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인공지능 기반으로 맞춤 및 적응형 학습 시스템의 고등 교육에서의 적용효과

조윤정
KDI국제정책대학원

요약

인공지능 기반 맞춤 및 적응형 학습을 대학원 이상의 수업에 적용에 따른 실증 연구는 매우 부족한 상황이다. 본 연구는, 인공지능 기반 맞춤 및 적응형 학습을 대학원 수업에 적용한 경우, 만족도 및 충성도를 연구 했으며, 테크놀로지관련 인식, 컨텐츠 및 시스템 특성에 대한 인식, 및 인공지능 기반 맞춤형 학습과 강의를 병행한 교육에 대한 전반적인 인식이 만족도, 효과성, 유용성, 동기부여, 및 다른 수업에 적용에 따른 의사에 어떻게 영향을 주는 지 조사하였다. 인공지능 기반 맞춤 및 적응형 시스템인 알렉스를 적용한 강의 직후 온라인 설문조사를 통한 데이터를 사용하였으며, 요인분석, 회귀분석, 분산분석 등을 활용하여 가설검증을 하였다. 본 연구의 결과로, 어떤 요인들이 유의하게 영향을 주는 지와 효과의 크기를 비교 검증하였고, 더불어 만족도가 충성도에 영향을 미치는 이론이 교육효과에도 적용됨을 입증하였다. 또한, 인공지능 기반 맞춤 및 적응형 시스템의 고등교육 특히 대학원 수업에도 효과가 있고, 고객관계관리에 도움이 된다는 시사점을 제시한다.

키워드 : 인공지능 기반 맞춤형 적응형 학습, 고등교육, 고객관계관리, 만족도, 충성도

Effects of AI-Based Personalized Adaptive Learning System in Higher Education

Yooncheong Cho
KDI School of Public Policy and Management

Abstract

The purpose of this study is to investigate the effects of assessment by adopting adaptive learning in higher education that are rarely examined in previous studies. In particular, this study applied research questions: 1) How does technical perception, perceived contents and features, and perceived integration of the AI-based adaptive system with lecture affect overall satisfaction, overall effectiveness, overall usefulness, overall motivation for the study, and intention to use it with other classes? 2) How do overall satisfaction, overall effectiveness, overall usefulness, motivation for the class, and intention to use affect loyalty on the AI-based adaptive system? This study conducted online surveys after the completion of the classes adopted AI-based adaptive learning system, ALEKS. This study applied ANOVA, regression, and factor analyses. The results of this study found that perceived integration of the AI-based adaptive learning system with the lectures on overall satisfaction, effectiveness, motivation, and intention to use for other classes showed significant with higher effect size. The results of this study provides implication that the AI-based learning system help improve learning outcomes in graduate level studies. The results provide policy and managerial implications that the AI-based adaptive learning system should improve better customer relationships in higher education.

Keywords : AI-Based Adaptive Learning, Higher Education, Customer Relationship Management, Satisfaction, Loyalty

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1. Introduction

With the rapid advancement of information technology, technology-enhanced pedagogies[19] have been adopted in higher education. Computer-based assessment for adaptive content in e-learning has been adopted rapidly[23] in higher education. El-Sabagh (2021) addressed that adaptive e-learning has become approach that is widely implemented by higher education institution[11]. Scalise, Bernbaum, and Timms (2007) called it differentiated e-learning that anticipates what the user wants or needs and makes suggestions or delivers a personalized services in many areas[32].

As stated by Kerr (2016) and Webley (2013), adaptive learning has been described as a hot concept that is poised to reshape education[20, 40]. The terms such as individualization and personalization are applied to provide customized services in higher education by examining individual needs and wants. Various studies determined adaptive learning with the system or software as a personalized learning[18]. Kerr (2016) applied terms of individualization and personalization for application of adaptive learning in educational contexts, since students can progress through the material at different speeds and the objectives and contents may all vary[20]. Personalized learning for students also has been described as part of a “quiet revolution”[17] in higher education. Hopkins (2004) also addressed that personalization is a major theme of public service reform and is one of the principles and government strategy for learners[17]. Sun, Abdourazakou, and Norman (2017) stated the role of customized and interactive online teaching and learning for better effectiveness[36].

Previous studies have addressed the importance of adaptive learning systems. Previous studies examined effects based on the learning curves that are provided by the system, while not many studies have analyzed effects based on perceptions of students. Therefore, the purpose of this study is to explore how the adoption of AI-based adaptive learning systems help improve better assessment of learning in higher education by investigating students’ perceptions. In particular, this study investigated perceptions of graduate level students that were rarely examined in previous studies. In order to measure effects of AI-based adaptive learning systems, this study classified effects of technical perception, perceived contents and features, and perceived integration of the AI-based adaptive system with lecture.

Research questions include the following: 1) How does technical perception of the AI-based adaptive system affect overall satisfaction, overall effectiveness, overall usefulness, overall motivation for the study, and intention to use it with other classes? 2) How do perceived contents and features of the AI-based adaptive system affect overall satisfaction, overall effectiveness, overall usefulness, overall motivation for the study, and intention to use it with other classes? 3) How does perceived integration of the AI-based adaptive system with lecture affect overall satisfaction, overall effectiveness, overall usefulness, and overall motivation for the study, and intention to use it with other classes? 4) How do overall satisfaction, overall effectiveness, overall usefulness, and motivation for the class affect loyalty on the AI-based adaptive system?

2. Literature Review

After the presence of the Internet, electronic-based learning (e-learning) has been generated in the field of education[4]. According to Albert and Mori (2001), e-learning has a broad meaning and captures terms like computer based learning and teaching, computer assisted learning, technology-based teaching, internet-based teaching, computer-assisted intelligent teaching system, etc.[4] This study investigates the effects of AI-based adaptive learning that is developed with advanced algorithm for personalized learning assessment.

2.1. AI-Based Personalized Adaptive Learning

According to Kerr (2016), adaptive learning means different things to different people and defines as a way of delivering learning materials online based on learner's interaction with previous content determines the nature of materials delivered subsequently[20]. Kerr (2016) also stated that adaptive learning is an educational technology that makes students' progress with their own speed, as the process is automated, dynamic, and interactive[20]. Oxman and Wong (2014) addressed that adaptive learning helps students by addressing common learning challenges, including student motivation, diverse student backgrounds, and resource limitations[27]. Adaptive e-learning is a learning process in which the content is taught or adapted based on the responses of the students' learning styles or preferences[24,27] as cited in El-Sabagh[11]. Harati, Sujo-Montes, Tu, Armfield, and Yen (2021) defined adaptive learning as an educational method that uses computer algorithms and artificial intelligence to customize learning materials and activities based on each user's model[15]. A study by Acampora, Gaeta, and Loia (2011) addressed that computational intelligence methodologies can support e-learning system by providing learning content and activities with efficient methods to develop "in time" e-learning environment[1].

According to Verdú, Regueras, Verdú, De Castro, and Pérez (2014), adaptive learning, also known as intelligent education systems, offers important advanced educational services since it provides students with individual and personalized learning[39]. Heller, Steiner, Hockemeyer, and Albert (2006) addressed that personalized learning aims to tailor teaching based on individual needs, interests, and aptitude, therefore, every learner achieves and reaches the highest standards possible[16]. Okoye (2018) stressed that the application for personalized adaptive learning systems as user-centric service plays a key role to improve learning effectiveness by monitoring changes in patterns or behaviors, track learners' activity executions and progress, and provide feedback to make adjustments to increase the user's motivation[26]. Popescu, Trigano, and Bădică (2007) explained that accommodating learning styles in adaptive educational systems represents an important step towards providing individualized instruction[28]. Taylor, Yeung, and Bashet (2021) addressed the importance of personalized and adaptive learning that provide students a flexible learning environment and accelerate learning by creating an individualized learning path directed by prior knowledge and continuous assessment of performance[38]. Popescu (2008) also highlighted that the ultimate goal of advanced educational hypermedia systems is to provide a learning experience with individualization based on the particular needs of learners from the point of view of knowledge level, goal, motivation, individual differences, etc[29].

2.2. Assessment Learning in Knowledge Space (ALEKS)

Taylor, Yeung, and Bashet (2021) highlighted that the individualized learning pathway provided by the adaptive learning platform provides remediation as needed, including appropriate feedback and scaffolding[38]. Scalise, Bernbaum and Timms (2007) introduced four adaptive technology for e-learning as follows: i) NetPass, developed based on a developmental perspective of student learning; ii) Quantum Tutors aligned with the goals of instruction for assessment; iii) FOSS Self-Assessment System produces valid and reliable evidence of what students know and can do for assessment; and iv) ALEKS (Assessment Learning in Knowledge Space) provides assessment data that is useful to teachers and students to improve learning outcomes[32].

ALEKS as a web-based, artificially intelligent assessment and learning system, uses adaptive questions by accurately determining exactly what topics a student knows and doesn't know in a course (www.mheducation.com, McGraw Hill)[43]. Harati, Sujo-Montes, Tu, Armfield, and Yen (2021) explained that ALEKS was designed for Math and Sciences courses, while it is available for K-12 and other higher education course[15]. After students registered ALEKS, they are asked to take the initial knowledge check that recognizes personalized knowledge level. Students start solving topics based on "objectives" (i.e., main topic for each week) that are selected by instructor. In order to pass each topic, students need to acquire expected points. ALEKS provides explanations if students could not solve questions, while students increase learning until they reach expected points and meet the goals. After ALEKS instructs the student on the objectives that he or she is most ready to learn, it periodically reassesses the students to ensure that topic learned are also retained[35]. Therefore, students who show a high level of mastery of an ALEKS course have the potential to do well in the actual course being taken[35]. According to Scalise, Bernbaum and Timms (2007), ALEKS is a comprehensive assessment program that assesses students' ability level and synthesizes relevant information into reports that are easily understood and used by those who make instructional decisions[32]. Nwaogu (2012) stated that ALEKS is interactive e-learning systems and assessment tools based on the knowledge space theory[25]. Scalise, Bernbaum, and Timms (2007) also addressed that ALEKS, as one of major e-learning products, assesses student knowledge states and attempts to provide individual and class reports on mastery to teachers and students[32].

According to Fang, Ren, Hu, and Graesser (2019), the role of ALEKS was defined as principal instruction when it took the place of traditional classroom instruction and was used as a major instructional method for a specific subjects such as math and statistics, while ALEKS was also regarded as a supportive instruction and supplement for homework, outside of regular classroom hours, etc.[14] Albert and Lukas (1999) stated that ALEKS determines what a student knows and is ready to learn, and provides personalized learning paths that are ideal for each student. ALEKS was empirically evaluated in some previous studies in various settings, and was observed to be effective in most of the studies[25], while Fang, Ren, Hu, and Graesser (2019) concerned that students' academic achievement with ALEKS did not reveal any significant difference[14]. Taylor (2006) also found that ALEKS did not yield better performance in a college algebra course than the traditional lecture[37]. When investigating the effect of ALEKS in a statistics course in a graduate school, a positive effect of ALEKS on test score was found[41]. Eze (2012) examined the effect of ALEKS on students' mathematics achievement in an online learning environment and the cognitive complexity of the initial (pretest) and final (posttest) assessmen[13]. Reddy and Harper (2013) examined that ALEKS assessments are effective measures of knowledge increase when students' performance is aggregated[30].

3. Theoretical Background

Various studies have supported the concept of adaptive learning. Experiential learning theory defined learning as the process whereby knowledge is created through the transformation of experience[22]. Albert and Mori (2001) applied cognitive psychology to support the future of e-learning and stated that cognitive psychology is fundamental for individualizing e-learning processes[4]. Albert and Mori (2001) also addressed that theoretical models and empirical results of cognitive psychology enable us to optimize the individual's learning of specific knowledge and skills by adapting the e-learning system to the student' pre-knowledge, to his or her growing knowledge and learning goal, and to the optimize individual learning processes by improving general learning skills[4].

Knowledge space theory by Doignon and Falmagne (1999; 2016) known as the psychological development in the field of e-learning, is a psychological mathematical theory using dependencies between the problems and other learning objects in a knowledge domain for structuring the assessment process and the teaching process[7.8]. Heller, Steiner, Hockemeyer, and Albert (2006) stated that knowledge space theory provides a set-theoretic framework for representing the knowledge of a learner in a certain domain, which is characterized by a set of assessment problems[16]. Further, Steiner, Nussbaumer, and Albert (2009) addressed that competence-based knowledge space theory provides a knowledge representation framework and has been successfully applied in various e-learning systems such as ALEKS by providing automated personalization to learners' current knowledge and competence level[33]. Steiner, Nussbaumer, and Albert (2009) also highlighted that competence-based knowledge space theory provides a powerful framework for domain and leaner knowledge representation and can be applied for realizing intelligent, adaptive e-learning, adaptive personalized e-learning services, and enhanced learning experience and knowledge transfer[33]. An extension of the theory of knowledge spaces introducted by Doignon and Falmagne (1985) is also presented by Albert, Schrepp, and Held (1994)[3,6].

4. Hypothesis Development

Previous studies (Verdú et al., 2014) stated that learners' opinion could be evaluated using students' degree of satisfaction, system adaption, preferences, and performance of adaptive learning[39]. This study proposed four factors that affect satisfaction including technical perception, perceived contents and features, perceived integration with lecture, and motivation. Previous studied stated that once learning experiences are customized, e-learning content becomes richer and more diverse (El-Sabagh & Hamed, 2020; El-Sabagh, 2021; Yang, Huang, & Li, 2013) with technical functions.[10,11,42] AI-based adaptive learning system used in this study, ALEKS, describes various technical functions using pop-up and animation for guides, alarm based on daily, weekly and monthly timeline, pie chart study mode, navigation menu, calculator, etc. (www.mheducation.com, McGraw Hill)[43]. Such technical functions help improve contents and features that also allow students to make study plans based on previous study experiences, remaining topics to study, timeline details, etc. (www.mheducation.com, McGraw Hill)[43]. Real-time learning progress also provided by mastered, learning, and remaining with different colors (www.mheducation.com, McGraw Hill)[43].

Stokes, Gillan, and Braden (2016) examined the effects of usability of interfaces from adaptive online learning and how their quality affects student performance and satisfaction[34]. A previous study by Sun, Abdourazakou, and Norman (2017) addressed the importance of integration of an interactive digital textbook could enhance student learning and learning effectiveness[36]. Previous studies explored that online courses with higher levels of interactivity related to higher levels of student motivation, academic performance, and satisfaction in interactive learning environment[12]. Xu, Meyer, and Morgan (2009) addressed that motivation is an influential factor in the statistics education and may be strengthened if individuals' complex needs are met[41]. Elliot and Dweck (2005) also addressed that achievement motivation should be considered in terms of competences[9].

Previous studies (e.g., Law, 2021) examined necessary improvement of student's attitude and satisfaction towards online learning and directed a better pedagogical approach on how to increase the effectiveness of online learning[21]. Verdú et al. (2014) also examined that the adaptive systems improve learning efficiency and learning satisfaction[390. Cho (2021) examined the effects of factors of higher education on satisfaction[5]. Hypotheses "a" applied to overall satisfaction, "b" applied to overall effectiveness, and "c" applied to overall usefulness, "d" applied to overall motivation for the study, "e" applied to intention to use it with other classes.

Therefore, this study hypothesizes the following:

H1a~e: Perceived technical aspects of the AI-based adaptive learning system affects overall satisfaction, overall effectiveness, overall usefulness, overall motivation, and intention to use.

H2a~e: Perceived contents of the AI-based adaptive learning system affects overall satisfaction, overall effectiveness, overall usefulness, overall motivation, and intention to use.

H3a~e: Perceived features of the AI-based adaptive learning system affects overall satisfaction, overall effectiveness, overall usefulness, overall motivation, and intention to use.

H4a~e: Perceived integration of the AI-based adaptive learning system with lectures affects overall satisfaction, overall effectiveness, overall usefulness, overall motivation, and intention to use.

This study also measures effects of overall satisfaction, effectiveness, usefulness, motivation, and intention to use on loyalty when adaptive learning system is adopted in higher education. Therefore, this study hypothesizes the following:

H5a~e: Overall satisfaction, overall effectiveness, overall usefulness, overall motivation, and intention to use of the AI-based adaptive learning system affect loyalty.

5. Methodology

5.1. Adoption of ALEKS in Class

Since ALEKS, as a research-based online learning program offers course products for Math, Chemistry, Statistics, and more (www.aleks.com)[44], this study explored the adoption of ALEKS in quantitative methods classes in higher education, particularly classes for the graduate level. This study conducted the use of the AI-based adaptive learning system in higher education institution in a globalized environment with students' bodies from more than 130 countries and with most of all classes taught in English. The institution adopted ALEKS in all quantitative methods classes from 2019 after conducting an experiment in 2018. Prior to adoption, professors took the seminar regarding ALEKS with practice and learning through diverse materials provided by McGraw-Hill. In particular, professors gained knowledge of technical aspects, contents and features of the ALEKS and considered how it could be integrated with the lectures. Professors prepared materials that support students' learning associated with ALEKS. Professors also select topics and objectives related to the lecture for each week after reviewing all topics provided by ALEKS. About four to eight topics were selected for each objective that is applied in each week. Before starting using ALEKS, students conducted an initial knowledge check applied by ALEKS for the use of a personalized adapted system. Students are also trained how to use ALEKS by watching recorded video clips for guidelines. Textbook was adopted by matching topics and objectives provided by ALEKS. ALEKS topics were selected based on 15 chapters from the textbook. Teaching assistants were selected based on those students who have experienced with ALEKS from the class in previous semester. In order to improve learning effectiveness and satisfaction, seminar and sessions by teaching assistants and office hours by professors were provided. Further, e-learning classes have been applied with the adoption of ALEKS. Class size was managed with 60 to 80 after the adoption of ALEKS. Students are assessed with the final exam after learning both from ALEKS and lectures.

5.2. Online Survey Design

This study conducted online surveys from the quantitative method classes after the end of the semester. The class is the graduate level core course that offers three different degree programs including the master of public policy, the master of public management, and the master of development policy. Survey questionnaire items consist of major questions with demographic questions. Major questions include questionnaire items regarding technical perspectives on the AI-based adaptive system, perceived contents and features of the AI-based adaptive system, perception on integration of the AI-based adaptive system with lecture, overall satisfaction, overall usefulness, overall effectiveness, intention to use, and loyalty on AI-based personalized adaptive systems This study applied a 5-point Likert scale (1 - Strongly disagree, 5 - Strongly agree). By asking gender, age group, programs enrolled, enrollment status such as full-time or part-time, and year entered the program, this study additionally analyzed effects in addition to the main effects. The survey was conducted voluntarily and anonymous and the data was stored confidentially. Total one hundred seventy one students out of two hundred eight students responded and completed the survey. The response rate was 0.82. Table 1 summarized demographics of respondents.

<Table 1> Demographics of Respondents

Characteristics		Number	%
Gender	Male	120	70.2%
	Female	51	29.8%
Age	Under 25 years old	1	1.2%
	25 years old ~ 30 years old	21	12.3%
	31 years old ~ 35 years old	24	14.0%
	36 years old ~ 40 years old	38	22.2%
	41 years old ~ 45 years old	69	40.4%
	46 years old ~ 50 years old	13	7.6%
	51 years old ~ 55 years old	4	2.3%
Programs Enrolled	Master of Public Policy	84	49.1%
	Master of Public Management	52	30.4%
	Master of Development Policy	35	20.5%
Nationality	Korean	136	79.5%
	International	35	20.5%
Total		354	100

This study conducted Cronbach alpha to check reliability. The results of Cronbach alpha include the following: 0.815 for technical perspectives of the AI-based adaptive system, 0.908 for perceived contents of the AI-based adaptive system, 0.731 for perceived features of the AI-based adaptive system, and 0.851 for integration of the AI-based adaptive system with lecture. Table 2 summarized mean and standard deviation.

<Table 2> Summary of Mean and St. Deviation

Items	Mean	St. Deviation
ALEKS system was easy to access through e-education.	4.86	0.48
The professor and teaching assistants responded to technical problems in a timely manner.	4.80	0.55
ALEKS interface was ease to use.	4.79	0.49
The difficulty of the contents in ALEKS was appropriate.	4.58	0.65

The questions in ALEKS was useful to learning new concepts.	4.79	0.50
The questions in ALEKS helped me improve my understanding of the topics.	4.76	0.52
The “Explain” feature when working in ALEKS was helpful.	4.75	0.53
The “Calculator” feature when working in ALEKS was helpful.	4.73	0.58
It was easy to track my learning progress through ALEKS system.	4.69	0.59
The time required to complete weekly objectives was appropriate.	4.67	0.64
The topics in ALEKS was properly covered in the lecture and teaching assistant sessions.	4.72	0.56
ALEKS helped to improve my understanding of the topics in line with lecture.	4.76	0.52
The class evaluation weight of ALEKS completion was appropriate.	4.75	0.53

6. Data Analysis

This study conducted factor and regression analysis to test hypotheses. Scale items were extracted by the constructs by applying factor analysis. Principal component analysis was used as the method for extraction with maximum iterations for convergence as 25, and factors whose eigenvalue is greater than 1 are extracted. VARIMAX with Kaiser normalization was applied as the rotation method with maximum iterations for convergence. Table 3 summarized the results of factor analysis.

<Table 3> Component Matrix for Perceived Technical Aspects, Contents, Features, and Integration of the AI-based Adaptive Learning System with Lectures

Items	Factor loading			
	1	2	3	4
ALEKS system was easy to access through e-education.	0.935			
ALEKS interface was ease to use.	0.861			
The difficulty of the contents in ALEKS was appropriate.		0.885		
The questions in ALEKS was useful to learning new concepts.		0.855		
The questions in ALEKS helped me improve my understanding of the topics.		0.767		
The “Explain” feature when working in ALEKS was helpful.			0.880	
The “Calculator” feature when working in ALEKS was helpful.			0.870	
It was easy to track my learning progress through ALEKS system.			0.834	
The time required to complete weekly objectives was appropriate.				0.870
The topics in ALEKS was properly covered in the lecture and teaching assistant sessions.				0.844
ALEKS helped to improve my understanding of the topics in line with lecture.				0.837
The class evaluation weight of ALEKS completion was appropriate.				0.811

After obtaining factor scores from factor analysis, multiple regression analyses were conducted to explore main effects for hypotheses testing. For the effects of factors on overall satisfaction, the results of the ANOVA find the models significant at the 0.01 level with F = 119.736 (r-square = 0.747). As shown in Table 4, hypotheses 2a, 3a, and 4a were accepted at 0.01 and 0.1 levels.

<Table 4> Effects of Perceived Technical Aspects, Perceived Contents, Perceived Features, and Perceived Integration with Lectures on Overall Satisfaction

Variables (Independent → Dependent)	Standardized Coefficient (t-value)
Perceived Technical Aspects → Overall Satisfaction	0.040 (0.644)
Perceived Contents → Overall Satisfaction	0.276 (3.508***)
Perceived Features → Overall Satisfaction	0.236 (2.815***)
Perceived Integration with Lecture → Overall Satisfaction	0.413 (4.495***)

***Significant at 0.01 (2-tailed);
**Significant at 0.05 (2-tailed);

For the effects of factors on overall effectiveness, the results of the ANOVA find the models significant at the 0.01 level with F = 128.413 (r-square = 0.759). As shown in Table 5, hypotheses 2b, 3b, and 4b were accepted at 0.01 and 0.1 levels. For the effects of factors on overall Usefulness, the results of the ANOVA find the models significant at the 0.01 level with F = 112.505 (r-square = 0.797). As shown in Table 6, hypotheses 3c and 4c were accepted at 0.01 level.

<Table 5> Effects of Perceived Technical Aspects, Perceived Contents, Perceived Features, and Perceived Integration with Lectures on Overall Effectiveness

Variables (Independent → Dependent)	Standardized Coefficient (t-value)
Perceived Technical Aspects → Overall Effectiveness	0.015 (0.242)
Perceived Contents → Overall Effectiveness	0.195 (2.610***)
Perceived Features → Overall Effectiveness	0.236 (2.967***)
Perceived Integration with Lecture → Overall Effectiveness	0.454 (5.196***)

***Significant at 0.01 (2-tailed);
**Significant at 0.05 (2-tailed)

<Table 6> Effects of Perceived Technical Aspects, Perceived Contents, Perceived Features, and Perceived Integration with Lectures on Overall Usefulness

Variables (Independent → Dependent)	Standardized Coefficient (t-value)
Perceived Technical Aspects → Overall Usefulness	0.049 (0.680)
Perceived Contents → Overall Usefulness	0.134 (1.615)
Perceived Features → Overall Usefulness	0.406 (4.659***)
Perceived Integration with Lecture → Overall Usefulness	0.443 (4.900 ***)

***Significant at 0.01 (2-tailed);
**Significant at 0.05 (2-tailed)

For the effects of factors on overall learning motivation for the study, the results of the ANOVA find the models significant at the 0.01 level with F = 91.585 (r-square = 0.692). As shown in Table 7, hypotheses 3d and 4d were accepted at 0.01 level. For the effects of factors on intention to use the AI system for other classes, the results of the ANOVA find the models significant at the 0.01 level with F = 47.999 (r-square = 0.544). As shown in Table 8, hypotheses 3e and 4e were accepted at 0.01 level.

<Table 7> Effects of Perceived Technical Aspects, Perceived Contents, Perceived Features, and Perceived Integration with Lectures on Overall Motivation on Study

Variables (Independent → Dependent)	Standardized Coefficient (t-value)
Perceived Technical Aspects → Overall Motivation	0.131 (1.919)
Perceived Contents → Overall Motivation	0.175 (2.023**)
Perceived Features → Overall Motivation	0.172 (1.875*)
Perceived Integration with Lecture → Overall Motivation	0.599 (5.951***)

***Significant at 0.01 (2-tailed);
**Significant at 0.05 (2-tailed)

<Table 8> Effects of Perceived Technical Aspects, Perceived Contents, Perceived Features, and Perceived Integration with Lectures on Intention to Use the System for Other Classes

Variables (Independent → Dependent)	Standardized Coefficient (t-value)
Perceived Technical Aspects → Intention to Use	0.124 (1.559)
Perceived Contents → Intention to Use	0.229 (2.378**)
Perceived Features → Intention to Use	0.085 (0.809)
Perceived Integration with Lecture → Intention to Use	0.505 (4.550***)

***Significant at 0.01 (2-tailed);
**Significant at 0.05 (2-tailed)

This study also conducted another multiple regression analysis for the effects of overall satisfaction, overall effectiveness, overall usefulness, overall motivation, and intention to use of the AI-based adaptive learning system on loyalty. The results of the ANOVA find the models significant at the 0.01 level with F = 63.090 (r-square = 0.736). As shown in Table 9, hypotheses 5a, 5b, and 5c were accepted at 0.01 and 0.05 levels.

<Table 9> Effects of Overall Satisfaction, Effectiveness, Usefulness, Motivation, and Intention to Use the System on Loyalty

Variables (Independent → Dependent)	Standardized Coefficient (t-value)
Overall Satisfaction → Loyalty	0.273 (2.853***)
Overall Effectiveness → Loyalty	0.297 (3.039***)
Overall Usefulness → Loyalty	0.229 (2.561**)
Overall Motivation → Loyalty	0.054 (0.765)
Intention to Use → Loyalty	0.103 (1.521)

***Significant at 0.01 (2-tailed);
**Significant at 0.05 (2-tailed)

Additionally, this study conducted independent samples t-test, ANOVA, 2-Way ANOVA, and MANOVA whether means of effects differ based on nationality, gender, age groups, programs enrolled, and enrollment status. The results of 2-Way ANOVA showed that means of intention to use differ based on nationality at 0.05 level. The results of MANOVA showed different effects on intention to use and overall satisfaction based on nationality at 0.05 and 0.1 levels.

7. Discussion

The purpose of this study is to explore the effects of the AI-based adaptive learning system on higher education. In particular, this study investigated effects of the AI-based adaptive learning system for graduate level studies that were rarely examined in previous studies. Among the effects, the results of this study found that effects of perceived contents, perceived features, and perceived integration of the AI-based adaptive learning system with the lectures on overall satisfaction, effectiveness, and learning motivation showed significant. For the effects on overall satisfaction, effectiveness, and motivation the effect size was greater with perceived integration of the AI-based adaptive learning system with the lectures than perceived contents and features. For the effects on overall satisfaction, the effect size of perceived contents was greater than perceived features, while for the effects on overall effectiveness, the effect size of perceived features was greater than perceived contents. The results implied that students perceived the effects of perceived integration of the AI-based adaptive learning system with the lectures as the most significant on overall satisfaction, effectiveness, usefulness, learning motivation, and intention to use the system for other classes. The results also implied that students perceived the effect of perceived contents on overall satisfaction is stronger than perceived features, while the effect of perceived features on overall effectiveness is stronger than perceived contents. Therefore, effects of perceived contents includes difficulty of the contents, questions' usefulness to learning new concepts, and questions' helpfulness to improve understanding of the topics more strongly affect overall satisfaction, while effects of features such as "explain" and "calculator" features that explain answers in the case of incorrect answers and help calculate problems more strongly affect overall effectiveness. For the effects on overall usefulness, perceived features and perceived integration of the AI-based adaptive learning system with the lectures showed significance, while the effect size was greater with perceived integration of the AI-based adaptive learning system with the lectures than perceived features. In particular, the effect size of perceived features on overall usefulness were much greater than the effect size on other variables such as overall satisfaction, effectiveness, and learning motivation. Effects of perceived technical aspects and perceived contents do not show significance on overall usefulness. For the effects on overall intention to use the AI-based adaptive learning system for other classes, perceived contents and perceived integration of the AI-based adaptive learning system showed significant, while the effect size was much greater with perceived integration of the AI-based adaptive learning system with the lectures than perceived contents.

Perceived features do not show significance on intention to use the system for other classes. The results implied that students are accustomed to using perceived features, therefore, such features are not a strong motivator for the intention to use the system for other classes. Effects of overall satisfaction, effectiveness, and usefulness on loyalty were significant. For the effect size on loyalty, the effect of overall effectiveness was greater than effects of overall satisfaction and usefulness. Further, the objective results from the final exam curve showed positively skewed compared to previous years. Therefore, overall learning effects by adopting AI-based adaptive learning systems have been improved. This study also conducted analyses for each semester and found that the results showed similar to the overall results.

8. Conclusion

8.1. Managerial and Policy Implications

The results of this study found that overall learning effects have been improved by adopting the AI-based adaptive learning system in higher education. In particular, this study explored the effects in graduate level studies that were rarely examined in previous studies. Overall, the results of this study found that class contents, learning new concepts, and understanding the class related topics were improved. The results of this study also implied that topics in the AI-based adaptive learning system were properly covered in the lecture and helped improve understanding in line with lectures. Therefore, particularly, the effects of perceived contents and perceived integration of the AI-based adaptive learning system on overall satisfaction, effectiveness, motivation, and intention to use it with other classes showed consistently significant, while effect size was different. Among effect sizes, the effect of perceived integration of the AI-based adaptive learning system on motivation for the study was greater than other effects. The effect of perceived technical aspects and features on intention to use the system with other classes and the effect of perceived contents on usefulness do not show significance. Therefore, the results provide implications that the AI-based adaptive learning system should improve better contents and features for further applications for usefulness and intention to use for other class in higher education. The effects of perceived technical aspects do not show significance on all proposed dependent variables including overall satisfaction, effectiveness, usefulness, motivation, and intention to use. The results also provide significant implications on how to improve the system's easy to access and interface's easy to use, otherwise, students perceive other aspects such as contents, features, and integration with lecture more importantly. The results also found that the effect size of perceived features on overall satisfaction and effectiveness were also lower than other effects. Therefore, the results provide managerial implications that certain aspects for the AI-based adaptive learning system should be improved for better effects that affect customer relationship management in higher education environments. Further, previous studies have examined effects of the AI-based adaptive learning system in undergraduate levels and other lower grade studies, while the results of this study provides an implication that the AI-based learning system helps improve learning outcomes in graduate level studies. This study also provides policy implications. Applications of the 4th industrial revolution such as the AI-based adaptive learning system should be more widely adopted in the field of education. As addressed by Reimann, Kickmeier-Rust, Vatrapu, and Wasson (2016)[31], how to utilize technology-enhanced learning environments in the 21st century school environment should be considered in higher education. The results of effects of satisfaction, effectiveness, and usefulness on loyalty also implied that more adoption of the AI-based adaptive learning system will improve customer relationship management in the era of human capital development. Academically, previous studies have proved the effects of satisfaction on loyalty on many occasions, while the effect was rarely examined in the field of education. The results of this study also support adaptive personalized e-learning services theories such as cognitive psychology and knowledge space theory by applying effects of the system in higher education. Therefore, theoretically, the results of this study prove cause and effect relationships between satisfaction and loyalty in the field of higher education that was neglected by previous studies.

8.2. Future Study and Limitations

This study examined the adoption of the AI-based adaptive learning system in quantitative method classes. Future study might consider the effects of the AI-based adaptive learning system in other classes. Since various studies have investigated the effects of the AI-based adaptive learning system in mathematics related courses, future study might consider exploring the effects in other classes rather than mathematics related courses. Future study might also be considered to improve sample size and comparison analysis across the country. Future research might also consider comparison analysis of offline, hybrid, and online classes with ALEKS.

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저자소개

Yooncheong Cho

2002 Ph.D. in Management, Rutgers University
1995 MBA, Cornell University
Current, Professor, KDI School of Public Policy and Management
Research interests: the 4th industrial revolution, Technology Adoption, Behavior, etc.
e-mail: ycho@kdischool.ac.kr