Navigating Online Learning Satisfaction in the Age of COVID-19: An Examination of Key Influencing Factors

Hyeon Jo[1], Eun-Mi Baek[2]*

[1] *Headquarters, HJ Institute of Technology and Management, Republic of Korea*
[2] *Department of Preventive Medicine, Catholic University of Korea, Republic of Korea*
sineoriz@gmail.com, hanel2004@naver.com

Abstract

This study explores the key factors determining the success of online learning during the COVID-19 isolation. The analytical framework clarifies the role of social distancing attitude, social distancing intention, attitude towards online learning, and perceived value in developing user satisfaction. The research model was validated by fitting data gathered from 490 students in Asian countries through structural equation modeling (SEM). The results indicated that both social distancing attitude and social distancing intention do not have a significant impact on user satisfaction. The findings showed that both attitude and perceived value are significantly associated with user satisfaction. Risk perception affects social distancing attitude, attitude toward online learning, and perceived value. However, it does not impact social distancing intention. Cabin fever syndrome positively affects social distancing attitude while it negatively influences social distancing intention. The results would help to understand online learning success and to improve education strategies, explained by students' perception of COVID-19.

Keywords: Online learning, COVID-19, Risk perception, Cabin fever syndrome, Social distancing

1 Introduction

Since the Wuhan case, COVID-19 has achieved a global spread [1]. The pandemic has brought about drastic changes in societies all over the world [2]. People are practicing social distancing, wearing masks, holding video conferences, and using e-commerce [3]. One of the most obvious changes among them is the shift from offline teaching to online lectures. In the absence of traditional classes, online learning has emerged as the closest substitute for offline education [4]. Successful online lectures would lead to beneficial education delivery and effective infection prevention. In this vein, it is vital to investigate the influencing factors in the formation of user satisfaction with online learning. Since the social aspect has completely changed after the COVID-19 outbreak, it is meaningful to consider the variables which are related to the perception of disease and the performance of health behaviors. Therefore, this study identifies the various leading factors of user satisfaction under COVID-19.

Social distancing is described as maintaining a distance from others of at least 1m-2m [5]. It is considered the most representative and priority among preventive measures. Several works have found that attitude toward social measures plays an essential role in forming intention or behavior [3, 6-7]. Attitude towards preventive action was verified to significantly affect behavioral intention [3]. Social distancing attitude serves as the major determinant of social distancing intention, which in turn affects social distancing behavior [7]. Both online learning and social distancing are implemented to prevent massive infection. The goal of online learning is similar to the one of social distancing. The stronger the attitude and intention towards social distancing are, the greater the attitudes towards online learning would be, which in turn may enhance user satisfaction. Accordingly, the present study clarifies the role of social distancing attitude and social distancing intention in generating both attitudes towards online learning and user satisfaction. Attitude determines intention, which affects human behavior [8-9]. The significant association between behavioral intention and satisfaction has been proved [10-11]. The greater the degree of the attitude towards online lectures, the higher the level of satisfaction towards online lectures. Therefore, this study posits that attitude is the key antecedent of user satisfaction. Perceived value has a significant association with intention and behavior [12-13]. In the context of online learning, users with a higher level of perception of value would increase attitude and user satisfaction. Hence, the current study explores the role of perceived value in generating attitude and user satisfaction.

Several studies have revealed that perceived risk forms attitude, which in turn leads to behavioral intention [14-15]. Both affective risk perception and cognitive perception have been found to have a significant impact on behavioral intention [3]. Students with higher levels of perceptions of risk may enhance the extent of social distancing attitude, social distancing intention, attitude, and perceived value. Hence, this study identifies the roles of risk perception in the shaping of social distancing attitude, social distancing intention, attitude towards online learning, and perceived value.

Cabin fever syndrome is described as a common negative feeling in people when they stay in a closed space for a long period [16]. Students may experience cabin fever under

*Corresponding Author: Eun-Mi Baek; E-mail: hanel2004@naver.com
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psychological stress due to social distancing and quarantine [6]. Cabin fever syndrome can influence social distancing positively or negatively. Students with a greater extent of cabin fever syndrome would wish to comply with social distancing to overcome current isolation early. On the other hand, some students might deny social distancing itself to address the claustrophobic restlessness. This two-edged logic can be equally applied to attitudes and perceived value in online lectures. Therefore, this study postulates that cabin fever syndrome is the key factor generating social distancing attitude, social distancing intention, attitude, and perceived value.

This study endeavors to identify the COVID-19 factors on online learning which appears to be the considerable contribution to existing literature. It strives to examine COVID-19 drivers such as social distancing, risk perception, and cabin fever syndrome. It also investigates the role of the individual factor which is perceived value. These factors have rarely been adopted in the online learning context before the pandemic.

This article is organized as follows. Section 2 describes the theoretical background and research model. Section 3 covers the research methodology and sample demographics. Section 4 shows the analysis results and Section 5 discusses the research results. The last section details several implications. Furthermore, the section offers the limitations of this study and directions for future research.

2 Theoretical Background

2.1 Online Learning

Online learning is justified as learning experiences in electronic education platforms using various devices based on network infrastructure [17]. In online environments, students can access education information system, interact with educators, and share the data. Online learning is also called e-learning, web-based learning, and m-learning [18-19].

Success in information systems (ISs) has been measured from various perspectives [20-22]. Satisfaction has been revealed to be a key factor of the success, usage, and effectiveness of ISs [22-24]. The latest studies assessed IS success using user satisfaction and perceived user benefits [20, 25-26]. In this vein, this article introduces user satisfaction as the final variable to measure an online learning system's success.

Previous studies on e-learning systems have mainly paid attention to technology adoption. Several types of research have verified the technology acceptance model (TAM) in the e-learning or m-learning context [21, 25, 27-30]. [28] explored the factors influencing e-Learning acceptance. They extended TAM and confirmed knowledge sharing, communication facility, and motivation as determinants of perceived usefulness. Mohammadi [31] suggested affecting factors such as subjective norm, self-efficacy, and innovativeness. Perceived usefulness and perceived ease of use were found to serve as the crucial antecedents of satisfaction. Al-Emran et al. [27] integrated TAM, theory of planned behavior (TPB), and expectation-confirmation model (ECM) to explain the actual use of m-learning. Confirmation and perceived usefulness were shown to influence significantly satisfaction.

A great deal of study has used the DeLone and McLean IS success model to gauge e-learning success [25-26, 32-33]. Aparicio et al. [26] employed the grit in the DeLone and McLean model to explain the success of e-learning. They introduced individual impact to measure success and verified the significance of grit on satisfaction. Al-Fraihat et al. [25] developed an integrated model based on DeLone and McLean IS success model, TAM, user satisfaction model, and e-learning quality model. They considered perceived satisfaction, use, and benefits to evaluate the e-learning system's success. The results showed that satisfaction is significantly influenced by technical support quality, information quality, service quality, and support system quality. Hassanzadeh et al. [32] revealed that technical system quality, content and information quality, service quality, user satisfaction, and intention are significant to goal achievement. Pituch and Lee [33] examined the role of system features on e-learning use. It was validated that e-learning use is determined by system functionality, self-efficacy, perceived ease of use, and perceived usefulness

Various studies have also been conducted on variables other than TAM and DeLone and McLean model. Nugroho et al. [34] unveiled that perceived value is the decision factor of satisfaction and e-learning continuance intention. Lee et al. [35] explored the factors influencing students' sustainable engagement in e-Learning. They conducted confirmatory factor analysis (CFA) and identified six factors. The factors were psychological motivation, cognitive problem solving, peer collaboration, community support, learning management, and interaction with instructors.

With the advent and prevalence of COVID-19, the role and importance of online learning have drastically increased. Many researchers have clarified the determinants of e-learning success under the pandemic [4, 36]. Sitar-Tăut [36] evaluated the degree of m-learning adoption in students during COVID-19 quarantine. Hedonic motivation was found to positively impact on behavioral intention. It was verified to mediate the relationship between facilitating conditions and behavioral intention. Khan et al. [4] investigated students' perceptions of e-learning under COVID-19. They performed CFA for the measurement verification. Perception of students toward e-learning was measured by four sub-scales which are perceived usefulness, perceived ease of use, perceived self-efficacy, and behavioral intention. Those constructs were proven to have reliability and validity.

From the various studies, little progress has been made in understanding the COVID-19 factors that impact e-learning. Therefore, this paper identifies the role of social distancing, risk perception, and cabin fever syndrome in the formation of satisfaction.

2.2 Research Model

Figure 1 illustrates the theoretical framework for examining the predictors of user satisfaction in the domain of online learning. The research model is based on COVID-19 factors, perceived value, and attitudes that form user satisfaction with online learning. This study postulates that social distancing attitude, social distancing intention, attitude, and perceived value as antecedents that form user satisfaction. This research also clarifies the role of perceived risk and cabin fever syndrome in enhancing antecedents of user satisfaction.

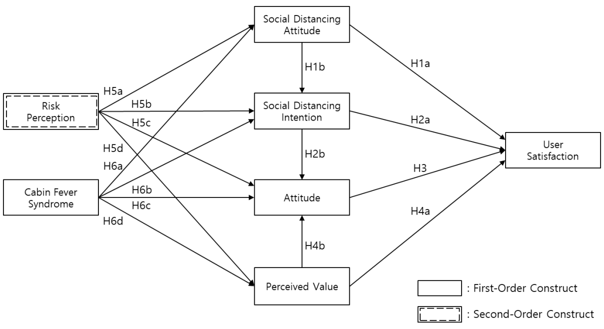

Figure 1. Research model

2.2.1 Social Distancing Attitude

Attitude represents an individual's overall evaluation of a certain event [14]. Attitude has been found to significantly affect behavioral intention [8, 37]. Social distancing attitude refers to a person's assessment of social distancing. In a pandemic situation, online learning systems deliver infection prevention and educational effects. Attitudes towards health-preserving behavior such as social distancing are closely tied to perceptions about the safety and effectiveness of online education [38]. Students who have a more positive attitude towards social distancing are more likely to develop stronger intentions to practice such behavior, recognizing its importance in limiting the spread of the virus [39]. The stronger the students' attitude towards social distancing, the higher their satisfaction with the online learning system is likely to be. Social distancing attitude also plays a crucial role in enhancing social distancing intention. Consequently, social distancing attitude is expected to have a significant influence on both user satisfaction and social distancing intention.

Hypothesis H1a. Social distancing attitude significantly affects user satisfaction.

Hypothesis H1b. Social distancing attitude significantly affects social distancing intention.

2.2.2 Social Distancing Intention

Social distancing intention is justified as the intention to participate in social distancing, as a means to inhibit the COVID-19 [6, 40]. It leads to social distancing behavior [7]. The perceived benefits of social distancing affect e-learning quality, which in turn influences student satisfaction [41]. The stronger the intention to practice social distancing, the more likely individuals are to adhere to preventive measures [42]. Students who commit to social distancing may feel their decision is validated by the online learning experience, leading to higher satisfaction. Therefore, it is anticipated that social distancing intention will have a substantial impact on both user satisfaction and attitude towards online learning.

Hypothesis H2a. Social distancing intention significantly affects user satisfaction.

Hypothesis H2b. Social distancing intention significantly affects attitude towards online learning.

2.2.3 Attitude

In this study, attitude means the extent to which an individual has a positive or negative assessment toward a online learning. Attitude was found to have a significant association with the behavioral intention toward preventive behavior [3]. The effect of behavioral intention on satisfaction has been revealed as significant in various domains [10, 43]. Students with a more positive attitude toward online learning are likely to be more satisfied with their online learning experience. This is because positive attitudes can lead to higher levels of engagement, commitment, and motivation, which subsequently result in a more satisfying learning experience [44]. Thus, this study tests the following hypothesis.

Hypothesis H3. Attitude towards online learning significantly affects user satisfaction.

2.2.4 Perceived Value

Perceived value is described as the financial and mental evaluation on services [12]. Previous research in marketing and ISs has demonstrated the significant impact of perceived value on satisfaction [45-47]. Additionally, perceived value has been identified as a key determinant of satisfaction among e-learning users [34]. Students are customers who pay tuition and receive educational services. If students perceive high value in their online learning (that is, they believe that the benefits they receive from it outweigh the costs), they are more likely to be satisfied with their online learning experience [48-49]. Therefore, it can be concluded that the perceived value of online learning significantly influences both user satisfaction and attitude towards it.

Hypothesis H4a. Perceived value of online learning significantly affects user satisfaction with it.

Hypothesis H4b. Perceived value of online learning significantly affects attitude towards it.

2.2.5 Risk Perception

Risk perception is defined as the people's cognitive and affective assumption of the likelihood of damage from danger [50]. Risk perception consists of affective risk perception and cognitive risk perception [50-51]. Affective risk perception is described as one's anxiety or worries about risk exposure, whereas cognitive risk perception contains a person's perceived severity and susceptibility to risks [52]. Both affective risk perception and cognitive perception affect behavioral intention to inhibit the spread of COVID-19 [3]. The perception of risk related to COVID-19 has been shown to have a significant impact on individuals' attitudes and behaviors towards preventive measures, such as social distancing [53]. Some research indicated that the majority of the educators and learners thought online learning beneficial and valuable to hinder infection [4, 54]. There is empirical evidence suggesting that individuals who perceive a higher risk of COVID-19 infection have more positive attitudes towards online learning [55]. People who perceive a high risk of the disease might appreciate the benefits of online learning more, such as the ability to continue their education while minimizing the risk of infection, therefore enhancing the perceived value of this mode of education [56]. As such, this work tests the following hypotheses.

Hypothesis H5a. Risk perception significantly affects social distancing attitude.

Hypothesis H5b. Risk perception significantly affects social distancing intention.

Hypothesis H5c. Risk perception significantly affects attitude towards online learning.

Hypothesis H5d. Risk perception significantly affects perceived value.

2.2.6 Cabin Fever Syndrome

Cabin fever refers to the irritable moods of individuals who stayed out in the country and are stuck in confined space [57, 58]. People experiencing higher levels of social isolation may exhibit stronger attitudes and intentions toward social distancing. This is possibly because individuals in isolation may become more sensitive to the risks associated with the virus, enhancing their adherence to social distancing [59]. With the absence of face-to-face social interactions, online learning may become more appealing and necessary for isolated individuals. These circumstances can result in a more positive attitude towards online learning, making it not just a convenient alternative, but a vital tool in continuing education [19]. Due to limited social interactions and mobility, the value of online platforms that allow for social connection, communication, and learning could be enhanced significantly [60]. Therefore, based on the previous discussion, this study proposes the following hypotheses.

Hypothesis H6a. Cabin fever syndrome significantly affects social distancing attitude.

Hypothesis H6b. Cabin fever syndrome significantly affects social distancing intention.

Hypothesis H6c. Cabin fever syndrome significantly affects attitude towards online learning.

Hypothesis H6d. Cabin fever syndrome significantly affects perceived value.

3 Research Methodology

3.1 Instrument Development

The current research conducted the survey method to analyze the proposed model. All question items were developed based on previously demonstrated measurements. The measurement items were modified to fit the online learning system context. Before distributing the questionnaire, experts in ISs and survey methodology thoroughly reviewed it to confirm structure, logical order, and content consistency. For all measures, multiple items were based on a seven-point Likert scale ranging from 1 (“strongly disagree”) to 7 (“strongly agree”). Risk perception was gauged as a hierarchical latent variable of second-order with scales of affective risk perception and cognitive risk perception [50-51]. The second-order construct were calculated by repeated indicator approach [61]. This approach is considered the most appropriate for reflective-reflective type models [62-63]. Appendix A lists the survey items.

3.2 Sample

The analytical model was demonstrated based on the data collected from the cross-sectional investigation. Research target was students having used an online learning program to avoid COVID-19. To complete the data collection, some educators were requested to gather data from the undergraduate and graduate students. Data also were obtained by using a snowball sampling technique. Participants could not move to the next page until they answered all questions on each page. The online link for survey was sent to university students in South Korea and Vietnam from June to September 2021. In South Korea, the 4th wave of COVID-19 infection started in July and the number of confirmed cases has risen to 2,222 (the highest number of cases since the first imported case) on 11th August 2021 [64]. In Vietnam, a social lockdown was implemented and all schools were closed during the survey timing. This collection is meaningful in that it provides a baseline for a series of future studies to observe the trend of COVID-19 [3, 65]. After eliminating incomplete responses, 490 data were used for analysis. Among the final samples, 180 respondents were Korean and 310 respondents were Vietnamese. 154 (31.4%) informants were male and 336 (68.6%) informants were female. The 378 (77.1%) respondents were between the ages of 20 and 23. 198 (40.4%) respondents took the online learning system 5-8 times per week in the regular semester. Table 1 shows the characterization of the final sample.

Table 1. Sample characterization

Demographics	Item	Subjects (N = 490)	
		Frequency	Percentage
Nationality	South Korea	180	36.7%
	Vietnam	310	63.3%
Gender	Male	154	31.4%
	Female	336	68.6%
Age	19 or younger	74	15.1%
	20-23310	378	77.1%
	24 or older	38	7.8%
Using frequency per week	1-4	79	16.1%
	5-8	198	40.4%
	More than 8	213	43.5%

4 Research Results

This study used the partial least square structural equation modeling (PLS-SEM) to analyze the measurement model and the structural model. The reason for using PLS is that it has some advantages with regard to restrictions on sample size [66-67]. The PLS method has been figured out to be useful in the IS domains [68]. The present study used SmartPLS 3.3.9 to conduct PLS-SEM [69]. This study performed a two-step analysis to evaluate the measurement model and the structural model.

4.1 Measurement Model

The current study evaluated the measurement model by the following criteria: reliability, convergent validity, and discriminant validity. Reliability was validated by calculating composite reliability (CR) and average variance extraction (AVE). CR should be greater than 0.70 and the AVE should be 0.50 [70]. As detailed in Table 2, CR and AVE estimates of all constructs were greater than the threshold, respectively. Hence, reliability was ensured. Convergent validity is accepted when the factor loadings are 0.60 or higher [71]. Since the lowest value of factor loadings was 0.836 (SDA3), convergent validity was confirmed.

Table 2. Descriptive statistics, factor loading, CR, and AVE

Construct		Items	Mean	St. Dev.	Factor loading	CR	AVE
User satisfaction		USA1	5.367	1.411	0.952	0.973	0.900
		USA2	5.243	1.437	0.948		
		USA3	5.278	1.420	0.947		
		USA4	5.196	1.432	0.948		
Social distancing attitude		SDA1	5.641	1.452	0.867	0.887	0.723
		SDA2	5.555	1.448	0.848		
		SDA3	5.259	1.582	0.836		
Social distancing intention		SDI1	6.047	1.187	0.942	0.959	0.885
		SDI2	5.990	1.211	0.947		
		SDI3	6.018	1.156	0.934		
Attitude		ATT1	5.580	1.290	0.924	0.954	0.839
		ATT2	5.535	1.306	0.936		
		ATT3	5.476	1.311	0.931		
		ATT4	5.073	1.507	0.873		
Perceived value		PEV1	5.198	1.440	0.933	0.961	0.892
		PEV2	5.110	1.434	0.944		
		PEV3	5.171	1.418	0.956		
Risk perception	Affective risk perception	ARP1	5.155	1.773	0.869	0.929	0.765
		ARP2	5.565	1.566	0.874		
		ARP3	5.492	1.583	0.887		
		ARP4	5.790	1.385	0.869		
	Cognitive risk perception	CRP1	5.351	1.800	0.927	0.913	0.840
		CRP2	4.916	1.907	0.906		
Cabin fever syndrome		CFS1	4.424	1.945	0.871	0.965	0.762
		CSF2	4.973	1.889	0.875		

Discriminant validity is satisfied when the square root value of AVE is over the correlations value between the construct and the other constructs [70]. As described in Table 3, diagonal scores were higher other estimates. Therefore, discriminant validity was satisfied.

Table 3. Correlation matrix and discriminant assessment

Construct	1	2	3	4	5	6	7	8
1. USA	0.949							
2. SDA	0.546	0.850						
3. SDI	0.423	0.657	0.941					
4. ATT	0.871	0.577	0.486	0.916				
5. PEV	0.841	0.536	0.433	0.850	0.945			
6. ARP	0.380	0.448	0.387	0.450	0.407	0.875		
7. CRP	0.214	0.402	0.242	0.256	0.196	0.567	0.917	
8. CFS	0.151	0.373	0.176	0.159	0.134	0.337	0.437	0.873

Note. Diagonal values are the square root of AVE

4.2 Structural Model

This research performed PLS-SEM to determine the significance of relationships among constructs within the structural model. A bootstrap resampling method (5000) was carried out. Figure 2 illustrates the results of PLS-SEM.

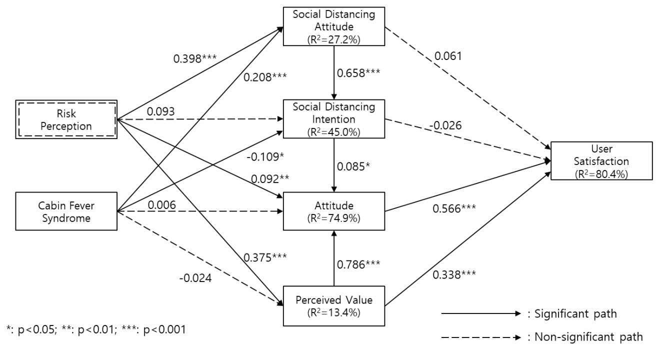

Figure 2. Results of PLS-SEM

As illustrated in Figure 2, ten of the fifteen paths in the research framework are supported. The structural model explained 80.4% of the variance of user satisfaction. Table 4 summarizes the study's results.

Table 4. Summary of the results

H	Cause	Effect	Coefficient	t-Value	Hypothesis
H1a	SDA	USA	0.061	1.675	Not Supported
H1b	SDA	SDI	0.658	15.754	Supported
H2a	SDI	USA	-0.026	0.834	Not Supported
H2b	SDI	ATT	0.085	2.486	Supported
H3	ATT	USA	0.566	9.943	Supported
H4a	PEV	USA	0.338	5.698	Supported
H4b	PEV	ATT	0.786	31.865	Supported
H5a	RIP	SDA	0.398	7.746	Supported
H5b	RIP	SDI	0.093	1.916	Not Supported
H5c	RIP	ATT	0.092	2.810	Supported
H5d	RIP	PEV	0.375	7.045	Supported
H6a	CFS	SDA	0.208	4.343	Supported
H6b	CFS	SDI	-0.109	2.386	Supported
H6c	CFS	ATT	-0.006	0.209	Not Supported
H6d	CFS	PEV	-0.024	0.477	Not Supported

5 Discussion

The current findings reveal that neither social distancing attitude nor social distancing intention significantly influences user satisfaction. These findings contradict previous studies indicating that social distancing attitude and intention can predict user satisfaction [38, 72]. Possible explanations might be the unique circumstances of the pandemic, varying individual experiences, or the evolution of attitudes toward online learning, requiring further exploration in future studies. The results of this study support a strong relationship between social distancing attitude and social distancing intention, which is consistent with previous research [39]. The findings indicate that individuals who hold a positive attitude towards social distancing are more likely to have the intention to engage in social distancing practices. On another front, the influence of social distancing intention on attitudes toward online learning underscores the interconnectedness of pandemic-related behaviors and perspectives toward educational modalities. Students with a stronger intention to adhere to social distancing guidelines also demonstrated a more positive attitude toward online learning. It implies that enhancing students' intention to engage in social distancing may be a potential pathway to foster more positive attitudes toward online learning amidst the pandemic.

In line with prior research [34, 44], our study confirmed that both attitude toward online learning and perceived value of it are significantly associated with user satisfaction. The findings suggest that students' attitudes towards online learning and their perceived value of it play crucial roles in determining their level of satisfaction. This underscores the importance of enhancing positive attitudes and conveying the value of online education as essential strategies to improve user satisfaction, particularly in situations like the ongoing pandemic where online learning is increasingly prevalent. As well, this study proved that perceived value of online learning significantly affects attitude towards it. This finding reinforces the necessity of making online learning experiences valuable to students, which can range from designing engaging and interactive content to providing support systems that enhance the overall online learning experience. This can significantly enhance students' attitudes towards online learning, which could ultimately lead to higher engagement and satisfaction levels.

Interestingly, while risk perception affected social distancing attitude, attitude toward online learning, and perceived value, it did not impact social distancing intention. This could be due to cognitive dissonance or selective risk perception that students might exhibit, possibly due to fatigue or desensitization to pandemic risks over time. The finding revealed that perceived risk does not have an impact on the attitude towards online learning, but it does affect perceived value. A possible explanation for this could be that the perceived risk of contracting the virus may not alter a student's attitude towards online learning because such learning is typically viewed as a safer alternative to traditional in-person classes. However, the same perceived risk could heighten the perceived value of online learning, as students may view it as a necessary and invaluable resource in a risky pandemic situation, hence increasing its value. The dichotomy of these findings suggests that while fear and risk perception may not directly influence attitudes, they have a tangible impact on how students assess the value of online education in the context of a global health crisis. Therefore, understanding these dynamics is crucial in designing and promoting online education initiatives in response to public health emergencies.

Finally, cabin fever syndrome, or social isolation, was found to have a positive effect on social distancing attitude but a negative effect on social distancing intention. This paradoxical finding might be understood in light of research demonstrating the psychological toll of isolation, which might simultaneously increase perceived necessity for distancing while reducing the motivation or perceived ability to maintain it. The analysis result indicates that cabin fever syndrome does not significantly influence attitudes towards online learning or the perceived value of such a system. The detachment from traditional classroom learning and consequent cabin fever syndrome may not have as much of an impact on students' perception of the worth of their online education as initially expected. It could suggest that students are capable of distinguishing between the effects of prolonged confinement and the intrinsic value of their education. This could also imply that they consider online learning an efficient substitute, irrespective of the adverse psychological impact of extended isolation. The neutrality of cabin fever syndrome on these variables could be because of students' resilience or the effectiveness of online learning strategies employed to maintain student engagement during this challenging time. However, this finding also underscores the need for future studies to probe further into the intricate relationship between isolation effects and online education perception.

6 Conclusion

6.1 Theoretical and Practical Implications

This paper offers several implications for theory and practice. First, this study explored the roles of social distancing attitude and social distancing intention on user satisfaction in the context of the online learning system. The analysis results showed that both social distancing attitude and social distancing intention have no significant impact on students' satisfaction with the online lecture. In the context of COVID-19, attitudes and intentions to take preventive measures do not affect the satisfaction of online learning systems. Students would want the pandemic to end and prefer face-to-face learning. Because social distancing is a social norm that everyone must follow, they may not voluntarily form an attitude and intention toward social distancing. Therefore, service providers and education managers should focus on communication or learning usefulness which are the core functions and effects of online learning.

Second, this study found that both attitude and perceived value play a key role in shaping user satisfaction. Existing studies have mainly treated attitude as an antecedent factor of behavioral intention or actual behaviors [8, 73]. However, the results uncovered that attitude directly affects user satisfaction which leads to post-adoption behavior such as continuance intention and recommendation intention [11]. In addition, students with higher perceptions of value had enhanced their level of satisfaction. The main value of an online learning system is transmission prevention and effective learning. Therefore, policymakers need to emphasize the effects of the prevention of COVID-19 and the effect of learning to enhance attitude and perceived value.

Third, this study examined the relationships among social distancing attitude, social distancing intention, attitude toward online learning, and perceived value. Students with higher levels of social distancing attitude increase social distancing intention, ultimately leading to an increase in attitude towards online learning. Moreover, users with greater degrees of the perceptions of value enhance the levels of attitude toward online learning. In a pandemic, students' awareness of social distancing and perceived values of online learning determine attitudes toward online learning, which in turn influence user satisfaction. Overall, the present research contributes to the literature on online learning systems by demonstrating the prevailing roles of social distancing and perceived value in generating attitudes toward online learning in the context of COVID-19.

Last, this study considered the risk perception by forming a second-order construct. The results indicated that risk perception is a high-order construct made by affective risk perception and cognitive risk perception. The second-order construct provides an in-depth explication of various perspectives of risk perception, resulting in an understanding of the impact of main factors on determinants of user satisfaction. Risk perception was triggered out to have a significant effect on social distancing attitude, attitude toward online learning, and perceived value. Students with higher levels of risk perception of COVID-19 had increased levels of social distancing attitude, attitude, and perceptions of value towards the online lecture system. Government authorities should investigate university students' awareness of the risk of COVID-19 and suggest effective measures to encourage them to participate in social distancing. Education ministries and university managers need to prepare non-face-to-face education programs, taking into account that university students' risk perception has a significant impact on user satisfaction with online learning. System providers should improve students' participation in online education by emphasizing that meeting programs are not just educational means, but also health functions such as infection prevention.

6.2 Limitations and Future Studies

Although the results identified salient factors of user satisfaction in the context of the online lecture, this work suffers from several limitations. First, data were gathered from only two Asian countries. The generality of the results would improve if various countries were examined. Second, this work did not reflect teachers' opinions about the online lecture. The online lecture system is a platform for educators and learners to communicate with each other and perform education. Thus, future research should endeavor to reflect teachers' views so that the results can be more comprehensive and generalizable. Finally, with COVID-19 continuously proceeding, longitudinal research to investigate how the determinants found in the results change over time might unveil additional novel findings.

Appendix A. Measurement Items

User Satisfaction is derived from Bhattacherjee [74].

How do you feel about your over experience with online lecture system?

Very dissatisfied/Very satisfied.

Very displeased/Very pleased.

Very frustrated/Very contented.

Absolutely terrible/Absolutely delighted.

Social Distancing Attitude is derived from Williams et al. [40].

In my opinion, the use of social distancing will have a positive impact to control COVID-19.

The use of social distancing is beneficial for the care of the patients.

I find it interesting to use social distancing for the control of COVID-19.

Social Distancing Intention is derived from Williams et al. [40].

I have the intention to use social distancing when it becomes useful to avoid COVID-19.

I have the intention to use social distancing when necessary to provide good results to avoid COVID -19.

I have the intention to use social distancing for the care of myself and others.

Attitude is derived from Ajzen [8].

Online lecture system is useful.

Online lecture system is valuable.

Online lecture system is beneficial.

Online lecture system is attractive.

Perceived Value is derived from Kim et al. [75].

All things considered, using online lecture system services provides very good value.

Using online lecture system services is worth my money and time.

It is of value for me to use online lecture system.

Affective Risk Perception is derived from Bae and Chang [3].

I am worried that I will contract COVID-19.

I am worried about my family members contracting COVID-19.

I am worried about COVID-19 occurring in my region.

I am worried about COVID-19 emerging as a health issue.

Cognitive Risk Perception is derived from Bae and Chang [3].

There is a high likelihood of acquiring COVID-19 compared to other diseases.

There is a high likelihood of dying from COVID-19.

Cabin Fever Syndrome is derived from Chakraborty et al. [6].

I feel restless staying at home.

I have food cravings while staying at home during social distancing/lockdown.

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Biographies

Hyeon Jo received his B.S., M.S., and Ph.D. degrees from the Korea Advanced Institute of Science and Technology (KAIST) in 2004, 2006, and 2012, respectively. His current affiliation is HJ Institute of Technology and Management which conducts the research related to emerging technology, business, and human behavior. His research interests are 4.0 industry, smart lighting, IT security, collaborative filtering, web data analysis, and Internet information.

Eun-Mi Baek received Ph.D. degrees from the College of Medicine, Catholic University of Korea in 2017, respectively. Her current affiliation is a professor at the College of Medicine, Catholic University of South Korea. Her current research interests are occupational disease, job stress, preventive behaviors and risk perception. She has published in BMC Public Health, PLOS One, International Journal of Environmental Research and Public Health among others.