent variables.

Table 6.5. Measurement change weight of model

Latent variable	Manifest variables	Outer weight	Outer weight (normalized)	Outer weight (Bootstrap)	Standard error	Critical ratio (CR)
ULSE	ULSE1	0.240		0.241	0.014	16.944
	ULSE2	0.231		0.232	0.016	14.752
	ULSE3	0.233		0.232	0.022	10.521
	ULSE4	0.276		0.275	0.019	14.376
	ULSE5	0.244		0.244	0.018	13.763
LR	LR1	0.405		0.403	0.020	19.819
	LR2	0.346		0.344	0.018	19.559
	LR3	0.386		0.388	0.017	22.855
SA	SA1	0.392		0.392	0.019	21.125
	SA2	0.360		0.357	0.021	16.766
	SA3	0.454		0.456	0.028	16.426
SN	SN1	0.388		0.388	0.011	35.518
	SN2	0.365		0.366	0.009	41.899
	SN3	0.361		0.360	0.009	38.267
MesCont	MesCont1	0.106		0.113	0.107	0.986
	MesCont2	0.162		0.141	0.088	1.845
	MesCont3	0.108		0.125	0.082	1.314
	MesCont4	0.133		0.131	0.091	1.465
	MesCont5	0.249		0.211	0.139	1.795
	MesCont6	0.062		0.075	0.084	0.742
	MesCont7	0.118		0.092	0.082	1.434
	MesCont8	-0.042		0.022	0.172	-0.244
	MesCont9	0.172		0.139	0.118	1.454
	MesCont10	0.222		0.186	0.175	1.270
MesInt	MesInt1	0.437		0.289	0.226	1.935
	MesInt2	0.023		0.180	0.212	0.110
	MesInt3	-0.382		0.041	0.419	-0.912
	MesInt4	0.144		0.145	0.227	0.637
	MesInt5	0.819		0.361	0.478	1.714
Sem	Sem1	0.331		0.325	0.215	1.538
	Sem2	0.782		0.591	0.336	2.327
	Sem3	-0.035		0.017	0.313	-0.110
	Sem4	-0.247		-0.108	0.332	-0.744
EmoSitu	EmoSitu1	-0.040		0.089	0.334	-0.120
	EmoSitu2	0.818		0.531	0.372	2.200
	EmoSitu3	0.083		0.108	0.318	0.261
	EmoSitu4	-0.075		-0.010	0.273	-0.274
	EmoSitu5	-0.607		-0.306	0.440	-1.381
Sec	Sec1	0.546		0.472	0.132	4.125
	Sec2	0.321		0.303	0.136	2.350
	Sec3	-0.199		-0.183	0.254	-0.783
	Sec4	0.194		0.202	0.159	1.220
	Sec5	0.272		0.220	0.177	1.542

	Sec6	0.317	0.296	0.184	1.722
PU	PU1	0.283	0.286	0.009	31.716
	PU2	0.286	0.286	0.007	38.450
	PU3	0.281	0.280	0.007	42.014
	PU4	0.261	0.260	0.008	31.008
PEU	PEU1	0.281	0.281	0.014	19.744
	PEU2	0.316	0.316	0.011	28.669
	PEU3	0.306	0.306	0.012	24.794
	PEU4	0.283	0.280	0.018	15.619
A	A1	0.391	0.388	0.016	24.829
	A2	0.263	0.262	0.022	11.724
	A3	0.267	0.263	0.022	12.366
	A4	0.372	0.375	0.016	23.765
BI	BI1	0.274	0.275	0.009	30.378
	BI2	0.297	0.295	0.009	33.911
	BI3	0.288	0.286	0.009	33.059
	BI4	0.271	0.273	0.009	29.309

Source: Created by Ahmet Yücel

Measurement change weight of the PLS-SEM model shows the contribution of each measure changes related to latent variables as listed in Table 6.5.

6.1. OTHER VARIABLES RELATED WITH PERCEIVED EASY OF USE (PEU)

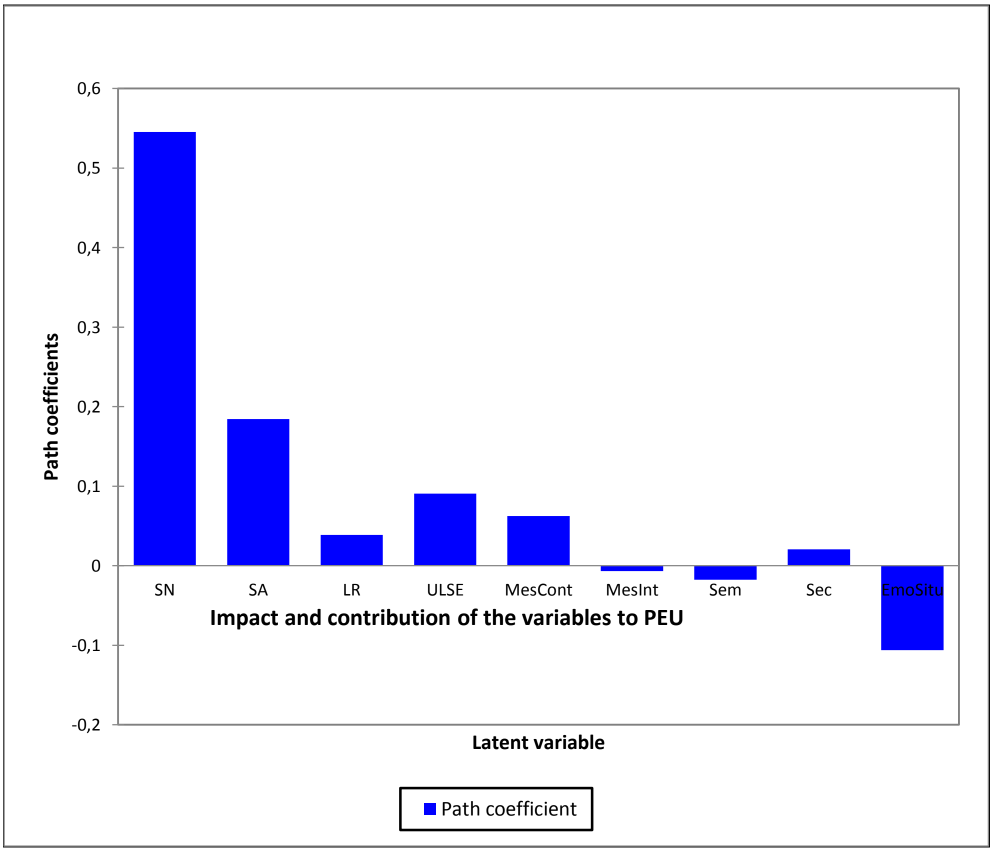
The standard error is under the 5%, which is equal to 0.038 and critical ratio is bigger than 2 which is 14.932; therefore, the R^2 value may lead us to be a model with moderate explanatory value as given in Table 6.6.

Table 6.6 Perceived Easy of Use (PEU)

R^2	F	Pr > F	R^2(Bootstrap)	Standard error	Critical ratio (CR)
0.564	49.766	0.000	0.581	0.038	14.932

Source: Created by Ahmet Yücel

Figure 6.1.Impact and contribution of the variables to Perceived Easy of Use



Source: Created by Ahmet Yücel

PEU depends on both the SN with the rate of 55 percentages, and SA with the rate of 18 percentages as given in Figure 6.1. MesInt, Sem, EmoSitu have effect in the opposite direction on PEU as listed in Table 6.7. This linear regression equation includes the factors related with PEU and their weights:

$$PEU = 0.091*ULSE + 0.039*LR + 0.184*SA + 0.545*SN + 0.062*MesCont - 0.007*MesInt - 0.018*Sem - 0.106*EmoSitu + 0.021*Sec \qquad \textbf{(6.1)}$$

Table 6.7 Path coefficients (PEU / 1)

Latent variable	Value	Standard error	t	Pr > |t|	f²
ULSE	0.091	0.046	1.987	0.048	0.011
LR	0.039	0.047	0.815	0.415	0.002
SA	0.184	0.051	3.583	0.000	0.037
SN	0.545	0.045	12.187	0.000	0.429
MesCont	0.062	0.057	1.090	0.276	0.003
MesInt	-0.007	0.043	-0.161	0.872	0.000
Sem	-0.018	0.052	-0.337	0.736	0.000
EmoSitu	-0.106	0.039	-2.729	0.007	0.022
Sec	0.021	0.038	0.542	0.588	0.001

Source: Created by Ahmet Yücel

6.2. OTHER VARIABLES RELATED WITH PERCEIVED USEFULNESS (PU)

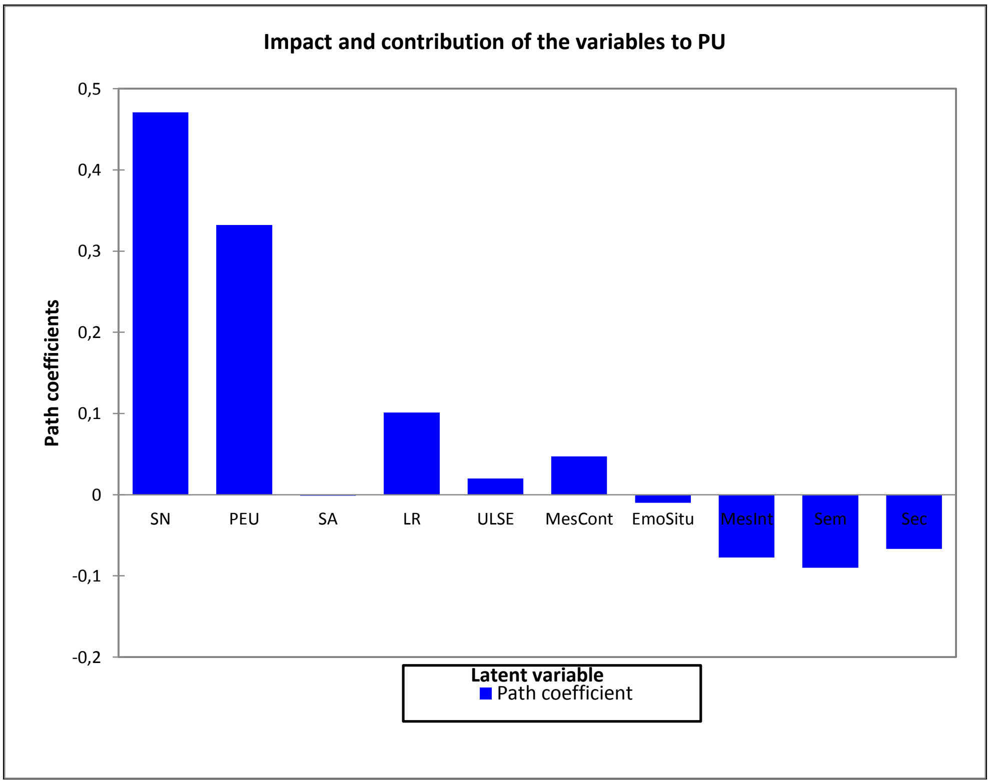
The standard error is under the 5%, which is equal to 0.028 and critical ratio is bigger than 2 which is 25.222; therefore, the R^2 value may lead us to be a model with high explanatory value because it is bigger than the 0.67 and according to Chin (1998) if the R^2 value is bigger than 0.67, then it can be said the model is strong as listed in Table 6.8.

Table 6.8 Perceived Usefulness (PU)

R²	F	Pr > F	R²(Bootstrap)	Standard error	Critical ratio (CR)
0.707	83.313	0.000	0.717	0.028	25.222

Source: Created by Ahmet Yücel

Figure 6.2. Impact and contribution of the variables to Perceived Usefulness



Source: Created by Ahmet Yücel

PU depends on the SN with the rate of 47 percentages, and with PEU the rate of 33 percentages as given in Figure 6.2. SA, MesInt, Sem, EmoSitu and Sec have an effect in the opposite direction on PU as listed in Table 6.9. This linear regression equation includes the factors related with PU and their weights

$$PU = 0.020*ULSE + 0.101*LR - 0.001*SA + 0.471*SN + 0.047*MesCont - 0.077*MesInt - 0.090*Sem - 0.010*EmoSitu - 0.067*Sec - 0.332*PEU \quad \textbf{(6.2)}$$

Table 6.9 Path coefficients (PU / 1)

Latent variable	Value	Standard error	t	Pr > |t|	f²
ULSE	0.020	0.038	0.528	0.598	0.001
LR	0.101	0.039	2.603	0.010	0.020
SA	-0.001	0.043	-0.034	0.973	0.000
SN	0.471	0.044	10.724	0.000	0.333
MesCont	0.047	0.047	1.002	0.317	0.003

MesInt	-0.077	0.035	-2.210	0.028	0.014
Sem	-0.090	0.043	-2.107	0.036	0.013
EmoSitu	-0.010	0.032	-0.316	0.752	0.000
Sec	-0.067	0.031	-2.139	0.033	0.013
PEU	0.332	0.044	7.523	0.000	0.164

Source: Created by Ahmet Yücel

6.3. OTHER VARIABLES RELATED WITH ATTITUDE (A)

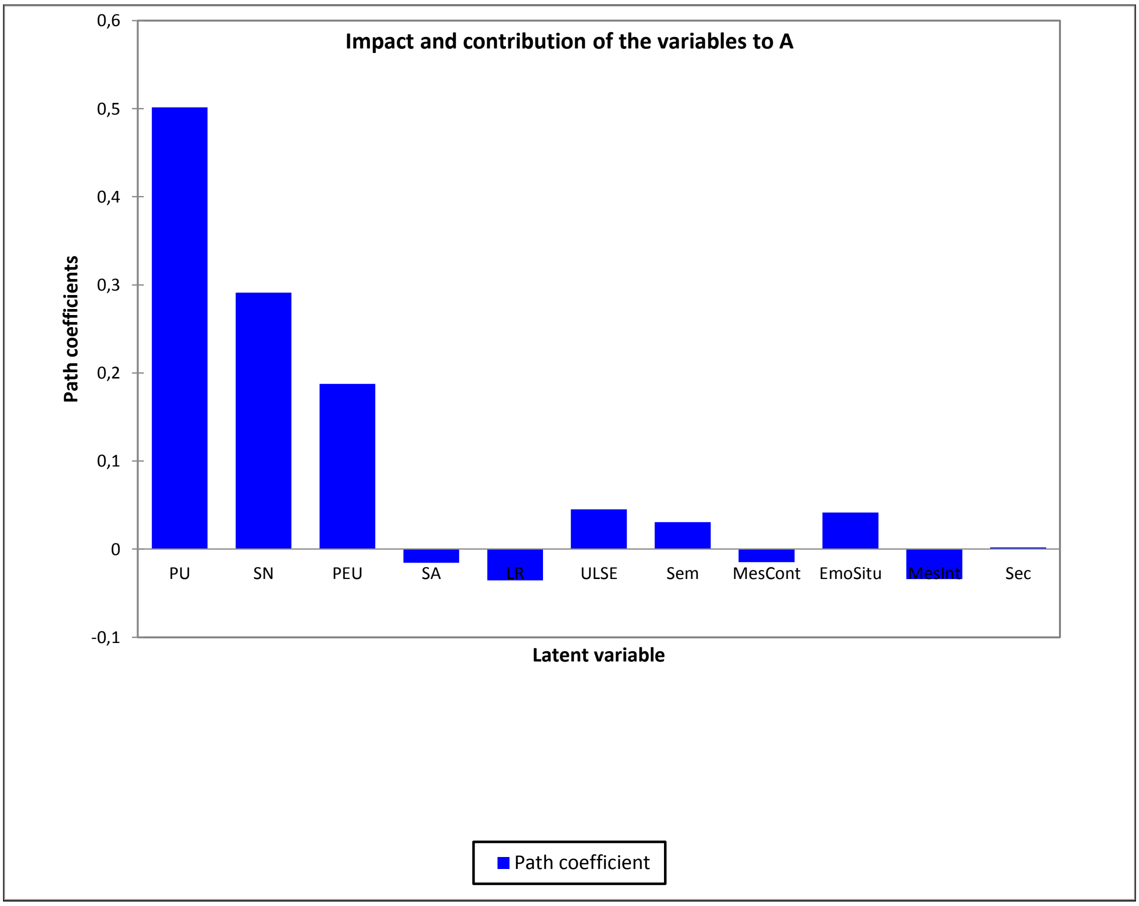
The standard error is under the 5%, which is equal to 0.025 and critical ratio is bigger than 2 which is 32.610; therefore, the R^2 value may lead us to be a model with high explanatory value and it is equal to 0.800 as given in Table 6.10.

Table 6.10. Attitude (A)

R^2	F	Pr > F	R^2(Bootstrap)	Standard error	Critical ratio (CR)
0.800	125.030	0.000	0.808	0.025	32.610

Source: Created by Ahmet Yücel

Figure 6.3. Impact and contribution of the variables to Attitude



Source: Created by Ahmet Yücel

Attitude depends on the PU with the rate of 50 percentages, and with SN the rate is 29 percentages as shown in Figure 6.3. LR, SA, MesCont and MesInt have an effect in the opposite direction on Attitude in Table 6.11. This linear regression equation includes the factors related with Attitude and its weights:

$$A = 0.045*ULSE - 0.035*LR - 0.015*SA + 0.291*SN - 0.015*MesCont - 0.034*MesInt + 0.031*Sem + 0.041*EmoSitu + 0.002*Sec + 0.188*PEU + 0.502*PU \quad \textbf{(6.3)}$$

Table 6.11 Path coefficients (A / 1)

Latent variable	Value	Standard error	t	Pr > |t|	f²
ULSE	0.045	0.031	1.450	0.148	0.006
LR	-0.035	0.032	-1.092	0.276	0.003
SA	-0.015	0.036	-0.430	0.667	0.001
SN	0.291	0.042	6.941	0.000	0.140
MesCont	-0.015	0.039	-0.373	0.709	0.000
MesInt	-0.034	0.029	-1.163	0.246	0.004
Sem	0.031	0.036	0.858	0.391	0.002
EmoSitu	0.041	0.027	1.556	0.121	0.007
Sec	0.002	0.026	0.075	0.940	0.000
PEU	0.188	0.039	4.762	0.000	0.066
PU	0.502	0.045	11.256	0.000	0.368

Source: Created by Ahmet Yücel

6.4. OTHER VARIABLES RELATED WITH BEHAVIORAL INTENTION (BI)

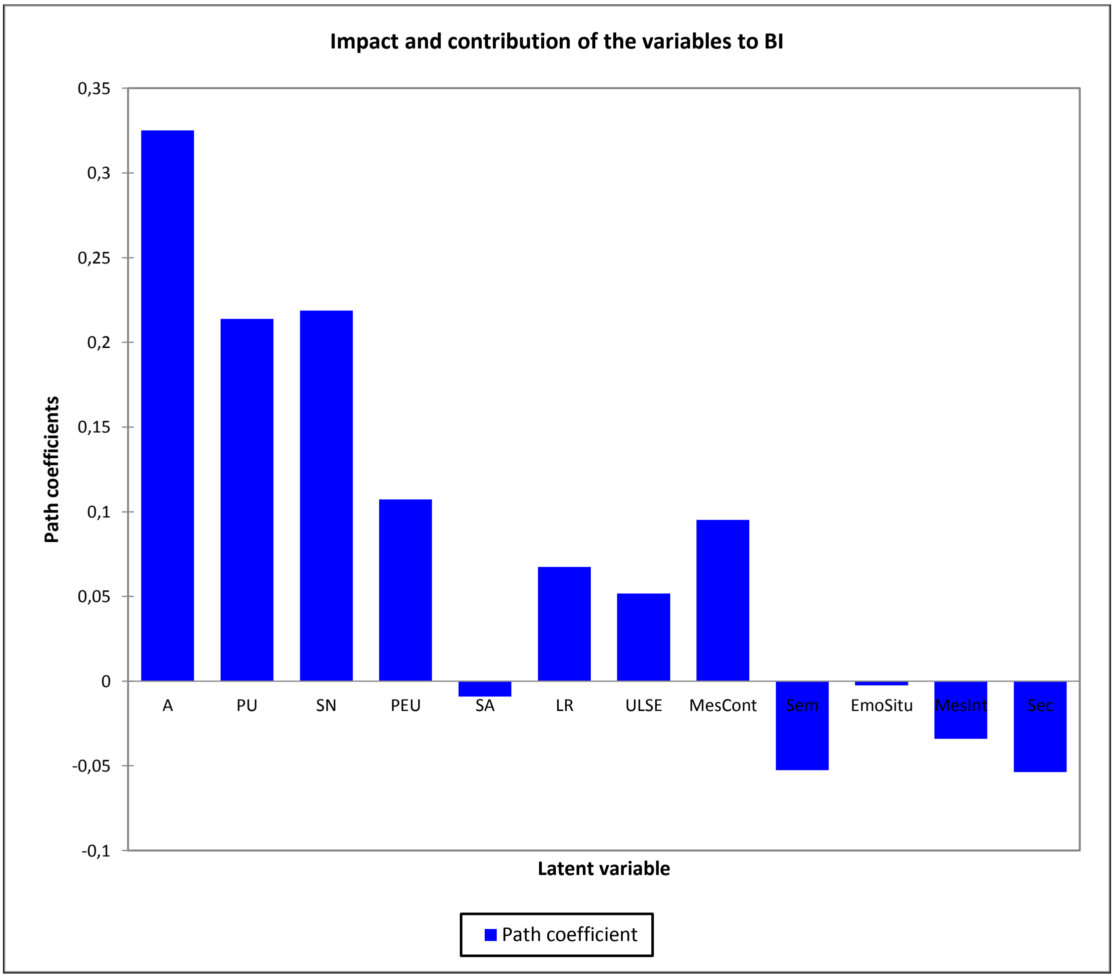
The standard error is under the 5%, which is equal to 0.023 and critical ratio is bigger than 2 which is 33.358; thus, R^2 value (0.756) may lead us to be a model with high explanatory value as listed in Table 6.12.

Table 6.12 Behavioural Intention(BI)

R²	F	Pr > F	R²(Bootstrap)	Standard error	Critical ratio (CR)
0.756	88.647	0.000	0.769	0.023	33.358

Source: Created by Ahmet Yücel

Figure 6.4 Impact and contribution of the variables to Behavioural Intention



Source: Created by Ahmet Yücel

BI depends on the Attitude on the rate of 33 percentages, and with SN on the rate of 22 percentages and with PU on the rate of 21%. SA, MesInt, Sem, EmoSitu and Sec have an effect in the opposite direction on BI as shown in Figure 6.4. , and listed in Table 6.13. This linear regression equation includes the factors related with BI and its weights:

$$BI = 0.052*ULSE + 0.067*LR - 0.009*SA + 0.219*SN - 0.095*MesCont - 0.034*MesInt - 0.053*Sem - 0.002*EmoSitu - 0.054*Sec + 0.107*PEU + 0.214*PU + 0.325*A \qquad \textbf{(6.4)}$$

Table 6.13 Path coefficients (BI / 1):

Latent variable	Value	Standard error	t	Pr > |t|	f²
ULSE	0.052	0.035	1.493	0.136	0.006
LR	0.067	0.036	1.871	0.062	0.010
SA	-0.009	0.039	-0.230	0.818	0.000
SN	0.219	0.050	4.417	0.000	0.057
MesCont	0.095	0.043	2.206	0.028	0.014
MesInt	-0.034	0.032	-1.053	0.293	0.003
Sem	-0.053	0.039	-1.337	0.182	0.005
EmoSitu	-0.002	0.030	-0.083	0.934	0.000
Sec	-0.054	0.029	-1.871	0.062	0.010
PEU	0.107	0.045	2.384	0.018	0.017
PU	0.214	0.058	3.710	0.000	0.040
A	0.325	0.060	5.454	0.000	0.087

Source: Created by Ahmet Yücel

6.5. SECOND ITERATION OF THE PLS-SEM MODELLING PROCESS

Cross loading values are shown in Table 6.14 and almost all of the values are clustered around 0.80 value. Then also cross loading values have been developed rather than the initial value in Table 6.4.

Table 6.14 Cross Loadings

	ULSE	LR	SA	SN	MesCont	MesInt	PU	A	BI	PEU	EmoSitu	Sec	Sem
ULSE1	0,792												
ULSE2	0,826												
ULSE3	0,797												
ULSE4	0,828												
ULSE5	0,839												
LR1		0,899											
LR2		0,865											
LR3		0,873											
SA1			0,852										
SA2			0,777										
SA3			0,852										

SN1	0,900									
SN2	0,899									
SN3	0,894									
MesCont1		0,767								
MesCont2		0,833								
MesCont3		0,799								
MesCont4		0,803								
MesCont5		0,847								
MesCont6		0,733								
MesCont7		0,721								
MesCont8		0,543								
MesCont9		0,732								
MesCont10		0,655								
MesInt1			0,574							
MesInt2			0,391							
MesInt3			0,105							
MesInt4			0,320							
MesInt5			0,896							
PU1				0,873						
PU2				0,914						
PU3				0,924						
PU4				0,885						
A1					0,906					
A2					0,570					
A3					0,611					
A4					0,893					
BI1						0,868				
BI2						0,900				
BI3						0,880				
BI4						0,890				
PEU1							0,856			
PEU2							0,905			
PEU3							0,900			
PEU4							0,698			
EmoSitu1								0,475		
EmoSitu2								0,996		
EmoSitu3								0,530		
Sec1									0,888	
Sec2									0,743	
Sec4									0,558	
SEM1										0,778
SEM2										0,965
SEM3										0,428

Source: Created by Ahmet Yücel

It is observed that different from the first iteration, some latent variables are removed because of their lower cross loading values. For example in the first iteration, semantic of message dimension has 4 latent variables. By removing Sem4 which has negative loading value (-0.136), cross loadings of other semantic variables are increased. Similarly, same operation is done for Emotional Situation and Security variables. For Emotional Situation variable, EmoSitu4 and EmoSitu5 variables which have negative cross loading values are removed. For Security, Sec3 and Sec6 are also removed.

6.5.1. Composite Reliability and Validity Analysis

If Table 6.15 is compared with Table 6.1, it can be said that Chronbach's alpha values are unchanged after the second iteration as listed in Table 6.15.

Table 6.15 Composite reliability

Latent variable	Dimensions	Cronbach's alpha	D.G. rho (PCA)
ULSE	5	0,875	0,909
LR	3	0,853	0,911
SA	3	0,771	0,868
SN	3	0,879	0,926
MesCont	10	0,919	0,933
MesInt	5	0,768	0,845
EmoSitu	3	0,703	0,835
Sec	3	0,620	0,798
Sem	3	0,731	0,848
PEU	4	0,861	0,908
PU	4	0,921	0,944
A	4		
BI	4	0,907	0,935

Source: Created by Ahmet Yücel

6.5.2. Application of Explotary Factor Analysis

AVE values are almost bigger than 0.50 that indicates convergent validity for constructs except MesInt variable as listed in Table 6.16.

Table 6.16 Discriminant validity (Squared correlations < AVE) (Dimension 1)

Variable	Mean Communalities (AVE)
ULSE	0,666
LR	0,773
SA	0,685
SN	0,805
MesCont	0,560
MesInt	0,280
Sem	0,500
EmoSitu	0,551
Sec	0,573
PEU	0,712
PU	0,809
A	0,579
BI	0,782

Source: Created by Ahmet Yücel

6.5.3. PLS-SEM Model for Control Group

GoF value is enhanced by removing the variables which have lower cross loading values between 0,626 and 0,661. CR values are greater that 2 and standard error of convergence 0 value means the model is consistent as given in Table 6.17.

Table 6.17 Goodness of fit index (1):

	GoF	GoF (Bootstrap)	Standard error	Critical ratio (CR)
Absolute	0,661	0,663	0,026	25,421
Relative	0,929	0,910	0,025	37,502
Outer model	0,964	0,959	0,023	41,854
Inner model	0,963	0,949	0,007	128,662

Source: Created by Ahmet Yücel

Measurement change weight of the PLS-SEM model shows the contribution of each measure changes related to latent variables as shown in Table 6.18.

Table 6.18 Measurement change weight of model

Latent variable	Manifest variables	Outer weight	Outer weight (normalized)	Outer weight (Bootstrap)	Standard error	Critical ratio (CR)
ULSE	ULSE1	0,240		0,239	0,017	14,253
	ULSE2	0,231		0,230	0,015	14,901
	ULSE3	0,233		0,235	0,021	11,001
	ULSE4	0,276		0,274	0,022	12,330
	ULSE5	0,244		0,246	0,017	14,329
LR	LR1	0,405		0,406	0,025	16,472
	LR2	0,346		0,348	0,019	18,128
	LR3	0,386		0,383	0,018	22,015
SA	SA1	0,392		0,392	0,022	17,957
	SA2	0,359		0,356	0,026	14,006
	SA3	0,454		0,454	0,027	16,868
SN	SN1	0,388		0,387	0,011	35,797
	SN2	0,365		0,367	0,010	36,396
	SN3	0,361		0,360	0,011	33,101
MesCont	MesCont1	0,106		0,096	0,120	0,884
	MesCont2	0,163		0,163	0,084	1,938
	MesCont3	0,108		0,112	0,084	1,286
	MesCont4	0,133		0,132	0,078	1,694
	MesCont5	0,249		0,230	0,115	2,172

	MesCont6	0,062	0,057	0,116	0,533
	MesCont7	0,117	0,102	0,092	1,281
	MesCont8	-0,042	-0,032	0,180	-0,233
	MesCont9	0,172	0,160	0,124	1,385
	MesCont10	0,222	0,199	0,113	1,969
MesInt	MesInt1	0,437	0,300	0,240	1,820
	MesInt2	0,025	0,161	0,208	0,120
	MesInt3	-0,381	-0,027	0,402	-0,948
	MesInt4	0,144	0,176	0,223	0,644
	MesInt5	0,819	0,406	0,461	1,774
Sem	Sem1	0,333	0,309	0,247	1,350
	Sem2	0,784	0,665	0,337	2,327
	Sem3	-0,035	-0,019	0,428	-0,083
EmoSitu	EmoSitu1	-0,048	0,092	0,370	-0,130
	EmoSitu2	0,973	0,709	0,423	2,301
	EmoSitu3	0,101	0,169	0,343	0,295
Sec	Sec1	0,655	0,599	0,192	3,411
	Sec2	0,386	0,386	0,175	2,202
	Sec4	0,235	0,243	0,233	1,007
PU	PU1	0,282	0,284	0,011	26,608
	PU2	0,287	0,285	0,007	39,205
	PU3	0,281	0,280	0,006	43,367
	PU4	0,262	0,263	0,008	31,179
PEU	PEU1	0,282	0,281	0,013	22,156
	PEU2	0,311	0,311	0,011	29,016
	PEU3	0,306	0,307	0,013	23,458
	PEU4	0,289	0,287	0,019	15,274
A	A1	0,393	0,392	0,016	24,523
	A2	0,260	0,259	0,024	10,663
	A3	0,276	0,270	0,024	11,345
	A4	0,367	0,371	0,017	21,518
BI	BI1	0,274	0,275	0,008	34,427
	BI2	0,296	0,294	0,010	30,132
	BI3	0,290	0,288	0,009	32,454
	BI4	0,271	0,273	0,009	30,002

Source: Created by Ahmet Yücel

6.5.3.1. Other Variables Related With Perceived Easy Of Use (PEU)

The standard error is under the 5% and critical ratio is bigger than 2, which mean R^2 leads us to be a model with moderate explanatory value as given in Table 6.19.

Table 6.19 Perceived Easy of Use (PEU)

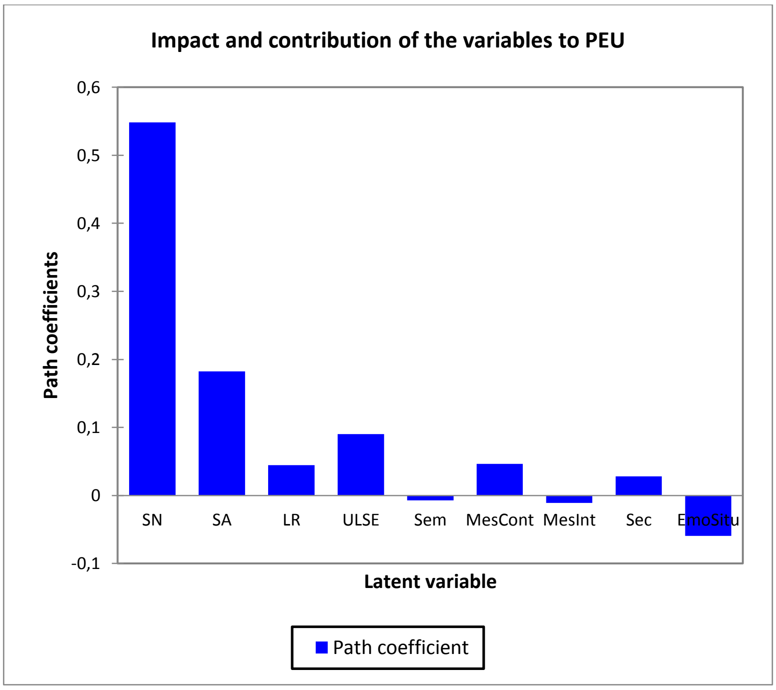
R^2	F	Pr > F	R^2(Bootstrap)	Standard error	Critical ratio (CR)
0,558	48,505	0,000	0,579	0,039	14,184

Source: Created by Ahmet Yücel

PEU depends on SN on the rate of 0,548 and with SA on the rate of 0,18 (Figure 6.5). This linear regression equation includes the factors related with PEU weights in Eq.6.5:

PEU = 9,04176665093492E-02*ULSE+4,46903406063703E-02*LR+0,182621840140416*SA+0,548151435473353*SN+4,66357083618973E-02*MesCont-1,08802375898499E-02*MesInt-5,92356974790621E-02*EmoSitu+2,79748842900976E-02*Sec-7,33967317594897E-03*Sem **(6.5)**

Figure 6.5 Impact and contribution of the variables to Perceived Easy of Use



Source: Created by Ahmet Yücel

Table 6.20 Path coefficients (PEU / 1)

Latent variable	Value	Standard error	t	Pr > |t|	f²
ULSE	0,090	0,046	1,963	0,050	0,011
LR	0,045	0,048	0,940	0,348	0,003
SA	0,183	0,052	3,521	0,000	0,036
SN	0,548	0,045	12,206	0,000	0,431
MesCont	0,047	0,063	0,742	0,459	0,002
MesInt	-0,011	0,044	-0,248	0,805	0,000
EmoSitu	-0,059	0,044	-1,347	0,179	0,005
Sec	0,028	0,039	0,718	0,473	0,001
Sem	-0,007	0,058	-0,126	0,900	0,000

Source: Created by Ahmet Yücel

6.5.3.2. Other Variables Related With Perceived Usefulness (PU)

The standard error is equal to 0.028 which is under the 5% and critical ratio is equal to 25.476 which are bigger than 2, which mean R^2 leads us to be a model with moderate explanatory value as shown in Table 6.21.

Table 6.21 Perceived Usefulness (PU)

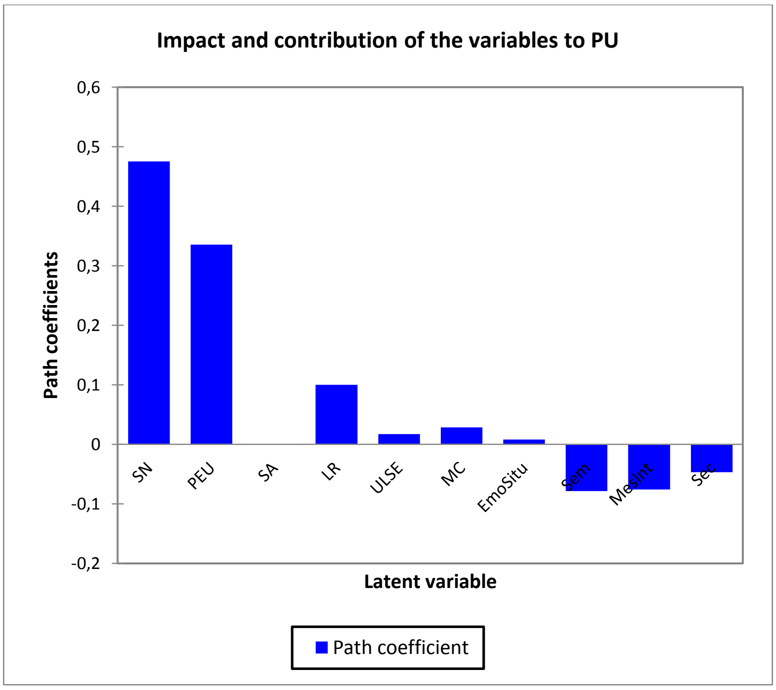
R^2	F	Pr > F	R^2(Bootstrap)	Standard error	Critical ratio (CR)
0,703	81,755	0,000	0,716	0,028	25,476

Source: Created by Ahmet Yücel

PU depends on SN with the rate of 0.475 and PEU with the rate of 0.336 as shown in Figure 6.6. This linear regression equation includes the factors related with PEU weights in Eq.6.6:

PU = 1,74452442974149E-02*ULSE+9,99527372728807E-02*LR-2,73161536934581E-04*SA+0,475255761469663*SN+2,89165369324889E-02*MesCont-7,53747920509629E-02*MesInt+8,05576783782816E-03*EmoSitu-4,67578139441885E-02*Sec-7,84742607877156E-02*Sem+0,335642308538833*PEU **(6.6)**

Figure 6.6 Impact and contribution of the variables to Perceived Usefulness



Source: Created by Ahmet Yücel

Table 6.22Path coefficients(PU/1)

Latent variable	Value	Standard error	t	Pr > |t|	f²
ULSE	0,017	0,038	0,459	0,646	0,001
LR	0,100	0,039	2,558	0,011	0,019
SA	0,000	0,043	-0,006	0,995	0,000
SN	0,475	0,044	10,784	0,000	0,337
MesCont	0,029	0,052	0,560	0,576	0,001
MesInt	-0,075	0,036	-2,091	0,037	0,013
EmoSitu	0,008	0,036	0,223	0,824	0,000
Sec	-0,047	0,032	-1,461	0,145	0,006
Sem	-0,078	0,048	-1,644	0,101	0,008
PEU	0,336	0,044	7,610	0,000	0,168

Source: Created by Ahmet Yücel

6.5.3.3. Relations with Attitude (A) and Other Variables

The standard error is equal to 0.023 which is under the 5% and critical ratio is equal to 35,234 which are bigger than 2, which mean R^2 leads us to be a model with moderate explanatory value as listed in Table 6.22.

Table 6.23Attitude (A)

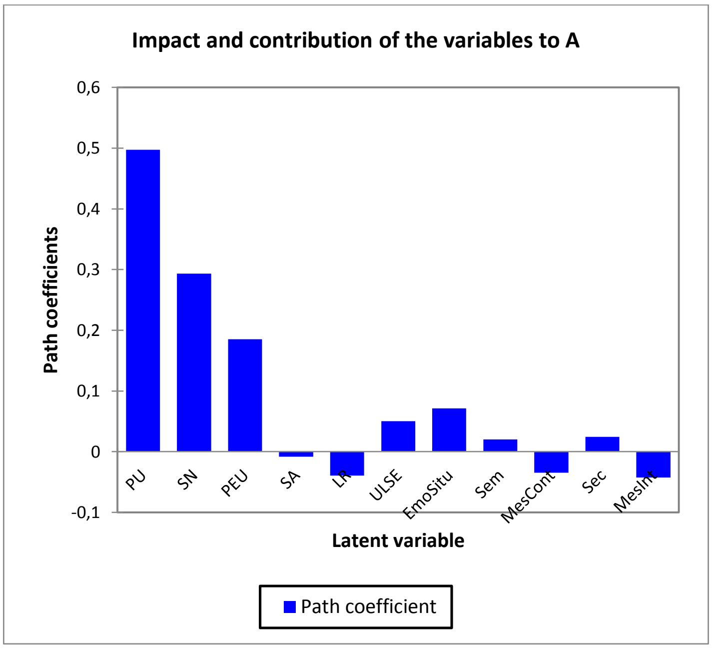
R^2	F	Pr > F	R^2(Bootstrap)	Standard error	Critical ratio (CR)
0,800	125,395	0,000	0,806	0,023	35,234

Source: Created by Ahmet Yücel

Attitude depends on PU with the rate of 0,497 and with SN the rate of 0,293 as shown in Figure 6.7. This linear regression equation includes the factors related with PEU weights in Eq.6.7:

A = 5,05469051702378E-02*ULSE-3,94125430984644E-02*LR-8,42444414751116E-03*SA+0,293448394029228*SN-3,44995818604028E-02*MesCont-4,25369524683719E-02*MesInt+0,071211204105424*EmoSitu+0,02427333923713*Sec+2,02175641961592E-02*Sem+0,185202286597086*PEU+0,497410362438144*PU **(6.7)**

Figure 6.7 Impact and contribution of the variables to Attitude



Source: Created by Ahmet Yücel

Table 6.24 Path coefficients (A / 1)

Latent variable	Value	Standard error	t	Pr > |t|	f²
ULSE	0,051	0,031	1,619	0,106	0,008
LR	-0,039	0,032	-1,217	0,225	0,004
SA	-0,008	0,036	-0,237	0,813	0,000
SN	0,293	0,042	7,011	0,000	0,143
MesCont	-0,034	0,042	-0,813	0,417	0,002
MesInt	-0,043	0,030	-1,428	0,154	0,006
EmoSitu	0,071	0,030	2,396	0,017	0,017
Sec	0,024	0,026	0,921	0,358	0,002
Sem	0,020	0,039	0,514	0,608	0,001
PEU	0,185	0,039	4,731	0,000	0,065
PU	0,497	0,044	11,249	0,000	0,368

Source: Created by Ahmet Yücel

6.5.3.4. Relationships between Behavioural Intention (BI) and Other Variables

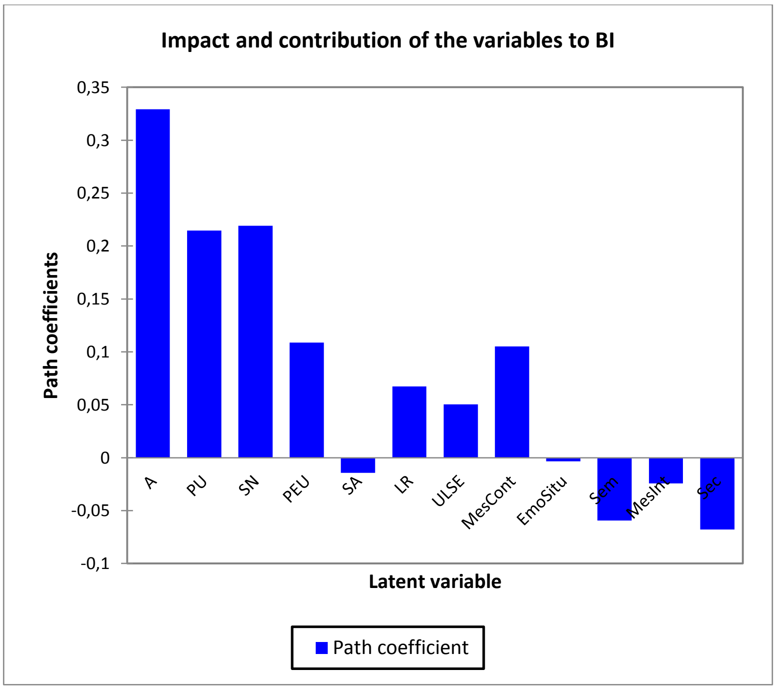
The standard error is equal to 0.026 which is under the 5% and critical ratio is equal to 29,503 which are bigger than 2, which R^2 leads us to be a model with moderate explanatory value as listed in Table 6.25.

Table 6.25 Behavioural Intention(BI)

R^2	F	Pr > F	R^2(Bootstrap)	Standard error	Critical ratio (CR)
0,758	89,468	0,000	0,768	0,026	29,503

Source: Created by Ahmet Yücel

Figure 6.8 Impact and contribution of the variables to Behavioural Intention



Source: Created by Ahmet Yücel

Path coefficients of BI are listed in Table 6.26, so, mostly related latent variables are 0,33*attitude, 0,22* PU, 0,11* PUE, 0,22* SN, 0,07* LR, 0,05 ULSE.

Table 6.26 Path coefficients (BI / 1):

Latent variable	Value	Standard error	T	Pr > |t|	f²
ULSE	0,050	0,035	1,454	0,147	0,006
LR	0,067	0,036	1,879	0,061	0,010
SA	-0,014	0,039	-0,363	0,717	0,000
SN	0,219	0,049	4,437	0,000	0,057
MesCont	0,105	0,047	2,245	0,025	0,015
MesInt	-0,024	0,033	-0,734	0,463	0,002
EmoSitu	-0,004	0,033	-0,106	0,915	0,000
Sec	-0,068	0,029	-2,331	0,020	0,016
Sem	-0,059	0,043	-1,368	0,172	0,005
PEU	0,109	0,045	2,439	0,015	0,017
PU	0,215	0,057	3,764	0,000	0,041
A	0,329	0,059	5,538	0,000	0,089

Source: Created by Ahmet Yücel

7. DISCUSSION

This thesis has provided an impression about the determinants that influence university students' intention to use Technology Acceptance. The research has shown that how latent variables change with Behavioural Intention, Attitude, Perceived Usefulness, and Perceived Ease of Use with CMC's variables.

When we consider latent variables of the Behavioural Intention such as $R^2 = 0.758$ represents high explanatory value.

There is a relationship between Behavioural Intention and Ubiquitous Learning Self Efficacy for Ubiquitous Learning Environment. Behavioural Intention depends on the Ubiquitous Learning Self Efficacy with 5 percent. This ratio is an accepted ratio for students who have Ubiquitous Learning Self Efficacy.

Behavioural Intention has relation with Learning Relevance about %6.7. It shows us learning experiences that are either directly applicable to the personal aspirations, interests, or cultural experiences of students (personal relevance) or that are connected in some way to real-world issues, problems, and contexts.

Behavioural Intention depends on System Accessibility with %1.4. The ratio between them is very low. University students ability or authority to interact with a computer system, resulting in a flow of information; a means by which one may input or output data from an information *Source* looks weak. In our study we observed System Accessibility has negative relevance with Behavioural Intention. This situation is expected and it validates the work we do.

There is a relationship between Behavioural Intention and Subjective Norm that is %21. Universty students perceived social pressure is very high for Ubiquitous Learning Environment. The direct effect of subjective norm on behavioral intent is difficult to isolate from the indirect effects from attitude, (Davis, 1989) treatment of the theory of reasoned action, the technology acceptance model (TAM) focuses on attitude as a determinant of behavioral intent (Ajzen & Fishbein., 1975) (Davis, 1989).

Behavioural Intention depends on Message Contens with 10.5 percent. It sows us the sum of the freshness, readability, relevancy, and usefulness of the information presented, and the manner in which it presented as possitive for studens who use Ubiquitous Learning Environment.

The correlation between Behavioural Intention and Message Interaction has 2.4 percent. Behavioural Intention affect negatively to Message Interaction.

Behavioural Intention depends on Emotional Situations with 0.004. Behavioural Intention has negative relevance with Emotional Situations. We have observed that the weakest relationship between Behavioural Intention is Emotional Situations for Ubiquitous Learning Environment.

Behavioural Intention depends on Security with the percent of 6.4. (Suganthi & Balachandran, 2001) (Daniel, 1999), (O' Connel, 1996) discovered that security concern in an important affecting acceptance and adoption of new technology or innovation. These are supported in our study too.

The relationship between Behavioural Intention and Semantic of Message is 5.9 percent. This supports the literature as well.

Behavioural Intention depends on Perceived Ease of Use with 10.9 percent. The proposed relationship between perceived usefulness and behavioral intention is based on the theoretical argument by (Wang, et al., 2003), (Guriting & Oly Ndubisi, 2006). (Wang, et al., 2003)found that perceived usefulness has a positive effect on behavioral intention. In other words, perceived usefulness has a significant relation on behavioral intention.

The correlation between Behavioural Intention and Perceived Usefulness is 21.5 percent. (Guriting & Oly Ndubisi, 2006)found that perceived usefulness and perceived ease of use significantly determine behavioral intention.

There is a significant interaction between Behavioural Intention and Attitude. Behavioural Intention depends on Attitude with 32.9 percent. The findings of the study have shown that students had highly positive attitudes toward Behavioural Intention of Technology acceptance.

Students' attitudes toward mobile learning technologies and their perceptions about the use of technologies play an important role for Ubiquitous Learning Environment. In our thesis the standard error is equal to 0.023 which is under the 5% and critical ratio is equal to 35.234 which are bigger than 2, which mean R^2 leads us to be a model with moderate explanatory value.

Attitude depends on Ubiquitous Learning Self Efficacy with 5.1 percent for Ubiquitous Learning Environment. It shows that the students have expected Self Efficacy towards attitude. Students had no problem with the use of the functionalities in the mobile devices such as downloading online materials, as well as reading and entering information for Ubiquitous Learning Environment.

Attitude depends on Learning Relevance with 3.9 percent. There has negative relevance between Attitude and Learning Relevance.

The more favorable the attitude and subjective norm, and the greater the perceived control, the stronger should be the student's intention to perform technology acceptance the behavior in question. That's why the correlation between attitude and Subjective Norm is 29.3 percent.

There has negative relevance between Attitude and Message Contens with 3.4 percent. It shows us atttitudes could be changed more easily by presenting message arguments that matched these different functions.

Attitude depends on Message Interaction with 4.3 percent. There has negative relevance between them. The use of technology in the message interaction attitude of students has an important role.

The correlation between Attitude and Emotional Situations is %7.1. Emotional situation is a potentially important construct in using technology attitude relationships.

Attitude depends on Security with the percent of 2.4. many researchers have called for information security culture (ISC) to be embedded into organizations to positively influence human attitude towards protecting organizational information (Da Veiga & Eloff, 2010) (Siponen, 2000).

Attitude measures were based on the semantic differential scales. The relationship Attitude and Semantic is 2 percent.

Attitude depends on Perceived Ease of Use with 18.5 percent. The study theorizes that Perceived Ease of Use directly affects attitude of Technology acceptance for Ubiquitous Learning Environment.

Students attitude are significantly and positively related to Perceived Usefulness with a 49.7 percent. PU is such an important antecedent of IT adoption is that in many cases a new IT is adopted primarily because it is instrumental in achieving tasks that are not inherent in the use of the IT itself. PU deals with user assessments of these aspects of a new IT (Davis, et al., 1992).
Students' Perceived Usefulness toward mobile learning technologies and their perceptions about the use of technologies play an important role for Ubiquitous Learning Environment. In our thesis the standard error is equal to 0.028 which is under the 5% and critical ratio is equal to 25.476 which are bigger than 2, which mean R^2 leads us to be a model with moderate explanatory value.

There is a relationship between Perceived Usefulness and Ubiquitous Learning Self Efficacy for Ubiquitous Learning Environment. Perceived Usefulness depends on the Ubiquitous Learning Self Efficacy with 1.7 percent.

Perceived Usefulness has relation with Learning Relevance about 10 percent. Student's usage decisions were more significantly influenced by their perception of usefulness of learning relevance.

There is no a relationship between Perceived Usefulness and System Accessibility. Howewer The correlation between Perceived Usefulness and Subjective Norm is 47.5 percent. There is a significant interaction between these values.

Perceived Usefulness depends on Message Contens with 2.9 percent whereas Perceived Usefulness depends on Message Interaction with 7.5 percent. Althought Message Contens positively affect Perceived Usefulness, Message Interaction negatively affect Perceived Usefulness.

Perceived Usefulness depends on Emotional Situations with 0.08 percent. Students' academic emotions, that is, their emotions relating to learning, instruction, and achievement in academic settings associate with attending class, studying, and taking tests and exams.

There has negative relevance between Perceived Usefulness and security with 4.7 percent. Perceived Usefulness negatively depends on semantic with 7.8

The correlation between Perceived Usefulness and Perceived Ease of Use has with 33.6 percent. According to TAM (Davis, 1989), PEOU and PU are important perceptions determining technology adoption. TAM identified two such beliefs: perceived usefulness (PU) and perceived ease of use (PEOU). The former is “the degree to which a person believes that using a particular system would enhance his or her job performance” (Davis, 1989); while the latter is “the degree to which a person believes that using a particular system would be free of effort” .

The influence of Perceived Ease of Use on Perceived Usefulness TAM posits a strong direct link between PEOU and PU. If all other factors are equal, users are likely to consider a technology to be more useful if they perceive that it is easier to use ((Brown & Licker, 2003).

Students’ Perceived Ease of Use toward mobile learning technologies and their perceptions about the use of technologies also play an important role for Ubiquitous Learning Environment. In our thesis the standard error is equal to 0.039 which is under the 5% and critical ratio is equal to 14.184 which are bigger than 2, which mean R^2 leads us to be a model with moderate explanatory value.

Perceived Ease of Use depends on Ubiquitous Learning Self Efficacy with 9.1 percent for Ubiquitous Learning Environment.

There has relevance between Perceived Ease of Use and Learning Relevance with 4.5 percent. In our study we have seen positive effect on Learning Relevance.

Perceived Ease of Use depends on System Accessibility with 18.3 percent.

There is a significant influence Perceived Ease of Use on the Subjective Norm that is 54.8 percent. In terms of subjective norm, it is necessary for universities to put more emphasis on Ubiquitous learning by offering a greater variety of mobile learning courses and advertising the benefits of mobile learning to attract students.

8. CONCLUSION

This study intends to explore the level of Technology Acceptance Model for u-learning among BAU Engineering students. Organized configuration of this model has been extended utilizing Computer Mediated Communication scale. Reliability as an indicator of reliability coefficient is calculated and it is high. Cronbach's alpha coefficient validaded the study is a positive way. These values demonstrate that the model is a good and is highly reliable. The relationship between Perceived Easy of Use, Perceived Usefulness, Attitude variables and Behavioral Intention has increased extremely high. In this study, CMC and TAM is combined and applied to university students in terms of education. As an affirmation we can apply this survey more scholastics in various high schools in Turkey and everywhere throughout the world. Additionally we can change our dimensions that may influence the issue.

REFERENCES

Ajzen, I., 1991. The theory of planned behavior. Organizational behavior and human decision processes , 50(2), pp. 179-211.

Ajzen, I. & Fishbein., M., 1975. Belief, attitude, intention and behavior: An introduction to theory and research. s.l.:s.n.

Ajzen, I. & Fishbein, M., 1972. Attitudes and normative beliefs as factors influencing behavioral intentions. Journal of personality and social psychology, 12(1).

Ajzen, I. & Fishbein, M., 1980. Understanding attitudes and predicting social behavior. Englewood Cliffs, NJ: Prentice-Hall.

Akaike, H., 1987. Factor analysis and AIC. Psychometrika, 52(3), pp. 317-332.

Alsheail, A., 2010. Teaching English as a Second/Foreign Language in a Ubiquitous Learning Environment: A Guide for ESL/EFL Instructors, s.l.: s.n.

Alwin, D. F. & Hauser, R. M., 1975. The decomposition of effects in path analysis. American sociological review, pp. 37-47.

Anderson, J. C. & Gerbing, D. W., 1988. Structural equation modeling in practice: A review and recommended two-step approach.. Psychological bulletin, 103(3), p. 411.

Bagozzi, R. & Fornell, C., 1982. Theorical Concepts,measurement and meaning. s.l., A second generation of multivariate analysis.

Balapumi, R. & Aitken, A., 2012. Concepts and factors influencing independent learning in IS higher education. s.l., ACIS 2012: Location, location, location: Proceedings of the 23rd Australasian Conference on Information Systems 2012.

Bal, C., Doğan, N. & Doğan, İ., 2000. Path Analizi ve Bir Uygulama. s.l., Biyoistatistik Kongresi Bildirileri.

Bollen, K. A., 1989. Structural Equation with Latent Variables. New York: Wiley International Publisher.

Brown, I. & Licker, P., 2003. Exploring differences in internet adoption and usage between historically advantaged and disadvantaged groups in South Africa. Journal of Global Information Technology Management, 6(4), pp. 6-26.

Brown, T. A., 2006. Confirmatory factor analysis for applied researchers. s.l.:s.n.

Byrne, B. M., 2013. Structural equation modeling with AMOS: Basic concepts, applications, and programming. s.l.:Routledge.

Carmona, M., Jones, V., Jo, J. H. & Guiramand, C., 2009. A Ubiquitous Learning Environment with an Online Tracking System which monitors navigation and usage. Proceedings of the 8th International Conference on Applications and Principles of Information Science.

Chu, H.-C., Hwang, G.-J. & Tsai, C.-C., 2010. A knowledge engineering approach to developing mindtools for context-aware ubiquitous learning. Computers & Education , 54(1), pp. 289-297.

Çömlekçi, N., 1998. Temel İstatistik İlke ve Teknikleri. s.l.:Bilim Teknik Yayınevi.

Da Veiga, A. & Eloff, J. H., 2010. A framework and assessment instrument for information security culture.. Computers & Security, 29(2), pp. 196-207..

Daniel, E., 1999. Provision of electronic banking in the UK and Republic of Ireland.. International Journal of Bank Marketing, 17(2), pp. 72-82..

Davis Jr, F. D., 1986. A technology acceptance model for empirically testing new end-user information systems: Theory and results , s.l.: Doctoral dissertation, Massachusetts Institute of Technology.

Davis, F. D., 1989. Perceived usefulness, perceived ease of use and user acceptance of information technology.. MIS Quarterly, 13(3), p. 319−339.

Davis, F. D., Bagozzi, R. P. & Warshaw, P. R., 1992. Extrinsic and intrinsic motivation to use computers in the workplace1.. Journal of applied social psychology, 22(14), pp. 1111-1132..

Díaz, J. & Rusu, C., 2014. Ubiquitous computer-supported collaborative learning: A literature review. s.l., Information Technology: New Generations (ITNG)11th International Conference on. IEEE.

Fishbein, M. & Ajzen, I., 1975. Belief, Attitude, Intentions and Behavior: An Introduction to Theory and Research. Boston, MA: Addison-Wesley.

G.J., H., C.C., T. & S.J.H., Y., 2008. Criteria, strategies and research issues of context-aware ubiquitous learning. .Educational Technology & Society, p. 81–91.

Godin, G., Valois, P. & Lepage., L., 1993. The pattern of influence of perceived behavioral control upon exercising behavior: an application of Ajzen's theory of planned behavior.. Journal of Behavioral Medicine.

Gong, M., Xu, Y. & Yu, Y., 2004. An enhanced technology acceptance model for web-based learning.. Journal of Information Systems Education, 15(4), p. 365.

Graff, J. & Schmidt, P., 1982. A general model for decomposition of effects. In: Systems Under Indirect Observation: Causality, Structure, Prediction. North-Holland, Amsterdam: s.n., pp. 131-148.

Guriting, P. & Oly Ndubisi, N., 2006. Borneo online banking: evaluating customer perceptions and behavioural intention.. Management research news, 29(1/2), pp. 6-15.

Hair, J. F. & al., e., 1998. Multivariate data analysis. s.l.:s.n.

Hara, N., 2000. Student distress in a web-based distance education course. Information, Communication & Society, pp. 557-579.

Hwang, G. J., Kuo, F. R., Yin, P. Y. & Chuang, K. H., 2010. A heuristic algorithm for planning personalized learning paths for context-aware ubiquitous learning. Computers & Education, 54(2), pp. 404-415.

Hwang, G. J., Yang, T. C., Tsai, C. C. & Yang, S. J., 2009. A context-aware ubiquitous learning environment for conducting complex science experiments. Computers & Education, 53(2), pp. 402-413.

Iqbal, S. & Zeeshan, A. B., 2015. An Investigation of University Student Readiness towards M-learning using Technology Acceptance Model. The International Review of Research in Open and Distributed Learning, 16(4).

Jones, V. & Jo, J. H., 2004. Ubiquitous learning environment: An adaptive teaching system using ubiquitous technology. s.l., Proceedings of the 21st ASCILITE Conference.

Jöreskog, K. G., 1990. New developments in LISREL: Analysis of ordinal variables using polychoric correlations and weighted least squares. Quality & Quantity , 24(4), pp. 387-404.

Jöreskog, K. G. & Moustaki, I., 2001. Factor analysis of ordinal variables: A comparison of three approaches. Multivariate Behavioral Research, 36(3), pp. 347-387.

Jöreskog, K. G. & Sörbom, D., 1986. LISREL VI: Analysis of linear structural relationships by maximum likelihood, instrumental variables, and least squares methods. s.l.:Scientific Software.

Jöreskog, K. G. & Sörbom, D., 1994. PRELIS 2: User's reference guide. s.l.:Scientific Software.

Kaygısız, Z., Saraçlı, S. & Dokuzla, K. U., 2005. İllerin gelişmişlik düzeyini etkileyen faktörlerin path analizi ve kümeleme analizi ile incelenmesi. s.l., VII. Ulusal Ekonometri ve İstatistik Sempozyumu, pp. 26-27.

Kelloway, E. K., 1995. Structural equation modelling in perspective. Journal of Organizational Behavior, 16(3), pp. 215-224.

Laroussi, M. & Derycke, A., 2004. New e-learning services based on mobile and ubiquitous computing: Ubi-Learn project. s.l., CALIE04, International Conference on Computer Aided Learning in Engineering education.

Legris, P., Ingham, J. & Collerette, P., 2003. Why do people use information technology? A critical review of the technology acceptance model. Information & management , 40(3), pp. 191-204.

Lin, F., Fofanah, S. S. & Liang, D., 2011. Assessing citizen adoption of e-Government initiatives in Gambia: A validation of the technology acceptance model in information systems success. Government Information Quarterly, 28(2), pp. 271-279.

Lin, F., Fofanah, S. S. & Liang, D., 2011. Assessing citizen adoption of e-Government initiatives in Gambia: A validation of the technology acceptance model in information systems success. Government Information Quarterly, 28(2), pp. 271-279.

Loehlin, J. C., 2004. Latent variable models: An introduction to factor, path, and structural equation analysis. s.l.:Psychology Press.

Loiacono, E. T., Djamasbi, S. & Kiryazov, T., 2013. Factors that affect visually impaired users' acceptance of audio and music websites. International Journal of Human-Computer Studies, 71(3), pp. 321-334..

Long, J., 1983. Confirmatory Factor Analysis: A Preface to LISREL. California: s.n.

Maruyama, G. M., 1997. Basics of structural equation modeling. s.l.:Sage publications.

Merlin, M., 1987. Transnational Corporations in the Philippines: Changing Dimensions and Modalities of Exploitation. World Bull, 3(1).

Mun, Y. Y. & Hwang, Y., 2003. Predicting the use of web-based information systems: self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model. International journal of human-computer studies, 59(4), pp. 431-449.

Muthén, B., 1984. A general structural equation model with dichotomous, ordered categorical, and continuous latent variable indicators. Psychometrika, 49(1), pp. 115-132.

Muthén, B. O., 2002. Beyond SEM: General latent variable modeling. Behaviormetrika, 29(1), pp. 81-117.

Muthén, B. O. & Satorra, A., 1995. Complex sample data in structural equation modeling. Sociological methodology, pp. 267-316.

O' Connel, B., 1996. Australian banking on the Internet - Fact or fiction?. The Australian Banker, pp. 212-214..

Ogata, H. & Yano, Y., 2004. Context-aware support for computer-supported ubiquitous learning.". Wireless and Mobile Technologies in Education.

Pai, F.-Y. & Huang, K.-I., 2011. Applying the Technology Acceptance Model to the introduction of healthcare information systems. Technological Forecasting & Social Change, 78(4), p. 650–660.

Preacher, K. J. & al., e., 2013. Choosing the optimal number of factors in exploratory factor analysis: A model selection perspective. Multivariate Behavioral Research, 48(1), pp. 28-56.

Reyna, O., 2016. Getting Started in Factor Analysis. [Online]
Available at: https://www.princeton.edu/~otorres/Factor.pdf
[Accessed 2016].

Rogers, E., 2003. Diffusion of innovations (5th ed.).. New York: Free Press.

Rogosa, D., 1993. Individual unit models versus structural equations: Growth curve examples." Statistical Modeling and Latent Variables. Amsterdam: s.n.

Romiszowski, A. J., 1995. Delivery systems for corporate training in the future.. Corporate Training for Effective Performance, pp. 227-244.

Saadé, R. G., Nebebe, F. & Tan, W., 2007. Viability of the'Technology Acceptance Model' in Multimedia Learning Environments: A Comparative Study. Interdisciplinary Journal of knowledge and learning objects, 3(2), pp. 175-184..

Sakamura, K. & Koshizuka, N., 2005. Ubiquitous computing technologies for ubiquitous learning. s.l., IEEE International Workshop on Wireless and Mobile Technologies in Education (WMTE'05), pp. 11-20.

Schumacker, R. E. & Lomax, R. G., 2004. A beginner's guide to structural equation modeling. s.l.:Psychology Press.

Selim, H. M., 2003. An empirical investigation of student acceptance of course websites. Computers & Education , 40(4), pp. 343-360..

Siponen, M. T., 2000. A conceptual foundation for organizational information security awareness.. Information Management & Computer Security, 8(1), pp. 31-41..

Suganthi, B. & Balachandran, G., 2001. Internet banking patronage: An investigation of Malaysia.. Journal of Internet Banking and Commerce.

Suhr, D. D., 2006. Exploratory or confirmatory factor analysis?. s.l.:Cary: SAS Institute.

Şimşek, G. G., 2007. Latent Değişkenli Yapısal Denklem Modellerine İlişkin Bir Uygulama, İstanbul: Marmara Üniversitesi SBE İstatistik Programı.

Tabachnick, B. G. F., 1996. Using multivariate statistics. New York: Harper Collins Publisher.

Towler, G. & Shepherd., R., 1991. Modification of Fishbein and Ajzen's theory of reasoned action to predict chip consumption. Food Quality and Preference , pp. 37-45..

Van De Bogart, W. & Wichadee, S., 2015. Exploring students’ intention to use LINE for academic purposes based on technology acceptance model. The International Review of Research in Open and Distributed Learning , 16(3).

Van Raaij, E. M. & Schepers, J. J., 2008. The acceptance and use of a virtual learning environment in China. Computers & Education , 50(3), pp. 838-852.

Venkatesh, V. & Davis., F. D., 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management science , 46(2), pp. 186-204..

Venkatesh, V., Morris, M. G., Davis, G. B. & Davis, F. D., 2003. User acceptance of information technology: Toward a unified view. MIS quarterly, pp. 425-478.

Wang, S.-L. & Wu, C.-Y., 2011. Application of context-aware and personalized recommendation to implement an adaptive ubiquitous learning system. Expert Systems with applications, 38(9), pp. 10831-10838.

Wang, Y. S., Wang, Y. M., Lin, H. H. & Tang, T. I., 2003. Determinants of user acceptance of Internet banking: an empirical study.. International journal of service industry management, 14(5), pp. 501-519.

Wang, Y. S., Wu, M. C. & Wang, H. Y., 2009. Investigating the determinants and age and gender differences in the acceptance of mobile learning.. British Journal of Educational Technology, 40(1), pp. 92-118.

Wixom, B. H. & Todd, P. A., 2005. A theoretical integration of user satisfaction and technology acceptance. Information systems research, 16(1), pp. 85-102.

Wright, S., 1934. The method of path coefficients.. The annals of mathematical statistics, 5(3), pp. 161-215..

Yahya, S., Ahmad, E. A. & Jalil, K. A., 2010. The definition and characteristics of ubiquitous learning: A discussion. International Journal of Education and Development using Information and Communication Technology.

Yılmaz, V. & Çelik, H. E., 2009. Lisrel ile yapısal eşitlik modellemesi-I: Temel kavramlar, uygulamalar, programlama. Ankara: Pegem Akademi Yayıncılık.

Zhao, X., Xin, W. & Toshio, O., 2010. Adaptive Content Delivery in Ubiquitous Learning Environment. The 6th IEEE International Conference on Wireless, Mobile and Ubiquitous Technologies in Education(IEEE WMUTE 2010).

APPENDIX

APPENDIX 1: Technology Acceptance Model (TAM) Survey

What kind of student you are? *

- Undergraduate
- Graduate
- PhD
- Other:

What is your department? *

- Biomedical Engineering
- Computer Engineering
- Electrical and Electronics Engineering
- Energy Systems Engineering
- Environmental Engineering
- Industrial Engineering
- Management Engineering
- Mechatronics Engineering
- Software Engineering
- Transportation and Logistic Engineering

Class *

- I
- II

- III
- IV

Most commonly used mobile devices as Netbook *

- Portable multimedia player
- IPod
- FDA
- Smart Phone
- Electronic dictionary
- Other:

Main method of ubiquitous learning is by downloading contents *

- Real time video lectures using wireless broadband
- Learning by downloading contents
- Internal contents in mobile devices

Most commonly used ubiquitous learning contents are *

- Lectures for getting job
- Lectures for getting certification
- Other:

Major place of ubiquitous learning *

- In the house
- In the University
- Travelling stations
- On the street

○ Other: [ ]

Questionnarie

	Strongly Disagree	Disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Agree	Strongly agree
1. I have the necessary skills for ubiquitous learning.	○	○	○	○	○	○	○
2. I have confidence in using mobile devices for ubiquitous learning.	○	○	○	○	○	○	○
3. I have confidence in using computer for ubiquitous learning.	○	○	○	○	○	○	○
4. I understand computer's terminology when using a computer for ubiquitous learning.	○	○	○	○	○	○	○
5.I understand mobile device's terminology	○	○	○	○	○	○	○

when using a mobile device for ubiquitous learning.							
6. Ubiquitous learning with mobile devices is necessary for my major study.	○	○	○	○	○	○	○
7. Ubiquitous learning with mobile devices is helpful for my major study.	○	○	○	○	○	○	○
8. Ubiquitous learning with mobile devices can help me to find a job in the future.	○	○	○	○	○	○	○
9. I can easily access information for ubiquitous learning.	○	○	○	○	○	○	○
10. Different mobile devices have a good compatibility with ubiquitous	○	○	○	○	○	○	○

learning.							
11. It is easy to access online resources for ubiquitous learning.	○	○	○	○	○	○	○
12. Ubiquitous learning is significant for university students.	○	○	○	○	○	○	○
13. Ubiquitous learning is a social necessity.	○	○	○	○	○	○	○
14. I need to experience ubiquitous learning for my future job.	○	○	○	○	○	○	○
15. I have intention to perform ubiquitous learning.	○	○	○	○	○	○	○
16. I am going to positively utilize ubiquitous learning.	○	○	○	○	○	○	○
17. I am interested in	○	○	○	○	○	○	○

computers to perform ubiquitous learning.							
18. I will be a power user in ubiquitous learning.	○	○	○	○	○	○	○
19. Studying through ubiquitous learning is a good idea.	○	○	○	○	○	○	○
20. I prefer using mobile devices over computers for ubiquitous learning.	○	○	○	○	○	○	○
21. I prefer using computers over mobile devices for ubiquitous learning.	○	○	○	○	○	○	○
22. I am positive toward ubiquitous learning.	○	○	○	○	○	○	○
23. Ubiquitous learning would improve my learning	○	○	○	○	○	○	○

performance.							
24. Ubiquitous learning is a faster way of learning.	◯	◯	◯	◯	◯	◯	◯
25. Ubiquitous learning is an easier way of learning.	◯	◯	◯	◯	◯	◯	◯
26. Ubiquitous learning can lead to a deeper learning.	◯	◯	◯	◯	◯	◯	◯
27. It is easy to download learning contents with mobile devices.	◯	◯	◯	◯	◯	◯	◯
28. It is easy to use menu of mobile devices software.	◯	◯	◯	◯	◯	◯	◯
29. It is easy to use ubiquitious learning contents with a mobile device.	◯	◯	◯	◯	◯	◯	◯
30. It is easy to use	◯	◯	◯	◯	◯	◯	◯

ubiquitious learning contents with a computer.

APPENDIX 2: Computer Mediated Communication

	Strongly Agree	Agree	Uncertain	Disagree	Strongly Disagree
01. Computer-Mediated Communication messages are social forms of communication.	◌	◌	◌	◌	◌
02. Computer-Mediated Communication messages are an informal and casual way to communicate.	◌	◌	◌	◌	◌
03. Computer-Mediated Communication messages convey feeling and emotion.	◌	◌	◌	◌	◌
04. Computer-Mediated Communication messages are impersonal (do not have qualities or characteristics).	◌	◌	◌	◌	◌
05. Computer-Mediated Communication is not confidential enough to use to communicate personal and/or sensitive information.	◌	◌	◌	◌	◌
06. Computer-Mediated	◌	◌	◌	◌	◌

Communication is a sensitive means of communicating with others.					
07. Using Computer-Mediated Communication to communicate with others is pleasant.	○	○	○	○	○
08. The replies to my Computer-Mediated Communication messages are immediate.	○	○	○	○	○
09. Users of Computer-Mediated Communication are normally responsive to messages.	○	○	○	○	○
10. The language people use to express themselves in online communication is stimulating.	○	○	○	○	○
11. It is difficult to express what I want to communicate through Computer-Mediated Communication.	○	○	○	○	○
12. The language used to express oneself in online communication is meaningful.	○	○	○	○	○
13. The language used to express oneself in online communication is easily understood.	○	○	○	○	○
14. I am comfortable participating, if I am familiar with the topics.	○	○	○	○	○
15. I am uncomfortable participating, if I am not familiar with the	○	○	○	○	○

topics.					
16. I am comfortable communicating with a person who is familiar to me.					
17. I am comfortable communicating with a person who is not familiar to me.					

	Extremely Likely	Likely	No Opinion	Unlikely	Extremely Unlikely
18. What is the likelihood that a computer system operator might read and/or re-post messages sent to or from you?					
19. What is the likelihood that someone else might read and/or re-post messages sent to or from you?					
20. What is the likelihood that you might accidentally send message(s) to someone other than the intended recipients(s)?					
21. What is the likelihood that someone might obtain					

personal information about you from the messages you send and/or receive?

	Extremely Reliable	Fairly Reliable	Neithter reliable nor unreliable	Fairly Unreliable	Extremely Unreliable
22. Do you consider your online communication to be technically RELIABLE (e.g., free of system or software errors that might compromise the reliability of your online messages reaching ONLY the target destination)?	○	○	○	○	○

*

	Extremely Private	Private	No Opinion	Public	Extremely Public
23. How PRIVATE are your messages on Computer-Mediated Communication?	○	○	○	○	○

*

	Extremely Important	Fairly Important	Neutral	Fairly Unimportant	Extremely Unimportant
24. How IMPORTANT is privacy of a Computer-Mediated Communication?	○	○	○	○	○

*

	Extremely	Fairly	Neither	Fairly	Extremely

	Secure	Secure	risky nor insecure	Insecure	Insecure
25. How SECURE/SECRET is your online participation?	◌	◌	◌	◌	◌

*

	Extremely Risky	Fairly Risky	Neither risky nor safe	Fairly Safe	Extremely Safe
26. How RISKY is it to share personal and sensitive topics online?	◌	◌	◌	◌	◌

*

	Yes	No
27. Do you know of any instance where someone has been personally or professionally embarrassed because of their online activities?	◌	◌

*

	It'll never happen to me	It's not likely to happen to me	I don't think about it and have no feeling	It's likely to happen to me	It's a sure thing that it'll happen to me
28. Which of the following statements most closely reflects how you feel about the possibility of you even being personally or professionally	◌	◌	◌	◌	◌

embarrassed through your online participation?

	They are close friend	They are casual friends	They are regular acquaintances	They are casual acquaintances	I don't have a relationship with them
29. What is your professional RELATIONSHIP to other participants with whom you communicate?	◌	◌	◌	◌	◌

*

	Extremely Concerned	Quite Concerned	Concerned	A little concerned	Not concered at all
30. If you are able to use online messages anonymously, how CONCERNED are you that your identity will be traced?	◌	◌	◌	◌	◌

1. How proficient are you in using Computer-Mediated Communication? (e.g., expertise with software and system commands, keyboard skills, etc.) *

	Expert	Above Average	Average	Below Average	Novice
E-mail	◌	◌	◌	◌	◌
Threaded Discussion	◌	◌	◌	◌	◌
Real-time chat	◌	◌	◌	◌	◌

2. How many years have you been using e-mail as a form of Computer-Mediated Communication?*

Ex: 1; 2.5; 3 etc.

3. How many years have you been using threaded discussion as a form of Computer-Mediated Communication? *

Ex: 1; 2.5; 3 etc.

4. How many years have you been using real-time chat as a form of Computer-Mediated Communication? *
Ex: 1; 2.5; 3 etc.

5. How many years have you been using the Internet? *
Ex: 1; 2.5; 3 etc.

6. How many hours do you spend on course related e-mails each week? *
Ex: 1; 2.5; 3 etc.

7. How many hours do you spend on course related threaded discussion each week? *
Ex: 1; 2.5; 3 etc.

8. How many hours do you spend on course related real-time chat each week? *
Ex: 1; 2.5; 3 etc.

	Male	Female
1. Gender *	○	○

	Under 18	18-25	26-35	36-45	Over 45
2. You are *	○	○	○	○	○

	No experience	Novice	Intermediate	Expert
3. Estimate of your level of computer expertise	○	○	○	○

4. Where do you presently use computer? (Check all that apply) *

☐ Home

☐ Computer Lab

☐ Library or Media Center

- [ ] Classrom
- [ ] Office
- [ ] Diğer:

*

	Caucasian	African American	Latino	American Indian or Alaska Native	Asian and Pacific Islander	Arabic	Turkish	Other
5. What is your predominant ethnic background?	○	○	○	○	○	○	○	○

6. Do you think people can easily behave ethically in computer-based communication?

7. Which group(s) are you affiliated with? (Check all that apply) *

- [ ] SEN1001 (Introduction to Programming with JAVA)
- [ ] SEN1002 (Object Oriented Programming with JAVA)
- [ ] SEN1900/SEN1901/SEN1903 (Introduction to Information Technologies)
- [ ] SEN2006 (Microsoft C# Laboratory)
- [ ] SEN2102 (IBM - DB Programming)
- [ ] GNG2200 (Engineering Ethics)
- [ ] SEN3304 (Human Computer Interaction)
- [ ] SEN3006 (Software Architecture)
- [ ] Other: