MS. Dissertation in Engineering

A Study on Identifying the Factors in the Adoption of Web-Based Education Focused on the Technology Acceptance and Innovation Resistance of Massive Open Online Course (MOOC)

MOOC 서비스를 중심으로 한 웹 기반 학습의
기술수용의도와 혁신저항에 관한 연구

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Abstract

A Study on Identifying the Factors in the Adoption of Web-Based Education Focused on the Technology Acceptance and Innovation Resistance of Massive Open Online Course (MOOC)

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This research aims to identify the factors that lead users to use MOOC, the web-based education platform, by using the concept of technology acceptance and innovation resistance. The UTAUT2 model is adopted to provide explanation on the basic premise of users' acceptance towards emerging technology, and afterwards, modifications on the existing model of UTAUT2 is done by adopting the concept of innovation resistance. Innovation resistance is considered as a form of construct affecting the users' intention to use, which is thought to have influence on human 's

behavior towards new technology.

The survey is conducted on the usage of the web-based education platform by collecting the data from 427 respondents, and the data is analyzed by using structural equation modeling (SEM) as the methodology. The exploratory factor analysis illustrates that performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating condition (FC), hedonic motivation (HM), habit (HB) are the potential constructs which can affect the innovation resistance (IR) and intention to use (IU).

After proceeding with the confirmatory factor analysis and path analysis, the empirical results show that effort expectancy, social influence, facilitating condition, hedonic motivation, and habit have a significant negative influence on innovation resistance, and habit, facilitating condition and innovation resistance have a significant negative influence on intention to use. Also, respondents with experience on using MOOC and those do not have been separated to carry out the comparison between groups. Tests highlight that the total sample results follow the results from the experienced group. By identifying the significant factors of technology acceptance, this paper presents implication and insights to those interested in utilizing MOOC.

Keywords: MOOC, Technology Acceptance, Innovation Resistance, UTAUT2

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Chapter 1. Introduction

A representative form of open education platform - MOOC, or massive open online course draws worldwide attention in that it makes use of IT resources to overcome the spatial, temporal and environmental limits that traditional educational systems have. The number of organizations which plan on adopting MOOC is expected to grow because MOOC allows users to participate in online classes with no limitation via the web. Therefore, MOOCs are attracting considerable interest among researchers regarding being the possible solution for problems such as inequality in education, the digital divide and so on. (Bonk, Lee, Reeves, & Reynolds, 2015; Hvorecký, 2004; Kaplan & Haenlein, 2016; Yuan, Powell, & CETIS, 2013)

However, aside from this popularity growth, concerns arise due to the low completion rate of courses enrolled by students, generating the widespread discussion whether instructors can use MOOC for sustainable education or not. Many experts content, however, that this major issue of MOOC is not conclusive; the phenomenon that the participation rate of users or learners decrease after some time the course enrollment proceeds desperately needs to be taken care. In this regard, the reason for adoption on MOOC has been identified as being the important breakthrough in solving the drop-out problem and advancing MOOC to a level of sustainable use.

Efforts on identifying and solving such problem had been quite an issue, since the advent of the concept of MOOC. Many studies have tried to come up with some empirical analysis of the behavior of learners using MOOC. (Mendoza, Jung, & Kobayashi, 2017) Some researchers have published articles of topics on understanding student motivation and behaviors on MOOC. (Zheng, Rosson, Shih, & Carroll, 2015) Others even suggested a potential solution to engagement using better video quality production. (Guo, Kim, & Rubin, 2014)

In this context, the following questions are brought up to be answered.

- ✓ *What are the influencing factors that affect the users' technology acceptance on MOOC?*
- ✓ *How will the researchers identify the resistance towards innovation from the users using MOOC?*
- ✓ *What is the implication for the instructors, content producers and platform providers on this remark?*

The paper is organized as the following: in Chapter 2, a review of the literature including the concept of MOOC, technology acceptance model and innovation resistance is provided. Chapter 3 deals with how the research model was built, along with the definition of variables and hypotheses. Chapter 4 shows the methodology used in this paper. Chapter 5 illustrates the empirical results and discussion. Lastly, in Chapter 6, this paper shares the implication obtained from the research, look over

the limitations and reveal some possibility of future research in need.

Chapter 2. Literature Review

2.1 Massive Open Online Course

2.1.1 General Concept

MOOC, or Massive Open Online Course, is the newly recognized form of innovative digital education in that it allows unlimited user participation to online courses consisting open educational resources. McAuley, Stewart, Siemens, and Cormier (2010) has put this, “A MOOC is an online course with the option of free and open registration, a publicly-shared curriculum, and open-ended outcomes.” Likewise, the current real-state of MOOC shows some features. “Massive” suggests that there may be more than thousand number of students in a single course, “Open” implies that the material is open to anyone, anywhere, and “Online” suggests that the application is accessible online, and “Course” shows that it is a form of education.

The terminology was first coined by Dave Cormier, in an attempt to create a connectivist course (CCK08) comprised of students, focusing on the participation of the learners by providing access to collaborative tools. (Cormier, 2008) This illustrates that the first attempt of this concept of online courses, was to give users’ connection on the class syllabus, provoking learners to write on discussion forums, etc., targeting both tuition-paying student groups and non-paying auditing groups.

However, the well-known practice of MOOC stands far different from the

beginning. It is held at a much larger scale focusing on the "auditing groups." According to an important article titled "The MOOC model for digital practice" written by McAuley et al. (2010), MOOC not only utilizes the connectivity of the social network but also builds the active engagement of "students" to the course, by motivating their learning goals.

Table 1. A Summary of the Major MOOC Providers around the World

MOOC Providers	Country	Management	Number of Students (Registered Users)	Number of Courses
Coursera	United States	Enterprise	25M	2,000
Udacity	United States	Enterprise	4M	200
EdX	United States	NPO	10M	1,500
FutureLearn	United Kingdom	University	6M	480
XuetangX	China	Government	1.5M	400
K-MOOC	South Korea	Government	-	280

Source: Massive List of MOOC Providers Around the World - Shah (2017)

2.1.2 History of MOOC's Development

Some preliminary work was carried out before the era of MOOC. The concepts of Open Courseware (OCW), Open Educational Resources (OER), e-Learning, and Learning Management Software (LMS) is introduced in this section.

Johnstone (2005) traced the advances in the development of Open Educational Resources and affirmed that OCW is also an extension of OER Movement, which was announced officially at the Paris UNESCO Forum in 2012. The OER Movement suggested sharing the goals of bridging the gap between those with educational opportunities and those do not.

In the meantime, efforts on developing a highly effective program on distance learning were also sustained by researchers in the field of educational technology. Romiszowski (2004) draws the researchers' attention to the rise and fall on e-Learning, which researchers in the past had a considerable amount of interest. By launching some diverse projects on utilizing online learning, web-based training, and technology-based training, however, he points out that the projects on e-Learning fail due to following the same hype-cycle pattern of diffusion of technological innovation, such as educational television, and programmed instruction. In the research field of educational technology, from the very past introduction of TV to the 21st century, many researchers have made continued attempts on studying the effectiveness of conveying educational materials on media, deploying the contents on the public, and finally distributing to those in favor of learning the subject. (Evans & Leppmann, 1968; Romiszowski, 2004; Sun, Tsai, Finger, Chen, & Yeh, 2008)

Is the current MOOC sustainable and revolutionary? As mentioned by Kay, Reimann, Diebold, and Kummerfeld (2013), MOOC is now widely accepted as the

innovation of distance education platform with so much potential; they found reasons from the high quality of the courses, the openness to the public, and online accessibility the MOOC provides, which will cause revolutionary attempts to provide education to a massively-scaled number of students.

Shah (2018), the writer at Class Central, illustrated the popularity of the MOOC by the graphics, which shows the dramatic growth over the years; the number depicts the on-growing demand of MOOC all over the world. According to Shah (2018), students using MOOC have steadily increased, reaching up to 81M students, with programs available on more than 800 universities, and more than 9.4k courses presented. The reports from Class Central also denoted that the number of courses from year 2012 have increased dramatically, almost breaking the ceiling of 10k courses.

Some researchers suggested that the form might be a disruptive innovation, which would bring changes to the formation of classes. (Christensen, Johnson, & Horn, 2010) Due to the high-rising popularity, the New York Times has even announced the year of 2012, as “the Year of the MOOC”(Pappano, 2012)

This type of system shows a considerable amount of difference than the traditional classroom style education and learning management systems because it more enables learners to overcome the spatial, temporal and environmental limits. For example, MOOCs are available online at any time, regardless of daily life hours, which implies that students can get access to all the course materials other than the

official school hours. Not only can the learner retrieve readings, texts, and video contents, but also live forum-based interaction from other students and instructors around the globe is made possible thanks to the assistance of the network, even solving the spatial limitation issue.

2.1.3 Problems of MOOC Adoption

However, the popularity growth of MOOC has hit the ceiling, resulting in many questions over the limitations on MOOC. Once praised as “the low-cost substitute of higher education,” the disappointing drop-out rates show that there were some problems with the participation of the platform. (Rivard, 2013) The phenomenon implied that the underlying pedagogy inside the e-Learning platform faces issues with the performance of learning. Other reports also indicated that the analysis from the first trends in enrolment and completion of the courses by learners was proved to be questioned regarding effectiveness, as the same situation occurs. (Jordan, 2014) Students drop out of classes and fail to complete in MOOC.

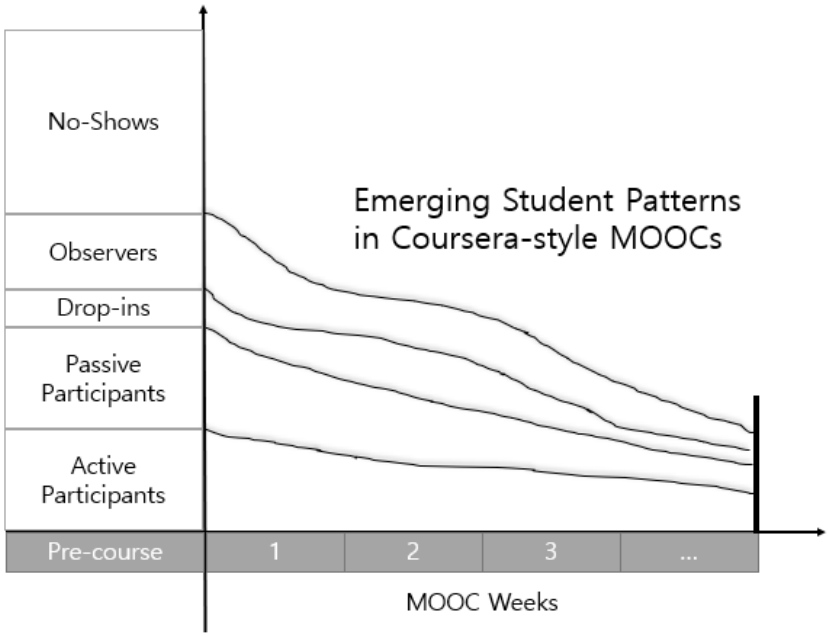

Figure 1. Emerging Student Patterns in MOOCs (Hill, 2013)

Even more, the view of MOOC as being open and free turned out to be having problems as well. Some researchers point out that the application for the educational platform requires more than a certain level of IT infrastructure for the users. (Bonk et al., 2015) Also, the leading enterprises of MOOC are diversifying their business models because the revenue from providing free educational contents itself is not sustainable. Instructor and the platform provider had to gather a considerable amount of initial fund to get the courses going. The concept of open and free educational resources was questioned fundamentally, whether MOOC is both sustainable and effective. (Bonk et al., 2015) For these reasons, some suggested that MOOC also had to endure the trough of disillusionment, as shown in the following

figure. (Bozkurt, Keskin, & de Waard, 2016) Therefore, additional measures were to be needed in expecting the future of MOOC. In this regard, a whole variety of research to identify the factors to implement a successful MOOC environment has taken place, e.g., its design, delivery, and assessment. (Daradoumis, Bassi, Xhafa, & Caballé, 2013)

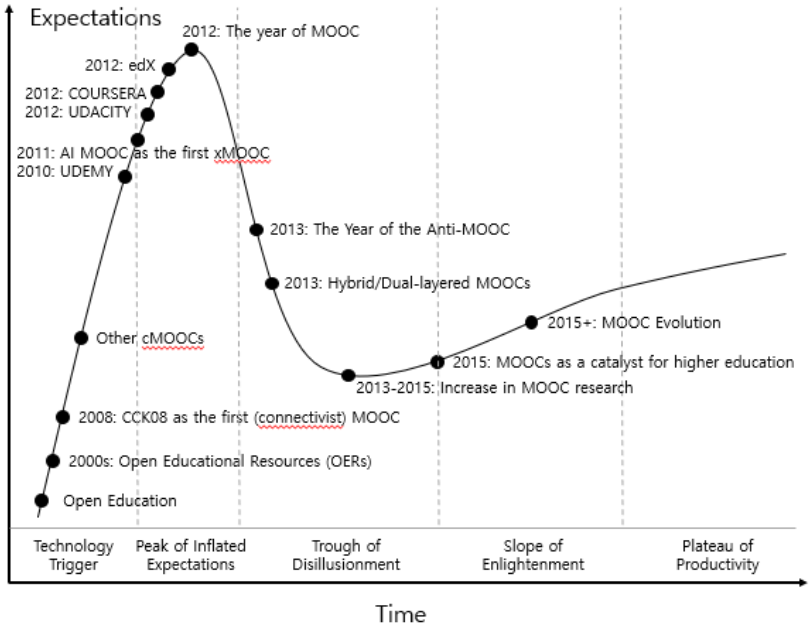

Figure 2. The Expectation of MOOC (Bozkurt et al., 2016)

2.2 Technology Acceptance Model

2.2.1 Concept

Technology Acceptance Model, or TAM, is widely used to understand user's behavior on new technology, such as computer technology. Many publications on analyzing the user's adoption behind the innovative product related to the Internet

Communication Technology (ICT), including the use of smartphones, internet banking, or computer systems have used this model since. Davis (1989) organized this model to understand the factors affecting users' acceptance of information technology. TAM focuses on discovering the external factors in which the belief, attitudes, and intention to use of the members of the organization leads to the actual use of technology innovation.

The TAM finds its theoretical background on the theory of reasoned action, or TRA, where Ajzen (1985) stated that human behavior is mostly goal-directed, and with that assumption, a plan of such consequence of activities would be required to proceed with the goal, either conscious or nonconscious plan would be comprised of the routineness of actions. With this in mind, researches on human behavior show that intention can be predicted with high accuracy from the attitudes, subjective norms, and perceived behavioral controls, which consists the theory of planned behavior. (Ajzen, 1991) This links with the previous technology acceptance model in compliance with the form that human's intention to plan and act, is highly likely to be caused by some underlying proceeding factors.

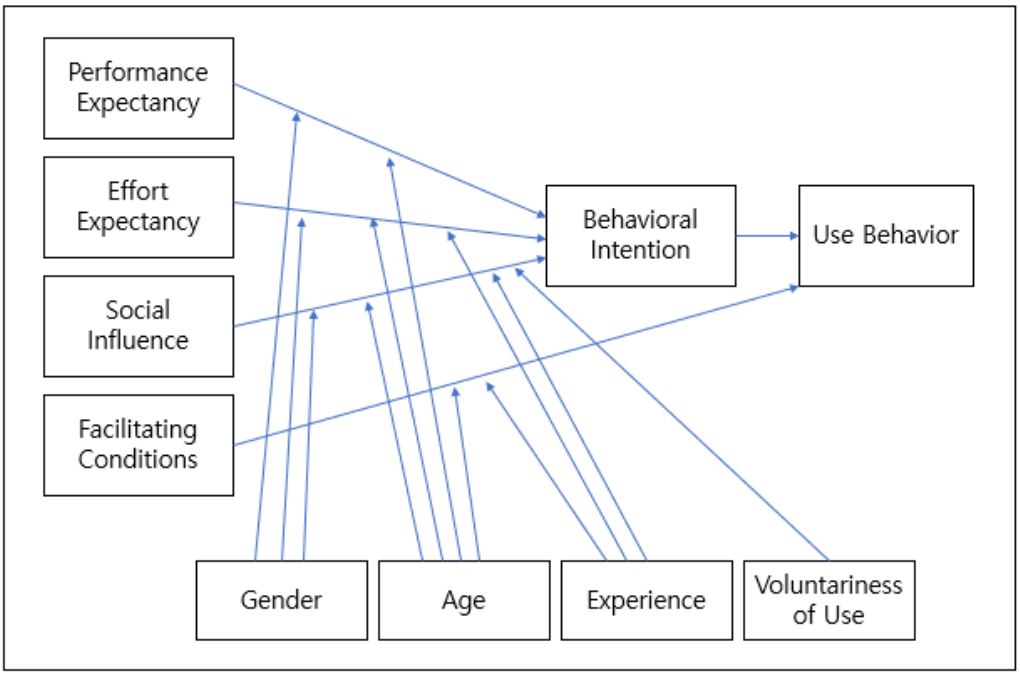

Figure 3. The Model of UTAUT from Venkatesh, Morris, Davis, and Davis (2003)

UTAUT, or Unified Theory of Acceptance and the Use of Technology, is a model proposed by Venkatesh et al. (2003). Venkatesh et al. (2003) proposed this model, integrating the previous TRA, TAM, and diffusion of innovation theory, and carefully redefining the constructs that affect the behavioral intention and the intention to use.

A newer model, UTAUT2 is proposed by Venkatesh, Thong, and Xu (2012), which shows a higher rate of explanatory powers on the technology acceptance model. This model holds additional terms such as hedonic motivation, price value, and habit; hedonic motivation, and price value affects behavioral intention,

meanwhile habit changing both intention and the use behavior, as depicted in the following model.

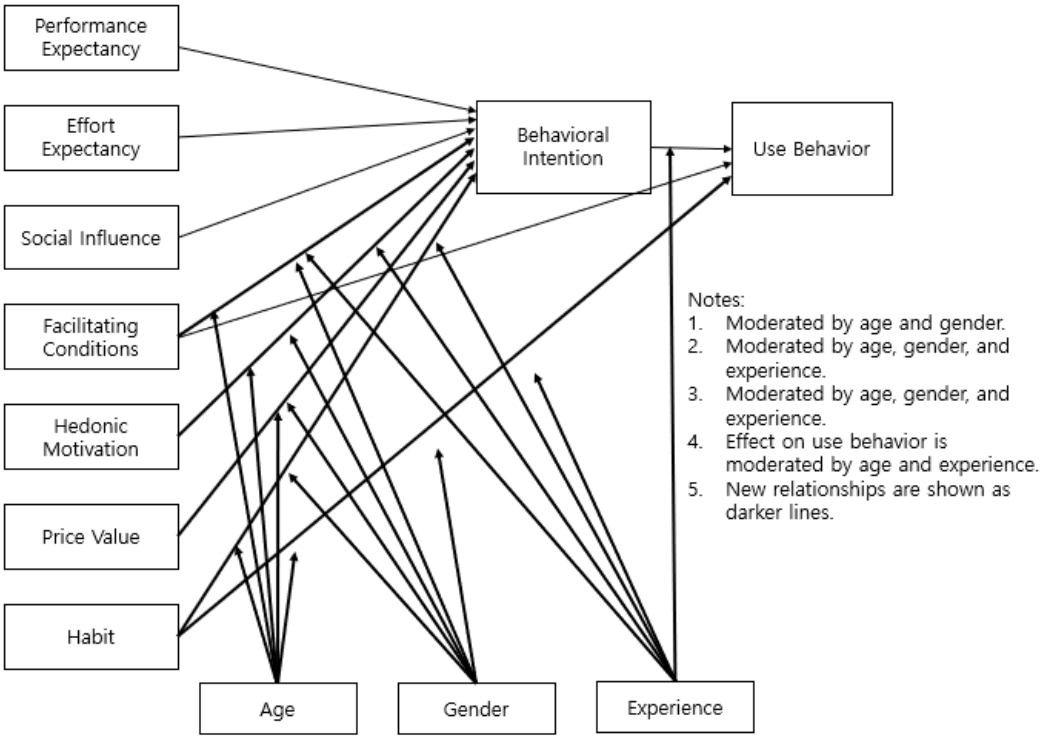

Figure 4. The Model of UTAUT2 from Venkatesh et al. (2012)

2.2.2 Previous Researches

Preliminary research using the UTAUT model has shown that performance expectancy, effort expectancy, social influence, facilitating condition affect the users' behavioral intention to utilize MOOC. (Mendoza et al., 2017) Also, other researchers reported a similar result. Kim (2017) points out that performance expectancy, effort expectancy, facilitating conditions, and hedonic motivation affect

satisfaction, and effort expectancy, hedonic motivation, habit, and satisfaction affect behavior intention to use MOOC.

In this regard, there have been a series of researches including users' intention to use MOOC, from the perspective of research using technology acceptance model. The following table summarizes the investigated result of MOOC's adoption.

Table 2. Summary of Previous Researches on MOOC's Adoption

Author	Survey	Model & Target	Mediating Variable	Dependent Variable
Yang (2013)	182	UTAUT2 / Mobile Learning	Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Price Value, Habit	Intention to Use
Xu (2015)	325	TAM3 / MOOC	Perceived Usefulness, Perceived Ease of Use	Use Behavior
Raman and Don (2013)	320	UTAUT2 / LMS	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation	Behavioral Intention, Use Behavior
Hyun-Jung, Sang-Won, and Moon-Hee (2014)	281	UTAUT2 / Wearable Device	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Perceived Risk	Intention to Use
El-Masri and Tarhini (2017)	833	UTAUT2 / e-learning systems	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Trust	Behavioral Intention
Gao and Yang (2015)	247	TAM, Institutional	Perceived Usefulness, Perceived Ease of Use, Coercive Pressure, Normative Pressure, Mimetic	Behavioral Intention

		Theory / MOOC	Pressure	
Kim (2017)	175	UTAUT2 / MOOC	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions	Satisfaction, Use Behavior

Source: Retrieved and revised references from Kim (2017)

2.3 Innovation Resistance

2.3.1 Concept

Innovation resistance refers to "the resistance offered by consumers to an innovation, either because it poses potential changes from a satisfactory status quo or because it conflicts with their belief structure." (Sudha Ram, 1987) To accept such innovation, the potential consumer faces changes such as information acquisition, subscription of a service, disposition of existing product, etc. Sudha Ram (1987) proposed the model to understand human behavior regarding status quo, arguing that the previous works have focused too heavily on the side that innovation is good; innovation is always acceptable to the consumers.

According to Sudha Ram (1987)'s work, innovation resistance is not an antonym of innovation acceptance in that after periods of innovation resistance, there is a possibility of approval if the innovation is amenable to modification. Extended research shows that a high level of innovation resistance causes a postponement, delaying the period of acceptance; too much high level might cause innovation to be rejected to the consumer market. (Sundaresan Ram & Sheth, 1989)

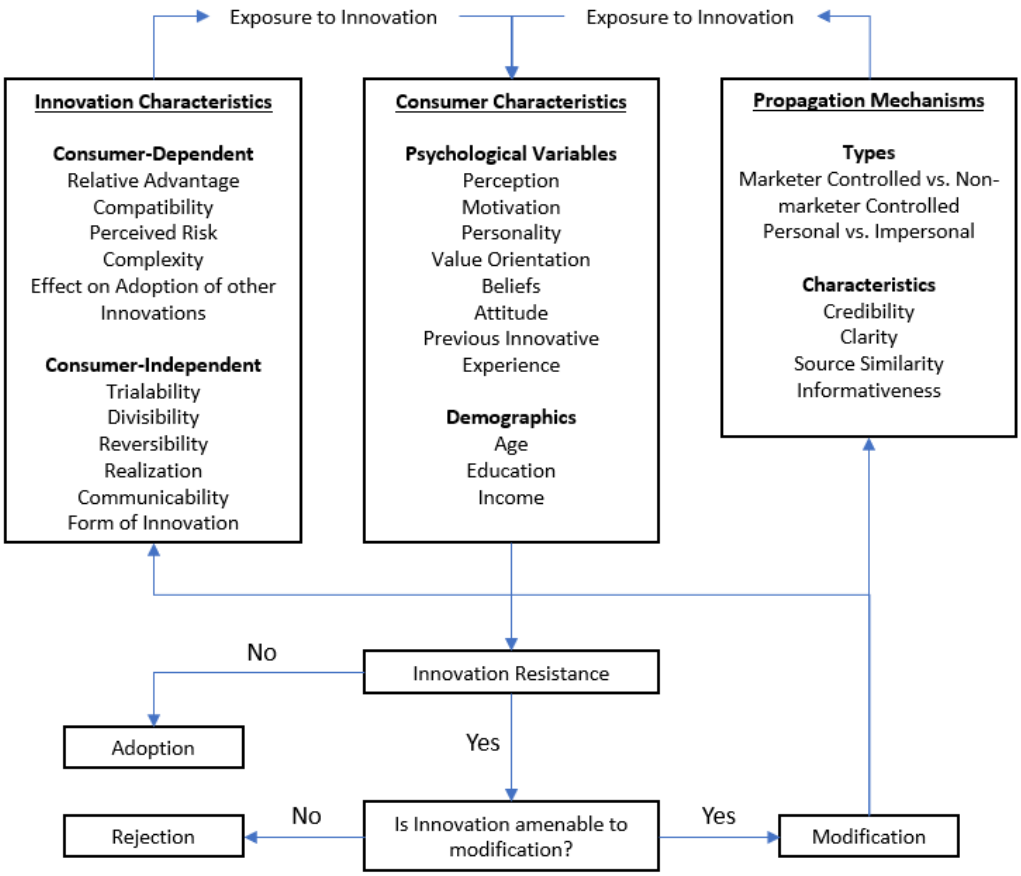

Figure 5. The Model of Innovation Resistance from Sudha Ram (1987)

The three major categories of factors are listed in the previous figure of the model; Sudha Ram (1987) lists innovation characteristics, consumer characteristics, and propagation mechanisms. Innovation characteristics, the feature that innovation has on itself, have been separated into two sections, whether it is consumer dependent or not. Relative advantage, compatibility, perceived risk, complexity, the effect on adoption of other innovation forms the consumer dependent innovation

characteristics; while trialability, divisibility, reversibility, realization, communicability, and forms of innovation explain the consumer-independent innovation characteristics.

Consumer characteristics include perception, motivation, personality, value orientation, etc., which centers on the consumer's inner-self, whereas information on demographics such as age, education, and income can also come into effect. Propagation mechanisms explain how innovation is spread through consumers, and it is possible to characterize with credibility, clarity, source similarity, and informativeness. In this paper, the concept of branching into innovation characteristic, consumer behavior, and propagation mechanism is used.

Chapter 3. Model and Hypothesis

3.1 Research Model

As MOOC falls in the scope of the digital system which has the characteristics of users' participation as an agent of the platform, this research adopted the technology acceptance model and the construct of innovation resistance.

The following figure shows the overall model designed for this research.

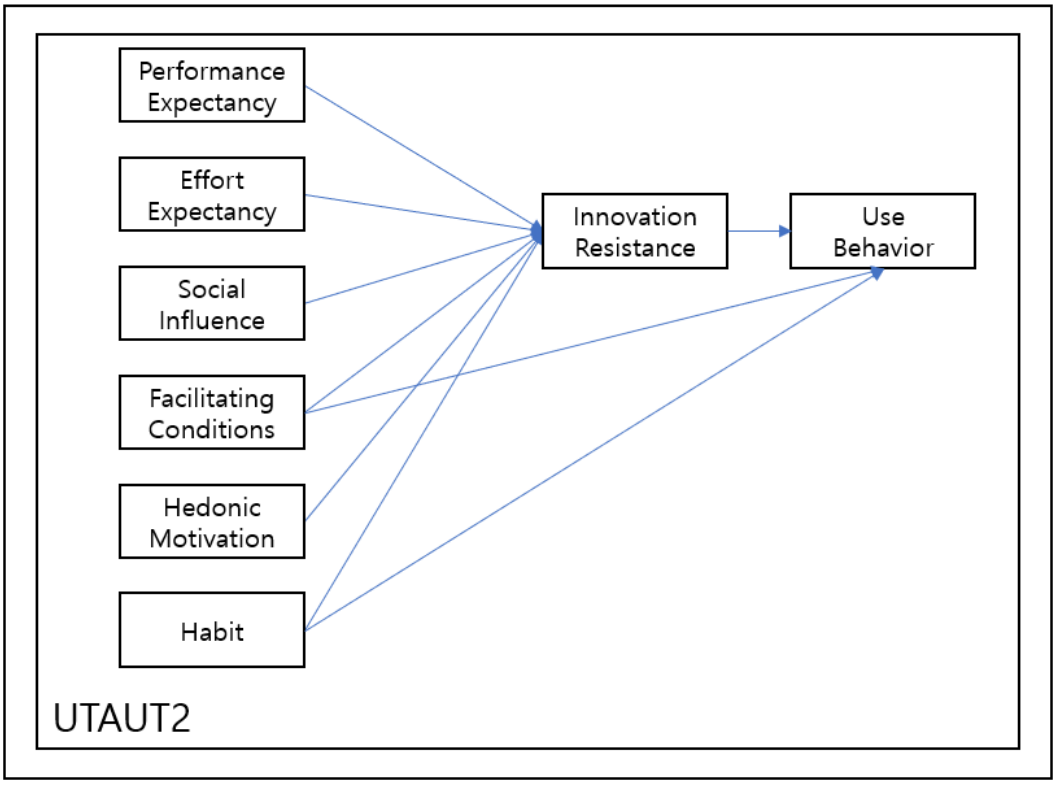

Figure 6. Research Model

3.1.1 Modification of the Existing Model

According to the existing UTAUT2 model, the scaling term for behavioral intention measures an individual's indication of readiness to perform a given behavior, which is assumed to be an immediate antecedent of behavior. (Ajzen, 1985) In this context, based on the existing UTAUT2 model, the behavioral intention is interpreted as the negative form of innovation resistance. The terminology, Intention to Use (IU), was used to refer to "use behavior," as some other models suggest.

3.1.2 Intersectional Concept between Models

While the existing UTAUT2 model used "behavioral intention" to connect the independent variables and the construct of "use behavior," this paper introduces the construct of innovation resistance from the innovation resistance model. The measurement plays a role as the intermediate variable both being affected and affecting the variables around. Specific reasons for such decision are explained further in the following section of operational definition.

3.2 Variables and Hypotheses

3.2.1 Description of Variables

The four basic constructs on technology acceptance are brought from the UTAUT model; Performance Expectancy (PE), Effort Expectancy (EE), Social

Influence (SI), Facilitating Condition (FC) and Intention to Use (IU). The extended theory of UTAUT2 is then adapted to draw out some additional constructs; Hedonic Motivation (HM), Habit (HB) were included to visualize the effects of these parameters. Lastly, Innovation Resistance (IR) was replaced with Behavior Intention to measure the individual's resistance to the innovation. Table 3 shows the description of each variable used in the model.

Table 3. Definition of variables

Variable	Definition	Source
Performance Expectancy (PE)	The degree to which using a technology will provide benefits to consumers in performing certain activity	(Venkatesh et al., 2003; Venkatesh et al., 2012)
Effort Expectancy (EE)	The degree of ease associated with consumers' use of technology	
Social Influence (SI)	The extent to which consumers perceive that important others (e.g., family and friends) believe they should use a technology	
Facilitating Condition (FC)	Consumers' perceptions of the resources and support available to perform a behavior	
Hedonic Motivation (HM)	The fun or pleasure derived from using a technology	(Venkatesh et al., 2012)
Habit (HB)	The extent to which people tend to perform behaviors automatically because of learning	
Innovation Resistance (IR)	The resistance offered by consumers to an. innovation, either because it poses potential changes from a satisfactory status quo or because it conflicts with their belief structure	(Sudha Ram, 1987)
Intention to Use (IU)	The strength of one's intention to perform a specified behavior	(Ajzen, 1985; Ajzen & Fishbein, 1975; Venkatesh et al., 2003; Venkatesh et al., 2012)

3.2.2 Operational Definition of Variables and Hypotheses

As we adjust the above definition of variables to fit the model, the following operational definition is constructed. **Table 4** shows the list of definitions.

Table 4. Operational Definition of Variables

Category	Variable	# of Items	Definition
Independent Variable (IV)	Performance Expectancy (PE)	4	The degree to which MOOC will provide benefits to users in performance (e.g., providing knowledge)
	Effort Expectancy (EE)	4	The degree of ease associated with using MOOC to users
	Social Influence (SI)	3	The extent to which users perceive that important others (e.g., family and friends) believe they should use MOOC
	Facilitating Condition (FC)	3	Users' perceptions of the resources and support available to use MOOC
	Hedonic Motivation (HM)	2	The fun or pleasure derived from using MOOC
	Habit (HB)	3	The extent to which users tend to perform behaviors automatically because of learning

Dependent Variable (DV)	Innovation Resistance (IR)	4	The resistance offered by users from using MOOC
	Intention to Use (IU)	3	An indication of an individual's readiness to perform using MOOC

Since Innovation Resistance (IR) refers to the meaning of resistance from innovation, it is highly likely to interpret such concept as the antonym of Behavioral Intention (BI), and the barrier to forming Intention to Use (IU). This designates the position of Innovation Resistance (IR) and constructs the sign of influence among the paths.

3.2.3 Summary of Hypotheses

Hypotheses regarding the constructs in the model are presented in Table 4.

H1: Performance expectancy will have a significant negative influence on innovation resistance.

H2: Effort expectancy will have a significant negative influence on innovation resistance.

H3: Facilitating condition will have a significant negative influence on innovation resistance.

H4: Social influence will have a significant negative influence on innovation resistance.

H5: Hedonic motivation will have a significant negative influence on innovation resistance.

H6: Habit will have a significant negative influence on innovation resistance.

H7: Facilitating condition will have a significant positive influence on intention to use.

H8: Habit will have a significant positive influence on intention to use.

H9: Innovation resistance will have a significant negative influence on intention to use.

Table 5. Summary of the proposed hypotheses

Hypothesis	Path	Dependent Variable Construct
H1	Performance Expectancy (-) → Innovation Resistance	Innovation Resistance (IR)
H2	Effort Expectancy (-) → Innovation Resistance	
H3	Facilitating Condition (-) → Innovation Resistance	
H4	Social Influence (-) → Innovation Resistance	
H5	Hedonic Motivation (-) → Innovation Resistance	
H6	Habit (-) → Innovation Resistance	
H7	Facilitating Condition (+) → Intention to Use	Intention to Use (IU)
H8	Habit (+) → Intention to Use	
H9	Innovation Resistance (-) → Intention to Use	

Chapter 4. Research Methodology

This chapter illustrates the methodology used for the research. Based on the consecutive progress of the research, the methodology is explained thoroughly.

4.1 Survey

The original data that is used in this research is from the collection of responses from the designed survey. The survey sheet was prepared with items regarding the constructs from the previous literature, construct consisting of items more than three questions each. For the respondents to understand the content of the survey, basic explanations on MOOC were given out at first. As Allen and Seaman (2007) proposed, items are measured into seven-point scales, reaching the more full range of choices given to respondents, offering more reliability on the measurement. The lower number indicates stronger disagreement, while the higher number indicates stronger agreement. The readers may find the question sheets used for the survey in the Appendix section.

4.2 Data Collection

To collect data from the potential respondents, cooperation with the survey firm, *Macromill Embrain*, was proceeded to guarantee the sample size of responses. The survey participants were selected from the list of panels that the firm holds. Precise

distinction between survey respondents over the experience over the use of MOOC environment had taken place. Online links were distributed among the potential respondents, and the total number of 427 responses were collected from November 1st, 2018 to November 6th, 2018. To prevent the missing values and ambiguity, respondents could enter the answers in a focused manner, and warnings of inappropriate input were given out before the survey. The following table depicts the demographical data of the respondents.

Table 6. Socio-demographic distribution of sample

Variable	Total Sample (%) (n=427)	Group 1 (Experienced) (%) (n=212)	Group 2 (Inexperienced) (%) (n=215)
Gender			
Male	31.9	39.2	24.7
Female	68.1	60.8	75.3
Age			
10s	2.8	1.4	4.2
20s	52.7	63.2	42.3
30s	36.1	30.2	41.9
40s	5.6	4.2	7.0
50s	1.9	0.9	2.8

60s	0.9	0.0	1.9
Education			
Less than Junior High	2.1	0.5	3.7
High School	6.8	5.2	8.4
University / college enrolled	18.3	24.5	12.1
University / college graduated	63.2	58.5	67.9
Graduate school enrolled	4.2	7.1	1.4
Graduate school graduated	5.4	4.2	6.5
Monthly Income			
Less than 1M KRW	21.5	19.8	23.3
1M – 2M KRW	17.6	18.9	16.3
2M – 3M KRW	31.6	28.8	34.4
3M – 4M KRW	16.2	15.1	17.2
4M – 5M KRW	6.6	8.0	5.1
Greater than 5M KRW	6.6	9.4	3.7
Occupation			
Student	19.9	28.3	11.6
Workforce	60.0	58.5	61.4
Unemployed / Job Searching	8.4	5.7	11.2

Self-employed	4.0	2.8	5.1
All-time homemaker	4.0	2.4	5.6
Military Service	0.5	0.9	0.0
Retired	0.2	0.0	0.5
Etc	3.0	1.4	4.7
Experience			100
Experienced Group	-	-	50.3
Inexperienced Group	-	-	49.7

From the socio-demographic distribution of the sample, a clear distinction between two groups, people with experience and those with no experience in MOOC, was found from the responses. According to Wolf, Harrington, Clark, and Miller (2013), considering the required factor loading value of 0.8, the number of respondents collected for each group must be safely over 200. Therefore, answering trials up to 1,465 counts were made to satisfy the number of people with MOOC experience. Thus, the possibility of a person in the general population to know about using MOOC does not fully match the above-answered ratio, which is 50.3%.

In the total sample, male respondents occupied 31.9% of the whole, while female respondents formed the majority of 68.1%. The number sorted out different when comparing experienced and inexperienced. Within the experienced group,

people tended to be younger, with a significant percentage as a university student. The fact that experienced group had a lot of students had an impact on the income result, whereas education does not positively correlate with income in this case, contrary to common sense. Since students had the opportunity to give a try and learn through MOOC, those having experience on MOOC are likely to be having an occupation as students.

4.3 Data Analysis

The Structural Equation Modeling (SEM) as the primary method of analysis. The software used to analyze the data was SPSS & AMOS 23, and the maximum likelihood calculated by the application, suggesting the appropriate critical point that this research should measure. As for the methodology, the key guideline was Lowry and Gaskin (2014)'s work on doing exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and path analysis. Statistical comparisons between the experienced and non-experienced groups were proceeded.

Chapter 5. Results and Discussion

5.1 Reliability and Validity Tests

Reliability analysis is a method to prove how accurate measurement has been enumerated. Single item questions are not reliable, and should not be considered to identify such measurement. (Gliem & Gliem, 2003) Here, this research makes use of Cronbach's alpha to determine the level of reliability and to justify the usage of these measurement scales. Cronbach's alpha is considered to be a tool for assessing the reliability of scales, in which the values are calculated among Likert-type scales for testing conformity. As there are eight number of variables, for each set of measurement scale, it is reasonable that the paper estimates the Cronbach's alpha as the following. Only items that were selected to sort out the pattern matrix had been included; others were removed to provide reliability. The measurement is considered reliable when the value is greater than 0.7. (Santos, 1999)

Table 7. Descriptive Statistics including Cronbach's Alpha

Dimension	Items	Mean	Cronbach's Alpha	Composite Reliability	AVE
Performance Expectancy (PE)	4	5.172	0.880	0.865	0.617
Effort Expectancy (EE)	4	5.207	0.879	0.832	0.556
Facilitating Condition (FC)	3	5.183	0.859	0.860	0.672

Social Influence (SI)	3	4.950	0.916	0.906	0.764
Hedonic Motivation (HM)	2	5.100	0.894	0.853	0.744
Habit (HB)	3	4.923	0.834	0.823	0.608
Innovation Resistance (IR)	4	3.875	0.911	0.934	0.779
Intention to Use (IU)	3	5.026	0.916	0.915	0.783

Additionally, composite reliability values and average variance extracted coefficients (AVE) were calculated to test convergent validity. (Bagozzi & Yi, 1988) These tests reveal that all dimensions of the latent variables show reliability and validity. Every value of Cronbach's alpha was greater than 0.7, which confirmed the internal consistency, as stated previously. Composite reliability values were greater than 0.7, and AVE values were greater than 0.5, respectively, which identifies the basic premise of convergent validity has been matched.

5.2 Exploratory Factor Analysis

Naturally, this paper calculates and shows the pattern matrix for proving discriminant validity. Analysis by the method of dimension reduction on the selected items was taken place. The analysis obtained the output values for KMO and Bartlett's Test by using maximum likelihood for extracting the factors, and Promax method with a Kappa value of 4 with the rotation of the matrix. To show

the appropriate results, researchers have done the compressing for small coefficients less than 0.3, to filter high factor loadings among a fixed number of eight factors.

Pattern Matrix[a]

	Factor							
	1	2	3	4	5	6	7	8
pe1	.642							
pe2	.916							
pe3	.747							
pe4	.767							
ee1				.453				
ee2				.439				
ee3				.975				
ee4				.856				
si2						.442		
si3						1.052		
si4						.670		
fc3					.747			
fc4					.869			
fc5					.510			
hm2								.457
hm3								.910
hb1		.753						
hb2		.645						
hb3		.776						
ir2			.820					
ir3			.883					
ir4			.863					
ir5			.858					
iu1							.715	
iu2							.905	
iu3							.642	

Extraction Method: Maximum Likelihood.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 7 iterations.

Figure 7. Pattern Matrix of Constructs

The Kaiser-Meyer-Olkin measure of sampling adequacy gives the value of 0.954, which is higher than 0.9 to show fitness. The cumulative percentage of loadings up

to the current eight factors were summated to have a value of 72.467, higher than 60%, implying the model is acceptable. Also, as presented on Figure 7, the factor loading values form a group with each latent variable. Each factor loading values is greater than 0.4, suggesting that items with less conformity have been removed carefully, therefore showing convergent validity.

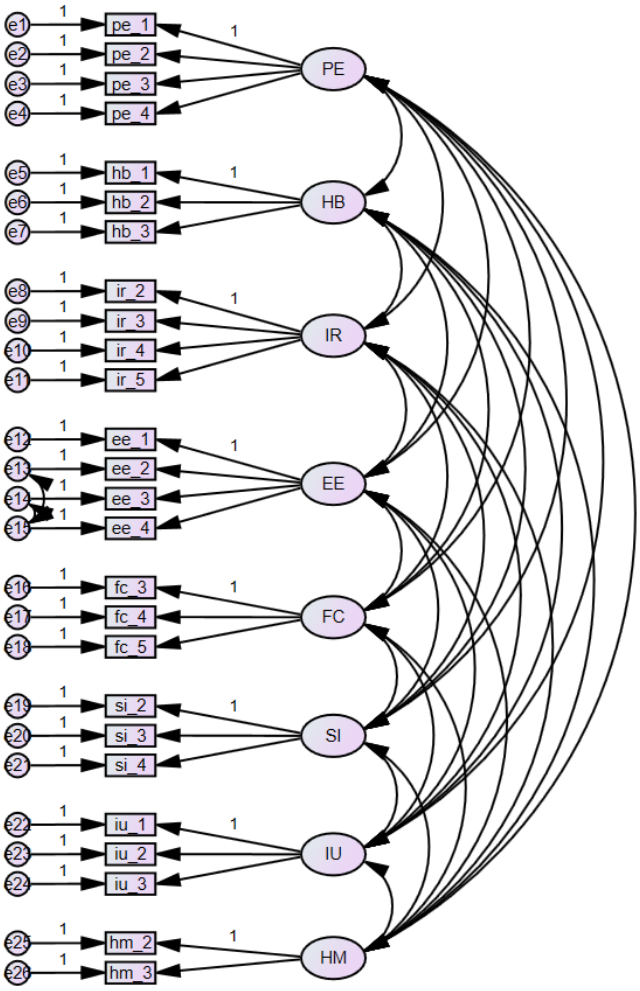

Figure 8. Exploratory Factor Analysis

The experimental method of this research follows Gaskin and Lim (2016)'s works to validate the discriminate validity and fitness of the model. This research performs the exploratory factor analysis with the calibrated eight factors with grouped factor loadings, shown in the previous section. According to Hu and Bentler (1999), cutoff criteria required for excellent model fit is suggested as follows; CMIN/DF greater than 1, CFI greater than 0.95, SRMR less than 0.08, RMSEA less than 0.06, and PClose greater than 0.05. The estimates that was obtained from this model, fit the criteria.

Table 8. Model Fit Measures of EFA

Measure	Estimate	Threshold	Interpretation
CMIN	964.576	--	--
DF	538	--	--
CMIN/DF	1.793	Between 1 and 3	Excellent
CFI	0.952	>0.95	Excellent
SRMR	0.047	<0.08	Excellent
RMSEA	0.043	<0.06	Excellent
PClose	0.995	>0.05	Excellent

The proceeding step is to analyze the model validity measures. Since this

research has already proven the convergent validity, the next target is to find out the discriminant validity. Same as the previous step, Gaskin and Lim (2016)'s tool was used to demonstrate the model validity. The results of the correlation matrix are given in Table 6.

Table 9. Model Validity Measures

	CR	AVE	MSV	MaxR(H)	PE	HB	IR	EE	FC	SI	IU	HM
PE	0.865	0.617	0.776	0.866	**0.785**							
HB	0.823	0.608	0.624	0.825	0.733	**0.780**						
IR	0.934	0.779	0.034	0.937	-0.146	0.112	**0.883**					
EE	0.832	0.556	0.776	0.849	0.881	0.637	-0.185	**0.746**				
FC	0.860	0.672	0.635	0.876	0.729	0.646	0.034	0.797	**0.820**			
SI	0.906	0.764	0.631	0.922	0.726	0.732	-0.050	0.706	0.563	**0.874**		
IU	0.915	0.783	0.682	0.917	0.821	0.790	-0.071	0.796	0.618	0.794	**0.885**	
HM	0.853	0.744	0.682	0.858	0.792	0.776	-0.041	0.776	0.633	0.753	0.826	**0.863**

The above results implied an issue of discriminant validity. The problem suggested that the set of responses of the different constructs tends to behave similarly with each other, which indicates that the level of distinction between scales is not satisfactory. A carefully-done calculation found that the square root of

the AVE for HB is less than its correlation with IU, meaning that habit (HB) has similar latent characteristics to intention to use (IU). The exact situation occurs for effort expectancy (EE), facilitating condition (FC) and hedonic motivation (HM). To solve the problem of discriminant validity, additional items from the model are removed to provide a clearer distinction between measurement scales. A total number of 6 items were removed from the model. In this case, the revised showed better quality of discriminant validity measure as of Figure 9; however, the trade-off of removing of items should be double-checked so that such action might disturb the interpretation on the actual human behavior. Considering this, the research was decided to maintain the original measurement model.

Model Validity Measures

	CR	AVE	MSV	MaxR(H)	IR	FC	HB	SI	EE	PE	HM	IU
IR	0.934	0.779	0.019	0.937	**0.883**							
FC	0.865	0.618	0.597	0.886	0.027	**0.786**						
HB	0.823	0.608	0.604	0.825	0.112	0.662	**0.780**					
SI	0.919	0.851	0.551	0.923	-0.041	0.576	0.711	**0.922**				
EE	0.858	0.752	0.597	0.860	-0.048	0.773	0.588	0.628	**0.867**			
PE	0.803	0.671	0.611	0.804	-0.139	0.719	0.655	0.637	0.712	**0.819**		
HM	0.854	0.745	0.622	0.862	-0.037	0.658	0.777	0.731	0.674	0.704	**0.863**	
IU	0.902	0.821	0.622	0.903	-0.080	0.636	0.767	0.742	0.614	0.782	0.789	**0.906**

Figure 9. Validity Measures for Revised Model

5.3 Confirmatory Factor Analysis

For the next section, the confirmatory factor analysis or CFA was processed. CFA is used to identify the theoretical assumption of the factor structure in the form of empirical study. This method estimates coefficients from the set-up path. Figure 10 shows the path of the hypothesis model.

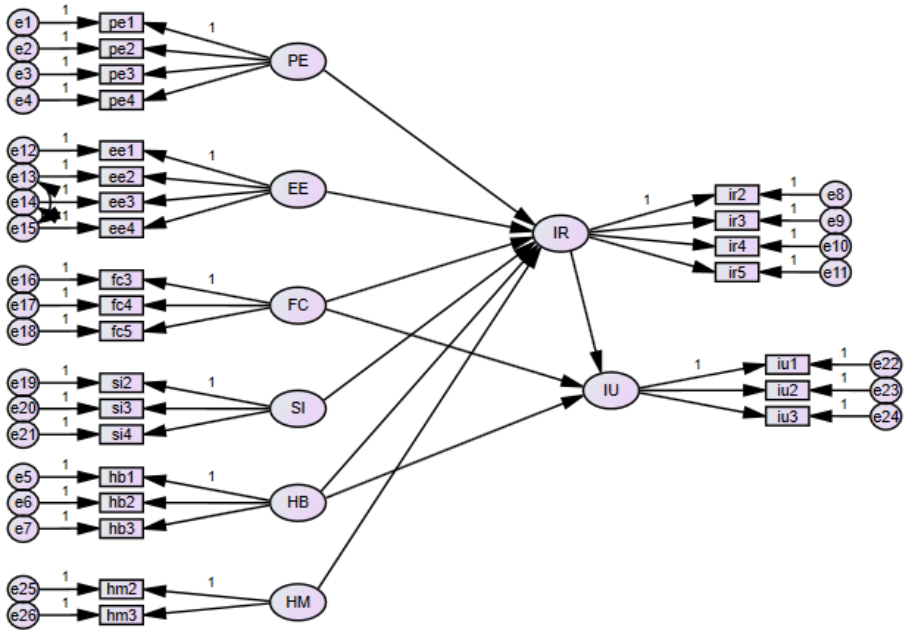

Figure 10. Path Analysis Model

The model fit measures for CFA is given in Table 7. This model showed an acceptable standard of fitness. The P-value is recommended to provide values over 0.05; however, due to the considerable size of the degree of freedom, other model measures could be used to prove the model fitness. The chi-square and degree of

freedom ratio are estimated to be slightly higher than 3.0, but as it is close to the recommendation level, the value was accepted as well-enough for research.

Table 10. Model Fit Measures for CFA

Measure	Estimate	Recommendation	Interpretation
$\chi 2$	2608.027 (837)		
P-value	0.000	>0.05	-
$\chi 2$/df	3.11	<3.00	Closely Acceptable
CFI	0.901	>0.90	Acceptable
AGFI	0.805	>0.80	Acceptable
RMSEA	0.050	<0.08	Acceptable
NFI	0.861	>0.80	Acceptable

5.4 Structural Equation Modeling Results

5.4.1 Total Sample

The SEM result for the full sample can be found in Table 11. The research obtained the unstandardized regression estimate values, along with the standard error, critical ratio, and p-value. The significance level is determined by the p-value, in that when the p-value is close to zero; the estimated value is significant as nonzero.

Table 11. Regression Weights for the Total Sample

Path			Estimate (Unstandardized)	S.E.	C.R.	P-Value	Significance
IR	<---	PE	-.218	.149	-1.461	.144	
IR	<---	EE	-.841	.245	-3.437	<0.001	***
IR	<---	FC	.608	.167	3.645	<0.001	***
IR	<---	SI	-.519	.221	-2.345	.019	*
IR	<---	HB	1.714	.570	3.009	.003	**
IR	<---	HM	-.734	.302	-2.430	.015	*
IU	<---	FC	.206	.035	5.936	<0.001	***
IU	<---	HB	.931	.062	15.035	<0.001	***
IU	<---	IR	-.128	.036	-3.604	<0.001	***

All paths leading to innovation resistance (IR) except performance expectancy (PE) had a significant value of coefficients. Effort expectancy (EE), facilitating condition (FC), had p-values less than 0.001, while habit (HB) had 0.003, and innovation resistance (IR), hedonic motivation (HM) for 0.019 and 0.015, respectively. Facilitating condition (FC), habit (HB), and innovation resistance (IR) strongly influenced the intention to use (IU) in significance level.

Having knowledge on which constructs have significance, the research then progresses onto obtaining the standardized coefficient of each path. Figure 11

explains the results of the standardized coefficients drawn on the research model.

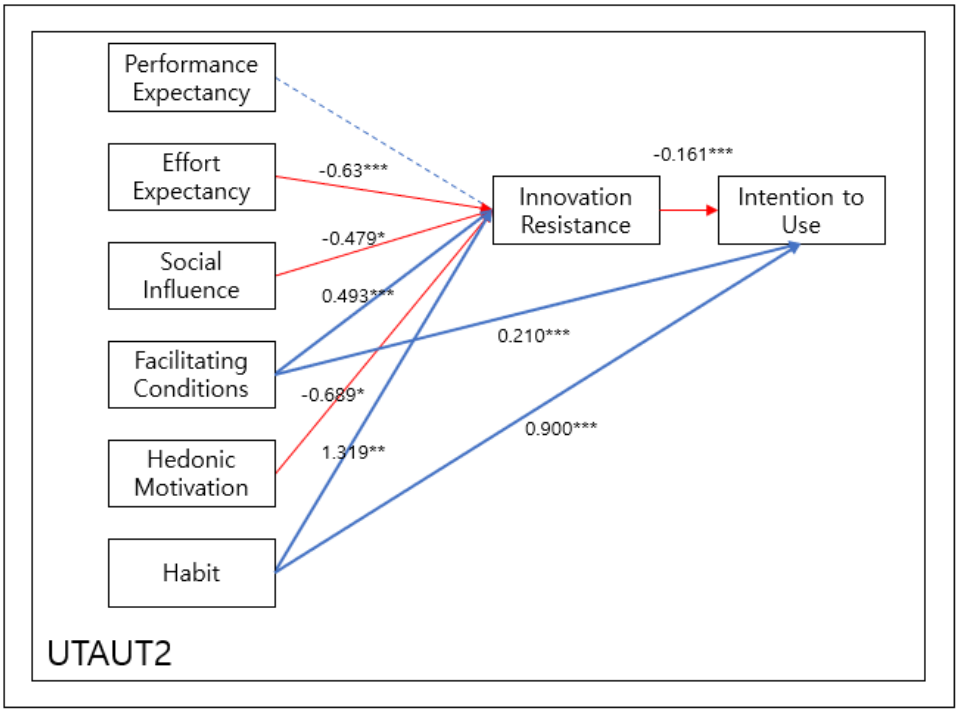

Figure 11. SEM Results of Total Sample

Hypotheses testing is done for investigating whether the result supports each hypothesis. Estimations show that performance expectancy had not negatively influenced innovation resistance regarding statistical significance and therefore, H1 is rejected. Meanwhile, for H2, H3, H4, H5, each construct had a significant negative influence on innovation resistance, and thus the hypotheses are accepted. The same logic for H7, H8, and H9 is applied here. However, for H6, expectations on habit was to have a significant negative influence on innovation resistance, but opposite signs of influence had been observed. Therefore, it is hard to say that this

supports H6. The overall results of the hypothesis testing are provided in Table 12.

The case of rejection on H1 has some implicative meaning. Because the operational definition for performance expectancy meant "The degree to which MOOC will provide benefits to users in performance (e.g., providing knowledge)," the researchers expected that the more an individual hope the performance gained through using MOOC be great, the less the degree of innovation resistance. However, in general, many researches have the common sense that if students be patient and take time using MOOC, they will learn a lot, but in reality, students have hard time making consistent devotion on using the application. Therefore, this phenomenon implies that both performance expectancy and innovation resistance could be high and moving in the same direction.

Table 12. Hypotheses Testing from SEM Results

	Hypothesis & Path	Path Coefficient	P-Value	Result
H1	Performance Expectancy (-) → Innovation Resistance	-0.163	0.144	Not Supported
H2	Effort Expectancy (-) → Innovation Resistance	-0.630	***	Supported
H3	Facilitating Condition (-) → Innovation Resistance	0.493	***	Supported
H4	Social Influence (-) → Innovation Resistance	-0.479	*	Supported
H5	Hedonic Motivation (-) → Innovation Resistance	-0.689	*	Supported
H6	Habit (-) → Innovation Resistance	1.319	**	Not Supported

H7	Facilitating Condition (+) → Intention to Use	0.210	***	Supported
H8	Habit (+) → Intention to Use	0.900	***	Supported
H9	Innovation Resistance (-) → Intention to Use	-0.161	***	Supported

5.4.2 Comparison of Group

The total sample is divided into two groups, experienced and inexperienced, as presented in the previous section. The same procedure of analysis is processed to show the following results.

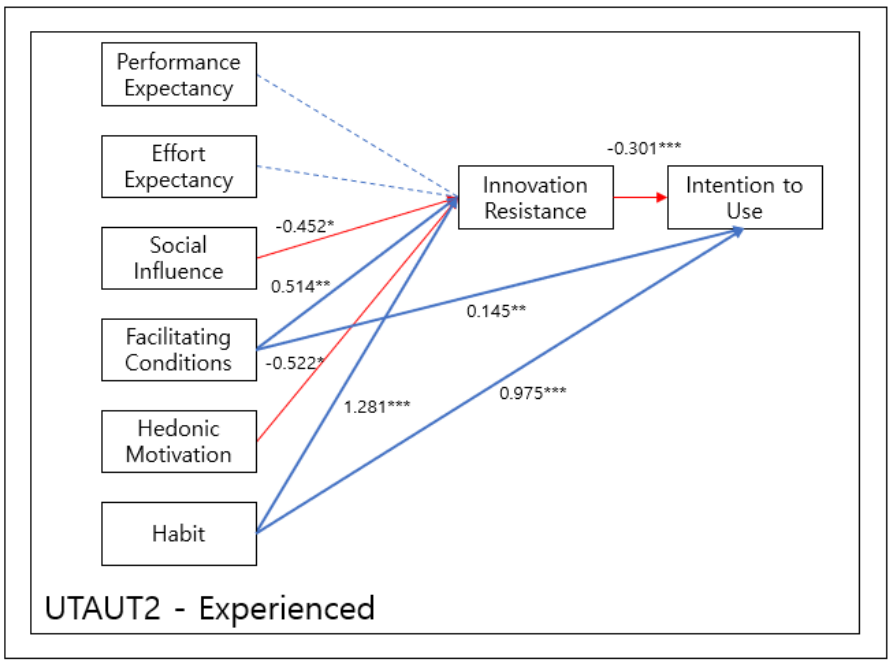

Figure 12. SEM Results for Experienced Group

Since the sample size is reduced from 427 to 212, some p-values of the

corresponding path have increased from those of results from the total sample. For example, effort expectancy used to be one of the significant factors that influence innovation resistance, but when limiting the sample to the experienced group, it is hard to find any significance on the same path. Such behavior is discovered on all paths. Luckily, the sign and the magnitude follow similar patterns when compared to the case of the total sample.

More drastic changes can be found when the research considers the case of the inexperienced group of 215 respondents. The construct of innovation resistance does not convey any meaningful path heading towards itself. Also, unlike the previous models where innovation resistance had a significantly negative influence on intention to use, the analysis implies high p-value and some unrelated coefficients. This implies that the model does not fit very well in the case of the inexperienced as described in Figure 13.

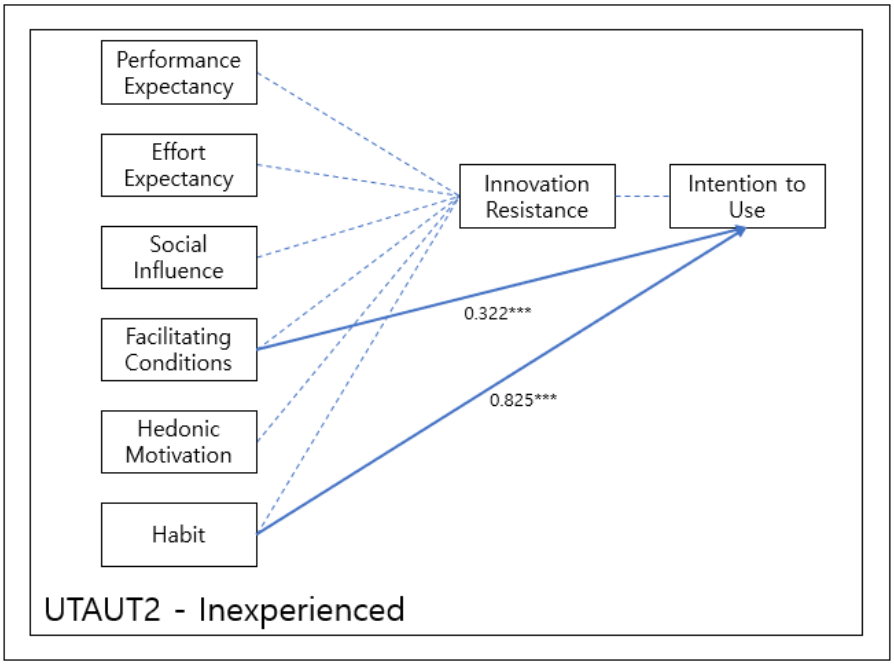

Figure 13. SEM Results for Inexperienced Group

The comparison of coefficients and p-value among the three models, which are the cases on the total sample, the experienced group and last the inexperienced group, is shown in Table 12. The precision of the model builds up when considerable number of samples are collected, and the samples follow the behavior of the planned model. It is found that the signs of the path coefficients are consistent among the three groups. Also, relatively small size and less accurate magnitude of the coefficients in the testing of the inexperienced group have been observed from the analysis of the samples.

Table 13. Comparison of Coefficients and P-Value on Groups

Hypothesis & Path		Total		Experienced		Inexperienced	
		Path Coefficient	P-Value	Path Coefficient	P-Value	Path Coefficient	P-Value
H1	PE (-) → IR	-0.163	0.144	-0.105	0.689	-0.075	0.569
H2	EE (-) → IR	-0.630	***	-0.739	0.052	-0.424	0.064
H3	FC (-) → IR	0.493	***	0.514	**	0.237	0.275
H4	SI (-) → IR	-0.479	*	-0.452	*	-0.11	0.737
H5	HM (-) → IR	-0.689	*	-0.522	*	-0.198	0.677
H6	HB (-) → IR	1.319	**	1.281	***	0.191	0.794
H7	FC (+) → IU	0.210	***	0.145	**	0.322	***
H8	Habit (+) → IU	0.900	***	0.975	***	0.825	***
H9	IR (-) → IU	-0.161	***	-0.301	***	-0.006	0.924

Chapter 6. Conclusion

6.1 Research Summary

This research explores the factors that affect the acceptance of MOOC, a web-based education platform technology, by using the constructs from the existing UTAUT2 model and the concept of innovation resistance. Performance expectancy, effort expectancy, facilitating condition, social influence, hedonic motivation, and habit is considered as the independent variable, while innovation resistance and intention to use to be the dependent variable, adopting the influencing path of UTAUT2. This paper have tested the hypotheses of the paths using Structural Equation Modeling (SEM) by analyzing the survey data of 427 respondents, where 212 people are answering having experience in using MOOC, and 215 people as inexperienced. The empirical results show that most of the hypotheses provided by the above model have been supported by the analysis, while hypotheses of whether performance expectancy and habit have a significant influence on innovation resistance have not been supported. Additional comparison between experienced groups and inexperienced groups was made to support the model.

6.2 Implications

6.2.1 Theoretical Implications

From a theoretical perspective, this study attempted to extend UTAUT2 into using the concept of innovation resistance, to indicate the critical factors of

acceptance on MOOC. Novelty could be found on the modification of the model, and the topic of research. Theoretically, the researchers have managed to find a way to link TAM and innovation resistance model and found some interesting empirical results. During the progress, this paper has provided further evidence that some latent constructs are valid by proving the hypotheses.

6.2.2 Practical Implications

Although this study focused on the empirical results, especially on improving and testing the model, some practical implications can be presented. The paper's data suggest that further research on performance expectancy towards MOOC is necessary because the present findings question the role of performance expectancy for persuading people to use MOOC. This may lead to reconsideration on advertising schemes of MOOC providers.

MOOCs are still in the development process, as various schemes of business model come out and diverge. Contents satisfying high levels of hedonic motivation may replace the current classroom style syllabus. Interesting researches include projects from Kloft, Stiehler, Zheng, and Pinkwart (2014), which elaborates the machine learning method used on predicting MOOC dropout over the weeks, and platform providers could prepare some solution concerning some factors identified in this research.

6.3 Limitations

It is plausible that several limitations may have influenced the results obtained. The first is that survey questions should have been more carefully designed to identify the construct more accurately and to reduce the number of items that were removed. In this regard, the issue of discriminant validity might not have been considered. The second limitation is that the logical gap between innovation resistance and behavioral intention exists. Technology acceptance model and innovation resistance model rooted out from the common studies involving human behavior. As done in this research, there might be a discrepancy when adopting one concept to the other model. A better understanding of both models would have been required for the participants to design better quality of research.

There are some more limitations that reside within the scope of the experiment setup. Respondents who do not know and no experience on MOOC have also been included in the analysis. Like the characteristics of the survey method, this sometimes causes randomness in behavior, not enabling us to identify other intolerant factors involved. Some might argue that statistical explanations would be enough, but more delicate screening of respondents might have been needed.

6.3.1 Future Research

The discussion on the future of MOOC is still on-going. With new participants steadily experiencing in the next-generation education platform, researchers'

expectation varies, from those who expect that it will substitute universities to those who believe this as just another hype. Apart from this discussion, however, it is impossible to deny the fact is that people are consistently using the innovative education platform and the style of the service is also changing to fit the needs of individuals. As mentioned above, diverse types of MOOC have been released, all platforms showing different styles of their own. What is the best form of MOOC? And what are the factors that researchers should consider? Unsolved answers leave space for future research, in this case, especially on the acceptance of MOOC.

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Appendix: Survey Sheet

온라인 공개 강좌 (MOOC)의 수용 요인에 대한 연구 설문

온라인 공개 강좌(MOOC)의 인식 및 사용경험

여기서 온라인 공개 강좌 (MOOC: Massive Open Online Course)는 대학 등의 교육기관에서 제공하는 강의를 온라인으로 제공하여 수많은 수강생이 지속적으로 수업을 들을 수 있도록 하는 플랫폼 및 교육 체계를 의미합니다.

- **MOOC에 대한 설명 (출처: K-MOOC 홈페이지)**

한국형 무크(K-MOOC)

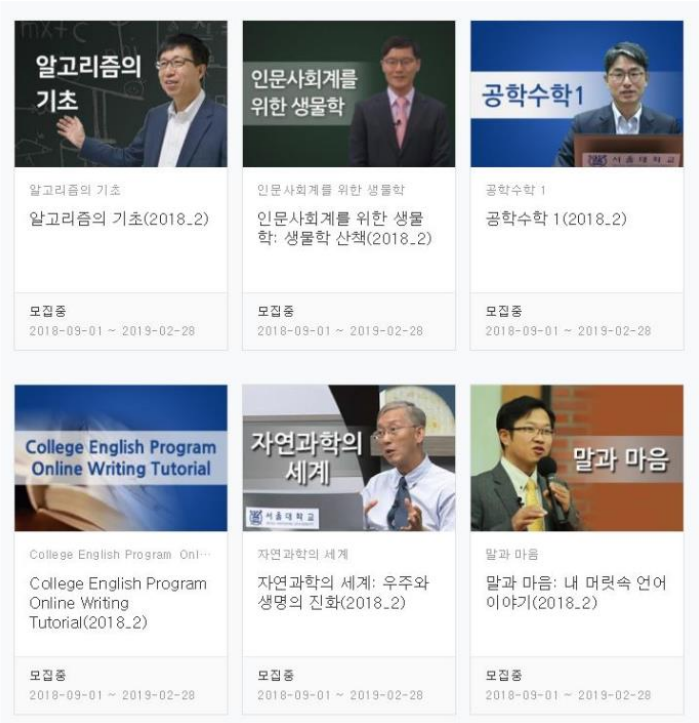
MOOC(Massive Open Online Course)란

수강인원에 제한 없이(Massive), 모든 사람이 수강 가능하며(Open), 웹 기반으로(Online) 미리 정의된 학습목표를 위해 구성된 강좌(Course)를 말합니다. 무크(MOOC)는 학습자가 수동적으로 듣기만 하던 기존의 온라인 학습동영상과 달리 교수자와 학습자, 학습자와 학습자간 질의응답, 토론, 퀴즈, 과제 제출 등 양방향 학습이 가능한 새로운 교육 환경을 제공합니다.

아울러, 학습자는 세계를 넘나들며 배경지식이 다른 학습자간 지식 공유를 통해 대학의 울타리를 넘어 새로운 학습경험을 하게 될 것입니다.

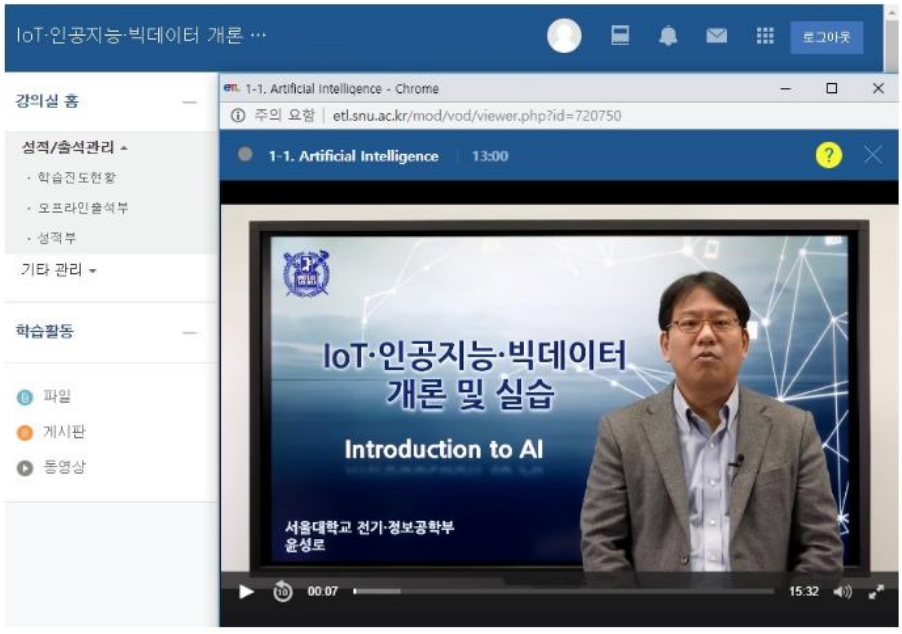
MOOC는 Coursera, EdX, Udacity 등 미국 온라인 강의 플랫폼으로부터 출발하여, 수학/공학 분야뿐만 아니라 다른 분야까지 확장하는 추세이며, 특정 인기강좌의 경우 수백만명에 달하는 수강생을 확보하는 등 그 인기가 점차 확대되고 있습니다. 현재는 한국에서도 평생교육원의 K-MOOC, 네이버의 edWith 등 정부, 대학, 기업과 연계하여 대중을 위한 온라인 강좌를 제공하고 있습니다. 특정 강의주제에 대하여 교수자와 학습자가 질문을 주고받으며 짜임새 있는 수업을 들을 수 있는 플랫폼이며, 대부분의 강좌는 모두에게 무료로 열려 있기 때문에 제한없이 수강생이 원하는 강의를 신청하고 들을 수 있습니다.

MOOC의 예시 (사진 출처: 서울대학교 SNUON 강의시스템)



다만, 현재 대학교 학점으로 MOOC가 인정되지 않는 것과 같이 MOOC를 실제 현장 수업을 대체하는 수단으로 보는 것에 대하여 회의적인 시각이 존재합니다. 또한, 수강생의 입장에서 수업을 신청하기 쉬운 만큼 수강을 도중에 중단하기도 쉬워 교육적 효과에 대한 논란이 있기도 합니다. 이에 따라 일부 체계적인 MOOC에서는 교육 성과를 위하여 적절한 수준의 학습 커리큘럼 (주기적인 수업 참여, 과제 및 시험 평가, 종합성적)를 제공하며, 주어진 모든 과제를 성실히 이수한 학생에게 유료로 수료증을 발급하는 등의 보상책을 마련하기도 합니다.

MOOC의 예시 (사진 출처: 서울대학교 SNUON 강의시스템)



1. 온라인 공개 강좌 (MOOC)에 대하여 알고 계셨습니까?

○ 나는 MOOC가 무엇인지 알고 있으며 현재 지속적으로 사용을 하고 있다.

○ 나는 MOOC에 대하여 들어봤으며 어느 정도의 실제 사용경험이 있다.

○ 나는 MOOC에 대하여 들어본 적이 있으나 사용해본 경험은 없다.

○ 나는 MOOC에 대하여 한번도 들어본 적이 없다.

설문응답자 기본 정보 조사

2. 귀하의 성별은 어떻게 되십니까?

○ 남성

○ 여성

3. 귀하의 나이대를 체크해주세요.

○ 10대

○ 20대

○ 30대

○ 40대

○ 50대

○ 60대 이상

4. 귀하의 최종학력은 어떻게 되십니까?

○ 중학교 졸업 이하

○ 고등학교 졸업

○ 대학교 재학

○ 대학교 (전문대) 졸업

○ 대학원 재학 (석, 박사)

○ 대학원 졸업

5. 현재 귀하의 월평균 소득은 얼마나 되십니까?

○ 100만원 미만

○ 100만원 ~ 200만원

○ 200만원 ~ 300만원

○ 300만원 ~ 400만원

○ 400만원 ~ 500만원

○ 500만원 이상

6. 귀하의 직업은 어떻게 되십니까?

○ 학생

○ 직장인

○ 실직/구직 중

○ 자영업

○ 전업주부

○ 군인

○ 은퇴자

○ 기타:_____

7. 현재 귀하의 직업에 대한 분류를 해주세요.

○ 해당 없음

○ 관리자

○ 전문가 및 관련 종사자

○ 사무종사자

○ 서비스 종사자

○ 판매 종사자

○ 농림 어업 숙련 종사자

○ 기능원 및 관련 기능 종사자

○ 장치 기계 조작 및 조립 종사자

○ 단순노무 종사자

8. 공부/일을 할 때 새로운 것을 익히고 배워야 할 상황에 자주 놓이십니까?

	1	2	3	4	5	6	7	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

온라인 공개 강좌(MOOC)의 수용 요인 조사

지금부터 온라인 공개 강좌(MOOC)에 대한 여러분들의 생각에 대하여 질문할 것입니다. 만약 여러분들께서 MOOC 사용경험이 없으시다면 앞서 기술된 인터넷 강의 기반 교육 서비스를 생각을 하시면서 예상되는 답변에 체크를 해주시면 됩니다. 사용경험이 있으시다면 실제 사용경험을 바탕으로 다음의 질문에 응답해주세요.

여러분은 질문에 대하여 1점 '매우 그렇지 않다'부터 7점 '매우 그렇다' 사이에 본인의 견해와 일치하는 번호를 선택하여 답변을 해주시면 됩니다.

A. 성과에 대한 기대 (Performance Expectancy)

9. 나는 MOOC를 이용하여 새로운 지식을 습득할 수 있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

10. MOOC를 활용하여 나는 회사/일터/교육기관 등에서 생산성을 높일 수 있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

11. MOOC가 나의 전반적인 사고력/창의력 증진에 기여를 할 수 있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

12. MOOC를 통해 학습을 하면 정리된 자료 및 평가를 통해 효율적으로 학습을 할 수 있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

13. MOOC를 이용하여 나는 과거에 배웠던 자료를 복습할 수 있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

B. 노력에 대한 기대 (Efforts Expectancy)

14. 내가 MOOC를 이용하여 학습하는 것은 쉬울 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

15. MOOC가 무언가를 배우는데 있어 편리한 방법일 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

16. 나는 MOOC 서비스를 어떻게 사용해야 하는지 잘 이해할 수 있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

17. 나는 MOOC를 처음 사용하는 사람에게 사용방법을 어렵지 않게 설명할 수 있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

C. 사회적 영향 (Social Influence)

18. 나의 주변인들 (가족, 동료, 친구, 친척 등)이 MOOC를 많이 사용한다면 나도 사용할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

19. 나의 주변인들 (가족, 동료, 친구, 친척 등)은 MOOC 서비스가 유용하다고 생각할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

20. 나의 주변인들 (가족, 동료, 친구, 친척 등)은 나에게 MOOC를 사용하길 권장할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

21. 나는 다른 사람들에게 MOOC의 사용을 권장할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

D. 촉진 조건 (Facilitating Conditions)

22. 나는 MOOC를 이용하는데 드는 비용이 저렴하다고 생각할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

23. 나는 MOOC 사용 도중 기술적 문제가 발생한 경우 충분한 도움을 구할 수 있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

24. 나에게는 MOOC를 활용할 수 있는 인터넷, 스마트 디바이스 등의 IT 환경이 마련되어 있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

25. 나는 MOOC 를 사용할 수 있을 정도 이상의 IT 환경에 대한 기본 지식과 경험을 갖추고 있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

26. 나는 MOOC 이용할 때 담당자와 소통할 수 있는 충분한 채널(메일, 게시판 등)을 보유할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

E. 오락적 동기 (Hedonic Motivation)

27. 전반적으로 MOOC 를 통해 학습을 하는 것은 재미있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

28. MOOC 를 제한없이 사용 가능하다는 사실이 나에게 흥미롭게 느껴질 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

29. 내가 MOOC를 통해 모르는 내용을 질문하여 답을 얻는 과정은 나에게 즐거울 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

30. MOOC에서 부여한 과제를 하는 것은 나에게 성취감을 부여할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

31. MOOC의 학습평가에서 높은 점수를 얻는 것은 나에게 성취감을 부여할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

F. 습관성 (Habit)

32. MOOC 수업에 참여하는 것은 충분히 나에게 습관이 될 수 있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

33. MOOC가 제공하는 학습 커리큘럼을 따르는 것은 나에게 중요할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

34. 나는 지정된 시간에 MOOC를 이용하려고 노력할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

35. 나는 만약 MOOC 를 통해 모르는 것을 질문하는 것이 부담스럽지 않다면 강의 교수자와 상호작용하는 것에 익숙해질 수 있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

36. 나는 하나의 MOOC 강의 수강을 완료한 이후에도 다른 유용한 강의들을 계속 들을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

G. 혁신저항 (Innovation Resistance)

37. 나는 내가 반드시 MOOC 를 사용하도록 강요를 받을 때 불만을 가질 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

38. 나는 MOOC가 혁신적/효율적인 교육방법이 아닐 것으로 예상할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

39. 나는 MOOC를 통하여 높은 학업성취도를 달성할 수 있다고 말하는 사람들이 이해가 되지 않을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

40. 나는 MOOC가 결국 배우는 방식에 대한 한계가 있을 것이며 기존의 교실 수업 방식을 넘어서지 못한다고 생각할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

41. 나는 MOOC가 미래에 주목받는 비중이 줄어들 것이라 생각할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

H. 사용의도 (Intention To Use)

42. 나는 앞으로 MOOC를 유용하게 사용할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

43. 나는 MOOC의 다양한 기능(강의 듣기, 온라인 포럼이용, 과제 및 평가)을 이용해보고 싶을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

44. 나는 나에게 유용한 새로운 MOOC 강좌를 지속적으로 탐색할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

45. 나는 만일 MOOC 강의를 이용하는데 조건 (유료화/시간 제한 등)이 생긴다면 그 조건을 맞춰서 수업을 수강할 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

46. 나는 MOOC를 내가 속한 조직에서 활용할 것을 건의할 의향이 있을 것이다.

	①	②	③	④	⑤	⑥	⑦	
매우 그렇지 않다	○	○	○	○	○	○	○	매우 그렇다

Abstract (Korean)

MOOC는 기존의 학습관리시스템 상위에 공개교육자료, 온라인 동영상 콘텐츠를 추가하여 강의를 수많은 대중에게 제공하는 서비스로 2010년 이후 전세계적으로 큰 인기를 끌고 있다. 그럼에도 불구하고 MOOC 서비스 내의 강좌 수강을 완료하는 인원 비율이 현저하게 떨어지기 때문에 그 실효성에 대한 토론이 진행되고 있는 실정이며, 이러한 맥락에서 학습자의 MOOC의 수용의도를 조사하는 여러 연구가 진행된 바 있다. 이 연구는 동일한 맥락에서 MOOC 서비스를 중심으로 하여 웹 기반 학습의 기술수용의도를 조사하기 위하여 기술수용모델(TAM)과 혁신저항을 차용한다.

본 연구는 이용자의 MOOC에 관한 사용의도를 분석하기 위하여 총 427명의 설문 데이터를 확보하였으며, UTAUT2 모형을 기반으로 성과기대, 노력기대, 촉진조건, 사회적 영향, 오락적 동기, 습관 등의 요인이 혁신저항 및 사용의도에 어떠한 영향을 미치는지 구조방정식 모형으로 분석을 실시하였다. 그 결과, 대부분의 잠재변인이 혁신저항 및 사용의도에 영향을 미쳤지만, 성과기대의 경우 혁신저항에 대하여 유의미한 부의 영향을 주지 못한다는 것을 확인하였다. 또한, 온라인 공개강좌에 대한 과거 경험에 따라 모형의 해석이 달라진다는 것을 확인하였으며, 경험이 있는 경우 전체 모형을 더욱 잘 따른다는 것을 검증하였다.

주요어 : 웹 기반 학습, 기술수용모델, 혁신저항, 온라인 공개 강좌, 구조방정식
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