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Structural Relationship of Key Factors for Student Satisfaction and Achievement in Asynchronous Online Learning

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Abstract: This study examines the structural relationship among key factors influencing student satisfaction and achievement in online learning. A structural model was developed by considering course structure, student–student interaction, instructor presence, student engagement, student satisfaction and achievement as key factors. In order to verify the effectiveness of the developed structural model, we utilized the survey data collected from a total of 250 students enrolled in two asynchronous online courses offered at Kyung Hee University in Korea in the fall semester of 2020. Then, the collected survey data were analyzed using the structural equation model. The verification of the statistical analysis results indicates that the course structure has a more significant effect on the student satisfaction and achievement than the other key factors such as the student–student interaction, instructor presence and student engagement. It also reveals that the student engagement affects only the student satisfaction and has a mediated effect between student–student interaction and student satisfaction.

Keywords: online learning; structural equation modeling; course structure; student engagement; student satisfaction; academic achievement; student–student interaction; instructor presence

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1. Introduction

The COVID-19 pandemic has created significant challenges for global higher education communities and forced them to initiate online teaching and learning. During the pandemic, most universities tried to provide support for teaching and learning activities to achieve effective online learning education. However, many university students in Korea expressed dissatisfaction with the quality of the online courses they took in 2020 [1]. This was mainly because faculty members did not have enough time to prepare for their online teaching due to the rapid outbreak of COVID-19. Most faculty members were used to teaching in a face-to-face class format, but had considerably fewer actionable instructional tactics in online instruction [2]. Several researchers have suggested instructional strategies to improve the quality of online courses, which identify the possible factors associated with learning outcomes such as student satisfaction, perceived learning outcomes, and academic achievement [3–8]. However, they are still controversial because multiple factors are related to the learning process, and there is little consensus on the nature and number of the dimensions that measure the learning experience precisely [4].

The transactional theory of Moore [9] is one of the most appealing and well-known theories about distance education. It provides educators with a theoretical framework of key variables that they should consider in online learning environments. Many researchers have tried to find the best way to conduct effective online courses, considering the dynamic relationships created by two variables such as structure and dialogue. Fern University in Germany and Open University in the UK found that a well-organized online course is the most important factor for effective learning [10]. This draws attention to the fact that, in general, massive online courses such as a type of xMOOC provided by distance education institutions are highly organized and have relatively low dialogue. Peter [10] implied that the lack of interaction can be compensated by a highly organized course. The importance of the course structure in online learning is emphasized even at campus-based universities, not only at distance education institutions.

Available literature about online learning is not univocal about the importance of student–student interaction [11]. Several researchers reported that such interaction has significant impact on student satisfaction, learning, and retention in the process of online learning [4,12–14]. In contrast, Eom et al. [4] found no positive relationship between learner interaction and perceived learning outcomes. Similarly, Gray and DiLoreto [5] and Kuo et al. [15] reported that the student–student interaction is not a significant predictor of student satisfaction. As all of these studies were conducted with varying contexts and targets, and their conclusions are inconsistent. Therefore, there remains a need to investigate the complex relationship among critical success factors that can improve the effectiveness of online learning.

Lack of interaction between the instructor and students often becomes a main source of criticism for online learning since it may cause students to feel isolated and result in low rates of completion [6,16]. Online instructors are expected to diminish this psychological isolation and to create opportunities for communication with their students [17]. Related research insists that the most important role of the instructor is to establish his/her presence and personality in the course content, discussion, and activities [18], and the effective facilitation and guidance of the instructor can generate successful outcomes in online learning environments [19]. Key factors such as course structure, student–student interaction and the sense of instructor presence strongly influence the level of student satisfaction and achievement in the online learning process [4]. Also, student engagement can bring mediating effects in the relationships among these factors according to Gray and DiLoreto [5].

Based on the review of relevant literature, this study investigates the structural relationship between four key factors such as the course structure, student–student interaction, instructor presence, student engagement, and two dependent variables such as student satisfaction and academic achievement in asynchronous online courses. The asynchronous online course in this study refers to a type of teaching and learning in which (1) communication among students and the instructor is not present in real time, and (2) the instructor offers pre-recorded lecture content and teaching materials on the learning management system (LMS). This study intends to develop a research model with hypothetical paths among the four key factors and two dependent variables. The validity of this model is verified using the structural equation modeling approach. The results of this study are able to assist online instructors in improving the quality of online courses by suggesting the clear relationship among these important factors.

2. Theoretical Background and Hypotheses

2.1. Theoretical Framework of Online Learning

In general, online learning is classified into two types: synchronous and asynchronous online courses [20]. The synchronous online course is a real-time session delivered through video conferencing systems such as ZOOM and WebEx. The asynchronous online course is not a real-time instruction, and the instructor provides a pre-recorded lecture and learning materials uploaded on an LMS such as CANVAS and Blackboard. Teaching and learning activities are separate from each other in the case of the asynchronous online learning [21]. Thus, it is necessary that a clear course description as well as the centralized teaching role of the instructor are provided to students [22].

The transactional theory of Moore describes the complex phenomena of teaching–learning in online learning environments in terms of two variables, structure and dialogue. Structure is related to the design of online courses as well as teaching organization [23]. Dialogue is related to the level of communication between the instructor and students [5]. Also, Moore discussed three types of interaction in online learning, which are content–student interaction, student–instructor interaction, and student–student interaction [9]. It was assumed that these types of interaction have positive effects on online learning outcomes. Regarding the content–student interaction, many researchers agree that well-organized courses help students to systematize and demonstrate the new knowledge [24]. In the student–instructor interaction, the online instructor performs instructional, facilitative, and organizational roles through interaction with students [22]. Lastly, the student–student interaction is an important part of learning and encourages social presence, which refers to the feeling that other students are also actually in the environment.

Based on Moore's theory and related literature, this study adopts the following three assumptions. First, the course structure has a positive effect on online learning outcomes by promoting interaction between learning content and students. Second, online instructors can implement instructional activities through interaction with students and improve the sense of instructor presence, which can promote students' engagement in learning. Third, interaction among students is a factor that can promote their engagement along with the sense of instructor presence.

2.2. Course Structure

The course structure expresses the rigidity or flexibility of learning objectives, teaching strategies, and evaluation methods. It describes the extent to which an educational program can accommodate or be responsive to each student's individual needs [4]. Quality Matters, which provides criteria for online course quality assurance, emphasizes the importance of course organization and presentation for a successful online course [25]. A student's experience with the course structure is viewed as interaction with course content and learning materials in Moore's theory [26]. This implies that a well-organized course facilitates content–student interaction, which is crucial for effective learning [4]. Compared to students in face-to-face class, online students independently and autonomously carry out their learning. For this reason, they need information on clearly stated course objectives, content, schedule, and guidelines.

Recent studies have suggested that a well-organized online course is correlated with student satisfaction and performance. Kuo et al. [15] investigated the relationship between student perception of interaction and blended learning online satisfaction. They revealed that the student–content interaction is the strongest predictor of student satisfaction if online courses contain a small amount of collaborative activities. Alqurashi [3] and Gunawardena et al. [27] showed that course design is a significant predictor of student satisfaction. Grandzol and Grandzol [28] insisted that a consistent and clearly structured course including navigational documents and instructions is vital to student success after reviewing a large amount of literature on online educational practices. On the other hand, Jaggars and Xu [25] reported that the course structure with well-specified learning objectives is desirable, but these qualities are not statistically significant for student grades. Eom et al. [4] examined the determinants of student satisfaction and perceived learning by using structural equation modeling. They revealed that the course structure has an significant effect on student satisfaction, but not on the perceived learning.

Based on the discussion above, the following two hypotheses are adopted in this study.

Hypothesis 1 (H1). *Course structure is positively associated with student satisfaction.*

Hypothesis 2 (H2). *Course structure is positively associated with academic achievement.*

2.3. Student–Student Interaction

Many researchers have suggested that the student–student interaction, regardless of being formally structured or not, can enrich learning outcomes [29]. Although it is considered an important factor in promoting students' participation in face-to-face classes, it plays an even more important role in online classes. This is mainly because it can alleviate students' disconnection from others in the online learning environment. It is important that the online instructor provide students with an opportunity of participating in online activities, and the students should be able to recognize their participation as an important part of learning [14]. There are several ways for instructors to promote interaction among students in both synchronous and asynchronous online courses, such as videoconferencing and chatting for the former and discussion boards and e-mail messaging for the latter.

Jaggars and Xu [25] found that the quality of interpersonal interaction within an online learning environment affects students' grades, both positively and significantly. Borohoski et al. [30] conducted a meta-analysis on the results of 74 empirical studies. It indicated that student–student interaction can produce a higher impact on achievement than student–instructor interaction. Moreover, it suggests that opportunities for collaboration among students should be provided to students in the course of online learning for effective student–student interaction.

In contrast to the discussion above, some researchers have reported that the student–student interaction is not a significant predictor of student satisfaction and performance. Alqurashi [3] investigated several important factors related to student satisfaction and perceived learning within online learning environments in higher education and concluded that the student–student interaction is not a significant predictor. Gray and DiLoreto [5] examined the indirect effect of student–student interaction on learning outcomes by including student engagement as a mediating variable. They reported from this study that a high level of interaction among students can lead to student engagement, which indirectly affects the perceived learning but not the student satisfaction. This is in contrast with other researchers' opinions that the student–student interaction is one of the most important considerations in online learning settings.

Considering the discussion above, the following hypothesis is adopted in this study.

Hypothesis 3 (H3). *Student–student interaction is positively associated with student engagement.*

2.4. Instructor Presence

In [31], Anderson et al. referred to teaching presence as the design, facilitation, and direction of cognitive and social processes for the realization of personally meaningful and educationally worthwhile learning outcomes. Furthermore, they suggested the following indicators for instructor presence: (1) presenting content and questions, (2) focusing the discussion on specific issues, (3) summarizing the discussion, (4) confirming understanding, (5) diagnosing misperceptions, (6) injecting knowledge from diverse sources, and (7) responding to technical concerns. These teaching activities are consistent with the instructor's performance to facilitate interaction with students as suggested by Oztok and his colleges [22]. The instructor presence can be established by regular communication with students, consistent feedback, and critical discourse modeled by the instructor [23]. Online instructors can promote student academic performance and retention for a long term by increasing their presence in the online learning environment [25].

Several researchers insisted that there exists an important association between the instructor presence and student satisfaction and performance. Shea et al. [32] analyzed the relationship between interaction types and perceived learning in web-based online learning. The results showed that both the student–instructor interaction and student–student interaction are significant contributors to student learning and satisfaction. The comparison of the two types of interaction demonstrated that the student–instructor interaction has a greater impact on learning outcomes than the student-to-student interaction. In a similar vein, Eom et al. [4] reported that instructor feedback significantly affects perceived learning and student satisfaction. Gray and DiLoreto [5] found that instructor presence is a predictor of student engagement and indirectly affects perceived learning. These results support the assertions of online instructors that the student–instructor interaction is one of the most critical factors in learning outcomes, and instructor feedback should be considered as one of the most important teaching actions.

The following statement is hypothesized from the above discussion:

Hypothesis 4 (H4). *Instructor presence is positively associated with student engagement.*

2.5. Student Engagement

Student engagement refers to the time and efforts that students devote to their learning [33]. According to Trowler [34], it requires not only activities but also feeling or sensemaking such as attending lectures, participating with enthusiasm, and showing interest [35]. In its meaning, several researchers have included emotional factors such as attitude toward technology use as well as interest and enthusiasm for learning [36]. Recently, researchers have begun to conceptualize student engagement as a multi-dimensional phenomenon comprising behavioral engagement, emotional engagement, and cognitive engagement [37]. Behavioral engagement refers to the student's level of participation in learning. Emotional engagement means the student's emotional reactions to instructors, peer students, and learning. Cognitive engagement focuses on cognitive and self-regulation strategies used in learning. Lee et al. [38] reported that peer collaboration and interaction with instructors are elements reflected in student engagement in online courses. The level of student engagement can be identified by surveying students or gathering indicative data such as the login records and number of participations in a discussion forum.

Carini et al. [39] revealed that student engagement is related to desirable learning outcomes such as critical thinking and high grades. In [37], Lei and Cui performed a meta-analysis and reported a significant correlation between student engagement and academic achievement. Gray and DiLoreto [5] found that student engagement can positively affect not only perceived student learning, but also student satisfaction. From this discussion, the following statements are hypothesized.

Hypothesis 5 (H5). *Student engagement is positively associated with student satisfaction.*

Hypothesis 6 (H6). *Student engagement is positively associated with academic achievement.*

Furthermore, in [5,23,25] it was reported that students show a tendency to participate in online learning if they are aware of active interaction among students and strong instructor presence. Ma et al. [36] found that the instructor's role is important for student engagement in online learning environments. They suggested that the main roles of online instructors to improve the student engagement include course preparation activities as well as guidance and assistance for their students. Also, Shea et al. [40] suggested that student satisfaction can be enhanced by students valuing interaction and opportunities for active communication. From this discussion, it can be inferred that the interactions among students and instructor presence have a positive effect on student engagement and may lead to improvement in student satisfaction and achievement. Considering this, the following hypotheses are adopted in this study.

Hypothesis 7 (H7). *Student engagement mediates the relationship of student–student interaction to student satisfaction and academic achievement.*

Hypothesis 8 (H8). *Student engagement mediates the relationship of instructor presence to student satisfaction and academic achievement.*

2.6. Structural Model

Based on the discussion from Sections 2.1–2.5, this study adopts eight hypotheses, which define the relationships among the key factors influencing student satisfaction and academic achievement. In these hypotheses, the course structure and student engagement are considered critical factors influencing student satisfaction and achievement. It is also assumed that the student–student interaction and instructor presence are important factors affecting student engagement and have indirect effects on student satisfaction and academic achievement.

A structural model illustrated in Figure 1 is created by defining paths among the key factors discussed. In this model, the paths of Hypotheses 7 and 8 are not visually expressed as they evaluate indirect effects among the key factors.

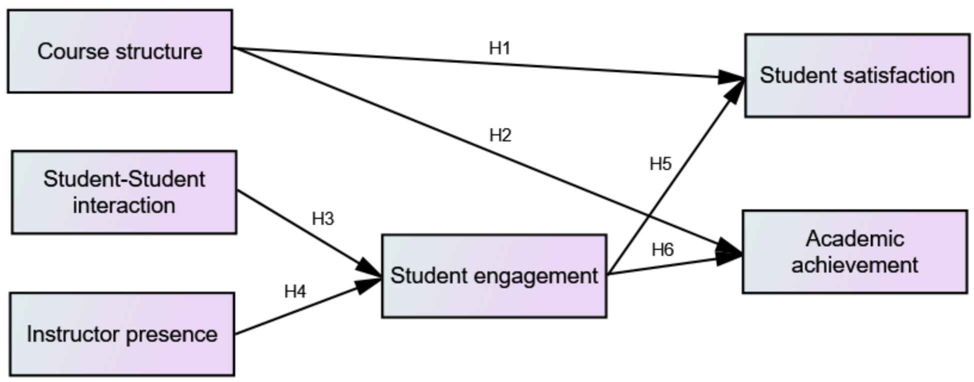

Figure 1. Hypothesized structural model.

3. Methodology

3.1. Survey Data

Survey data utilized in this study were collected from undergraduate students enrolled in two asynchronous online courses offered at Kyung Hee University in Korea in the fall semester of 2020. The authors participated in these two courses as instructional designers and helped the course instructors to design and implement learning materials that can produce greater outcomes. The online survey was distributed and collected from the 7th to 8th week of the entire 16 week period in the fall semester. Among 595 students enrolled in the online courses, 268 students voluntarily participated in the survey. After discarding 18 unreliable responses, a total of 250 survey responses were selected and analyzed in this study. The statistical summary of the survey participants is given in Table 1.

Table 1. Statistical summary on the survey participants. (N = 250).

Undergraduate Year	Frequency	Percentage (%)
Freshman	92	36.8
Sophomore	58	23.2
Junior	46	18.4
Senior	54	21.6
Total	250	100

3.2. Measurement Instrument

The survey questions were composed of 25 items, which were designed to measure the key factors such as the course structure, student–student interaction, instructor presence, student engagement, and student satisfaction. They were developed by modifying the survey items utilized in the study of Gary and DiLoreto [5], which were originated from the IDEA (Individual Development and Educational Assessment) student rating systems of Kansas State University [4]. All of the items were rated based on a 5-point Likert scale, which ranges from 1 indicating "strongly disagree" to 5 "strongly agree". In most previous studies, learning outcomes were measured by perceived learning, reflecting the students' perceptions of their learning in a specific online course [4,5,7]. In contrast, these ratings were directly evaluated from students' actual examination scores in this study. Table 2 summarizes the details of the measurement instrument. The representative examples of the survey questions are summarized in Table 3. The value of Cronbach's alpha for the measurement instrument is 0.875.

Table 2. Measurement instrument.

Key Factor	Number of Items	Scales
Course structure (CS)	5	5-point Likert scale
Student–Student interaction (SSI)	6	
Instructor presence (IP)	5	
Student engagement (SE)	4	
Student satisfaction (SS)	5	
Academic achievement (AA)	-	Mid-term score
Total	25	

Table 3. Representative examples of the survey items.

Key Factor	Examples of Survey Items
Course structure (CS)	'Course objectives are clearly presented' 'Course content is logically well-organized'
Student–Student interaction (SSI)	'I frequently interact with other students in this course' 'There are opportunities for active learning in this course'
Instructor presence (IP)	'The instructor's feedback on assignment is clearly stated' 'The instructor provided timely feedback about my progress in the course'
Student engagement (SE)	'I participated in synchronous and/or asynchronous communication with the instructor during the online course' 'I completed learning activities as assigned during the course'
Student satisfaction (SS)	'I am satisfied with overall experience in this course' 'I am satisfied with the instructor in the course'

3.3. Data Collection and Strategies for Statistical Analysis

In order to explore the construct validity and internal reliability of the measurement instrument, exploratory factor analysis (EFA) with Varimax rotation was performed using SPSS (version 25.0). The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy (=0.886) and Bartlett's test of sphericity (=2932.46, df = 1136, $p < 0.001$) confirmed that the measurement instrument adopted was appropriate for the EFA. Eight survey items with a factor loading less than 0.40 and with multiple cross-loadings, which were CS3, SSI2, IP2, IP4, SE3, SE4, SS3, and SS4, were removed from the original 25 items, and a total of 17 remaining items were considered in the process of subsequent statistical analysis. Five factors were extracted from the 17 items by performing the EFA, and the total variance explained was 75.1%.

Next, descriptive statistics and correlations among the 17 measurement variables were analyzed using SPSS. In order to confirm the convergent and discriminant validity, confirmatory factor analysis (CFA) with maximum likelihood estimation was performed using AMOS (version 22.0). The construct validity was examined by computing the standardized factor loadings of the measurement variables, composite reliability (CR), average variance extracted (AVE), and model fit indices [41]. For checking the goodness-of-fit, minimum sample discrepancy (CMIN), comparative fit index (CFI), Tracker–Lewis index (TLI), and root-mean-square error of approximation (RMSEA) were calculated in this study.

Lastly, path analysis of the structural model was performed using AMOS. The structural model was tested by examining the relationships among the five factors, and the indices of goodness-of-fit (CMIN, CFI, TLI, and RMSEA) to the proposed model were checked.

4. Results and Discussion

4.1. Descriptive Statistics and Correlations

Table 4 shows the descriptive statics and correlations among the measurement variables. It summarizes the values of correlation, mean, standard deviation, skewness, and kurtosis for each measurement variable. The normal distribution of the statistical data was checked from skewness and kurtosis values. It can be seen from the table that the maximum of the absolute values of skewness is 2.86, which is less than 3, and the maximum of the absolute values of kurtosis is 9.41, which is less than 10. This indicates that the assumption for the multivariate normal distribution of data is satisfied with the proposed structural equation model [42,43].

Table 4. Descriptive statistics and correlations. (N = 250).

Variable	CS1	CS2	CS4	CS5	SSI1	SSI3	SSI4	SSI5	SSI6	IP1	IP3	IP5	SE1	SE2	SS1	SS2	SS5
CS1	-																
CS2	0.726	-															
CS4	0.724	0.684	-														
CS5	0.618	0.618	0.569	-													
SSI1	0.064	0.008	0.035	0.172	-												
SSI3	0.070	0.003	0.080	0.150	0.789	-											
SSI4	0.054	−0.040	0.013	0.087	0.716	0.770	-										
SSI5	0.074	−0.027	0.022	0.102	0.746	0.714	0.863	-									
SSI6	0.060	0.013	0.067	0.075	0.569	0.571	0.622	0.700	-								
IP1	0.396	0.403	0.464	0.366	0.123	0.131	0.099	0.100	0.221	-							
IP3	0.347	0.314	0.347	0.373	0.285	0.291	0.290	0.290	0.292	0.545	-						
IP5	0.430	0.426	0.419	0.413	0.250	0.234	0.232	0.260	0.321	0.658	0.572	-					
SE1	0.166	0.157	0.196	0.183	0.524	0.430	0.442	0.511	0.491	0.369	0.380	0.411	-				
SE2	0.369	0.371	0.314	0.369	0.253	0.175	0.151	0.183	0.241	0.412	0.372	0.462	0.444	-			
SS1	0.518	0.603	0.464	0.564	0.125	0.146	0.127	0.131	0.124	0.489	0.458	0.536	0.245	0.441	-		
SS2	0.505	0.575	0.523	0.501	−0.005	0.064	−0.014	−0.014	0.046	0.466	0.354	0.475	0.158	0.366	0.718	-	
SS5	0.471	0.584	0.503	0.526	−0.001	0.101	0.009	0.045	0.095	0.420	0.398	0.463	0.177	0.368	0.736	0.807	-
Mean	4.75	4.82	4.81	4.63	2.61	2.69	2.17	2.19	2.52	4.58	4.15	4.29	3.28	4.00	4.65	4.76	4.71
SD	0.493	0.449	0.460	0.634	1.16	1.18	1.15	1.11	1.25	0.701	0.907	0.833	1.09	0.597	0.574	0.524	0.571
Skewness	−2.05	−2.86	−2.84	−1.79	0.341	0.369	0.855	0.770	0.415	−1.87	−0.836	−1.05	−0.336	−0.255	−1.58	−2.38	−2.12
Kurtosis	4.74	9.41	9.06	3.11	−0.510	−0.578	0.056	0.005	−0.837	3.93	0.106	0.674	−0.390	−0.424	2.18	5.64	4.65

CS: Course structure, SSI: Student–Student interaction, IP: Instructor presence, SE: Student engagement, SS: Student satisfaction.

4.2. Validity of the Measurement Model

Table 5 summarizes the results of the CFA performed. It provides the value of the standardized factor loading for each measurement variable as well as the values of Cronbach's alpha (CA), CR, and AVE of each latent variable.

Table 5. Results of the confirmatory factor analysis. (N = 250).

Latent Variable (Key Factor)	Measurement Variable	Standardized Factor Loading	CA	CR	AVE
Course structure (CS)	CS 1	0.849	0.872	0.965	0.874
	CS 2	0.855			
	CS 4	0.815			
	CS 5	0.729			
Student–Student interaction (SSI)	SSI 1	0.826	0.929	0.897	0.636
	SSI 3	0.828			
	SSI 4	0.912			
	SSI 5	0.922			
	SSI 6	0.719			
Instructor presence (IP)	IP 1	0.776	0.709	0.880	0.711
	IP 3	0.698			
	IP 5	0.839			
Student engagement (SE)	SE 1	0.750	0.647	0.707	0.550
	SE 2	0.592			
Student Satisfaction (SS)	SS 1	0.830	0.901	0.968	0.910
	SS 2	0.887			
	SS 5	0.893			

CA: Cronbach's alpha, CR: composite reliability, AVE: average variance extracted.

It can be observed from the table that the standardized factor loadings of all measurement variables are higher than 0.50, which confirms adequate validity of the key factors in the measurement model, as suggested by Hair and his colleagues [44]. The discriminant and convergent validity of the latent variables are confirmed as the AVE and CR values of the latent variables are greater than 0.50 and 0.70, respectively.

The Cronbach's alpha values of the latent variables range from 0.64 to 0.85, which can be described as reasonable. The internal reliability of the latent variables is reasonable as their Cronbach's alpha values range from 0.64 to 0.85 [45]. The goodness-of-fit indices shown in Table 6 indicate that the measurement model is a reasonable fit with the collected data (χ_2/df = 2.634, CFI = 0.938, TLI = 0.923, RMSEA = 0.080).

Table 6. Model fit results for the measurement model. (*N* = 250).

	CMIN (χ_2)	CMIN/df	*p*	*df*	CFI	TLI	RMSEA
Measurement model	287.139	2.634	0.000	109	0.938	0.923	0.080
Criteria					>0.90	>0.90	<0.08

4.3. Structural Model and Hypothesis Testing

In order to verify the hypothesized structural model shown in Figure 1, this section examines the goodness-of-fit and statistical significance of the hypothesized paths among the latent variables. The model fit results of the hypothesized structural model are given in Table 7, and their values are χ_2/df = 2.589, CFI = 0.931, TLI = 0.917, and RMSEA = 0.080, indicating that the proposed hypothesized model is a good fit. The path coefficients of the hypothesized model were calculated and checked to test Hypotheses 1 to 6 (H1~H6) discussed in Section 2. The computed results show that all of *p*-values for paths H1 to H5 are less than 0.05 except path H6. This indicates that all paths H1 to H5 are statistically significant, but H6 is not supported. Detailed values are given in Table 8.

Table 7. Model fit results for the structural models analyzed. (*N* = 250).

	CMIN (χ_2)	CMIN/df	*p*	*df*	CFI	TLI	RMSEA
Hypothesized model	328.847	2.589	0.000	127	0.931	0.917	0.080
Modified model 1	330.749	2.584	0.000	128	0.931	0.917	0.080
Modified model 2	290.934	2.291	0.000	127	0.944	0.932	0.072
Criteria					>0.90	>0.90	<0.08

Table 8. Results of the hypothesis and path coefficients of the hypothesized model. (*N* = 250).

Hypothesis	Path	Unstandardized Coefficient (B)	Standard Coefficient (β)	SE	*T*	Supported
H1	CS→SS	0.778	0.675	0.081	9.607 ***	Yes
H2	CS→AA	10.085	0.320	2.301	4.383 ***	Yes
H3	SSI→SE	0.150	0.401	0.029	5.201 ***	Yes
H4	IP→SE	0.332	0.646	0.048	6.890 ***	Yes
H5	SE→SS	0.238	0.178	0.087	2.729 *	Yes
H6	SE→AA	3.907	0.107	2.828	1.381	No

*** $p < 0.001$, * $p < 0.05$.

Therefore, we considered a new model, in which the path corresponding to H6 was removed from the original hypothesized model, and performed path analysis again on the modified model, denoted as Modified model 1 in Table 7. The results of the path analysis on Modified model 1 indicated that it is also a good fit with χ_2/df = 2.584, CFI = 0.931, TLI = 0.917, and RMSEA = 0.080, as reported in Table 7.

Although these results were good, a new model was considered in order to achieve a better goodness-of-fit of Modified model 1. The most popular piece of information for model modification was the modification index (MI) [46]. The modification indices suggested adding various covariances between error terms. The highest modification index (MI = 35.057) was selected from the results of Modified model 1, and the covariance between SSI1 and SSI3 was added. The covariance term is theoretically justifiable because these are strongly related concepts, and it is feasible that these measures have something specific in common that is lacking in other indicators [47]. This new model was denoted as Modified model 2, and path analysis was performed on it again. The model fit results showed that Modified model 2 presented a better fit than Modified model 1 as $\chi_2/\mathrm{df} = 2.291$, CFI = 0.944, TLI = 0.932, and RMSEA = 0.072, as shown in Table 7. The result of the chi-difference test for comparison between Modified model 1 and Modified model 2 showed that Modified model 2 was found to be significant with the significance level of 0.05($\Delta\chi_2(1) = 39.815$, p <0.05). Therefore, Modified model 2 was confirmed as the final research model. The modified paths and path coefficients of Modified model 2 are illustrated in Figure 2, and detailed values are given in Table 9.

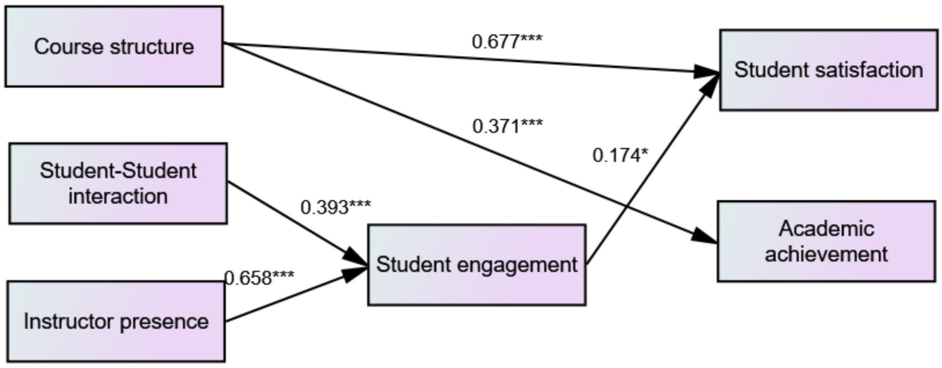

Figure 2. The final structural model with standardized coefficients. (*** $p < 0.001$, * $p < 0.05$).

Table 9. Results of path coefficients of the modified model 2. (N = 250).

Path	Unstandardized Coefficient (B)	Standard Coefficient (β)	SE	t
CS→SS	0.781	0.677	0.081	9.590 ***
CS→AA	11.698	0.371	2.021	5.789 ***
SSI→SE	0.153	0.393	0.030	5.084 ***
IP→SE	0.338	0.658	0.048	6.976 ***
SE→SS	0.231	0.174	0.087	2.652 *

*** $p < 0.001$, * $p < 0.05$.

To verify Hypotheses 7 and 8, the indirect effect of student–student interaction and instructor presence on student satisfaction were examined by performing path analysis with the option of the Bootstrap method in AMOS. The verification of the indirect effect of the two variables on the academic achievement was excluded because the direct effect of student engagement on academic achievement was not statistically significant in the hypothesized model. The results of the new path analysis are given in Table 10, and show that the indirect effect of student–student interaction on student satisfaction is significant, but not robust (β = 0.068, p < 0.05). The indirect effect of the instructor presence is not significant (β = 0.114, p > 0.05). Although the indirect effects of the two variables are all small, they have different results in terms of the significance level of 0.05. This is a result of the difference in the Bootstrap standard errors of the two variables.

Table 10. Effect decomposition of Modified model 2. (N = 250).

Path	Standard Coefficient (β)		
	Direct Effect	Indirect Effect	Total
SSI→SE	0.393 ***	-	0.393 ***
SSI→SS (through SE)	-	0.068 *	0.068 *
IP→SE	0.658 ***	-	0.658 ***
IP→SS (through SE)	-	0.114	0.114
SE→SS	0.174 *	-	0.174 *

*** $p < 0.001$, * $p < 0.05$.

4.4. Discussion

From the results discussed in the previous sections, we can draw several important conclusions. First, course structure has significantly positive effects on both student satisfaction and academic achievement in asynchronous online courses. It indicates that course structure is the critical factor for increasing student satisfaction and academic achievement. This coincides with the findings of other researchers such as Alqurashi [3], Gray and DiLoreto [5], Kue et al. [15], Gunawardena et al. [27], and Grandzol and Grandzol [28]. In particular, Kuh et al. suggested that a well-structured course can promote students' understanding of course content, which can increase the effectiveness of learning, especially when few collaborative activities are required in the online course. Consequently, course design should be done in such a way that learning objectives are clearly stated and detailed guidelines on the tasks and activities required during the class are provided.

Second, both the student–student interaction and instructor presence positively affect the student engagement. This is consistent with previous research results such as Gray and DiLoreto [5], Garrison [23], and Jaggard and Xu [25]. They reported that students actively participate in the learning process when they are highly aware of peer interaction and instructor presence. Dennen et al. [13] pointed out the importance of the instructor's role in encouraging a meaningful learning experience in the online learning environment. They insisted that the instructor's understanding of the learning experience of students can enhance their learning outcomes. Feedback provided by instructors can improve the quality of the learning experience and result in meaningful learning [4–6,23,25].

Lastly, student engagement has a positive effect on student satisfaction, although it does not have a significant impact on academic achievement. One possible explanation for this is that the relationship between student engagement and academic achievement is influenced by various factors related to the method of reporting student engagement and other individual differences, such as cultural values and age [37]. The participants in this study reported the level of their engagement by themselves and were of various majors and grades. This may have influenced the relationship between student engagement and academic achievement. Contrary to past findings from Gray and DiLoreto [5], student engagement only mediates the effect of student–student interaction on student satisfaction, not that of the instructor presence on student satisfaction. It is important to notice that Bootstrap standard errors statistically may have an effect.

In the context of the growing importance of online teaching and learning in higher education, it is a challenge for online instructors to lead students to successful learning. Student satisfaction and academic achievement are representative indications to gauge the effectiveness of learning in online courses. This study expands upon prior studies on online learning in higher education and confirms the importance of course design as a key role of online instructors.

5. Conclusions

In this study, we investigated the relationships among key factors that influence student satisfaction and academic achievement in asynchronous online courses. A structural model was developed by considering the course structure, student–student interaction, instructor presence, student engagement, student satisfaction and achievement as the key factors. In order to verify the effectiveness of the developed model, we utilized survey data collected from a total of 250 students enrolled in two asynchronous online courses offered at Kyung Hee University in Korea. Then, the collected survey data were analyzed using the structural equation model. From the results of the model verification, the following conclusions were obtained:

1. Course structure has significantly positive effects on both student satisfaction and academic achievement in asynchronous online courses. It is desirable to design the overall organization of online courses such that learning objectives are clearly stated and detailed guidelines on tasks and activities required during the class are provided.
2. Both student–student interaction and instructor presence positively affect student engagement. The quality of students' learning experiences can be enhanced by providing instructor feedback.
3. Student engagement has a positive effect on student satisfaction although it does not have a significant impact on academic achievement.
4. Student engagement only mediates the effect of student–student interaction on student satisfaction, and not that of instructor presence on student satisfaction. Instructor presence may encourage students to take part in learning activities, but does not have a positive effect on enhancing student satisfaction.

These conclusions should be helpful in providing online instructors with useful instructional strategies for successful online learning. To extend the research performed in this study, the proposed structural model can be verified using survey data collected from various online learning environments such as synchronous online courses. Also, in future research, it may be worthwhile to consider individual characteristics such as motivation and self-direction as well as external environmental factors such as community support and learning management systems.

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