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Online or Traditional Learning at the Near End of the Pandemic: Assessment of Students' Intentions to Pursue Online Learning in the Philippines

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Abstract: Online learning has been utilized due to the sudden shift taken among educational institutions to continue students' learning during the COVID-19 pandemic. Three years into the pandemic, universities now offer different modalities of education due to the establishment of online and modular learning modalities. Hence, the intention of students to adapt to online learning despite the availability of traditional learning is underexplored. With the limited availability of face-to-face learning at the near end of the epidemic in the Philippines, this study sought to analyze the factors that influenced behavioral intentions towards continuing online learning modalities. Five hundred students from different universities in the Philippines participated and answered 42 adapted questions in an online survey via Google Forms. Structural equation modeling (SEM) was used in this study, with factors such as an affective latent variable, attitude towards behavior, autonomy, relatedness, competency, expectation, confirmation, satisfaction, and behavioral intention. The study found that attitude towards behavior has the highest positive direct effect on students' intentions to pursue online learning, followed by expectation and confirmation, satisfaction and behavioral intention, competence and behavioral intention, and the affective variable and satisfaction. The effect of expectations on satisfaction and the affective variable on behavioral intentions was seen to have no significance regarding students' intentions. This also study integrated expectation–confirmation theory, the theory of planned behavior, and self-determination theory to holistically evaluate students' intentions to pursue online learning despite the availability of traditional learning. The educational sector can utilize these findings to consider pursuing and offering online learning. Additionally, the study can help future researchers evaluate students' behavioral intentions concerning online learning.

Keywords: face-to-face learning; student attitude; self-determination theory; online learning; student intention

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1. Introduction

The coronavirus (COVID-19) created a global disaster that affected all facets of human life. The World Health Organization (WHO) officially announced in March 2020 [1], three months after discovering the deadly virus, that the spread of the COVID-19 virus constituted a pandemic, thus impacting various different sectors. The impact of COVID-19 was felt heavily in the education sector. As recognized by the United Nations Education, Scientific, and Cultural Organization (UNESCO), this outbreak took a toll on the education sector, affecting 1.5 billion learners in 165 countries worldwide [2]. According to a study conducted by the UNESCO Institute for Statistics (UIS), March 2020 was when school closures started due to the COVID-19 pandemic. By April 2020, 95.2% of students were affected by this globally [2]. Education is the foundation for the growth and development of every country, especially developing countries. That is why the need to assess mitigations taken to help learners is essential [3].

Students and youth across the globe were then affected and concerned that their future education rights were threatened [4]. The education system was shifted from a traditional face-to-face or classroom setting to fully online learning [5]. More than 400 college students who had recently shifted to online learning participated in a Barnes and Noble Insights survey. It was shown that 60% of the students felt somewhat prepared for the sudden change, particularly those who had previously taken an online course. However, 64% of the survey participants raised concerns about their ability to concentrate and sustain the self-discipline required for distance study. Moreover, in a recent College Reaction/Axios survey, 77% of more than 800 college students stated that online or distance learning is far worse than face-to-face classes [6].

In developing countries, when governments announced lockdowns, the economy declined and schools needed to be closed and shift to distance learning [7]. A study by Hossain [8] stated that due to the lack of suitable facilities or infrastructure and severe poverty in some developing countries, students' experience of distance learning might be highly unequal depending on their socioeconomic background or location. Due to their restricted access to information technology, students in low-resource environments are more likely to be out of school [9]. A study by Muca et al. [9] presented information about how the current development of other developing and developed countries in Europe and the United Kingdom has demonstrated the implementation of online learning, even for veterinary students. However, online learning in the Philippines still affected students, and the lack of resources is still a problem that persists. Many students in the country did not experience school due to a lack of infrastructure, computers, and other technology-related tools, thus causing their families to develop poor learning motivations. Instead, their children would help support their families through farming or other jobs rather than spend time on education.

With the different challenges developing countries such as the Philippines have faced, several studies focused on an evaluation of online learning during the COVID-19 pandemic. In an article by Prasetyo et al. [10], the challenges presented to students regarding online learning included familiarity with the use of online learning platforms such as Blackboard Collaboration, Microsoft Teams, and Zoom as they have different features. Additionally, the challenge of adapting to online learning is based on perceived ease of use, perceived usefulness, information quality, system quality, and the behavioral intentions of the students. In their study of student preferences, Chuenyindee et al. [11] also highlighted that undergraduate students preferred how online learning structures fit their needs. A study by Ong et al. [12] identified that fully online master's degree students in the Philippines preferred mixed types of learning with Zoom as a delivery platform. They chose to learn as much as possible but with less academic workload. Lastly, master's and doctorate students considered publication the final requirement with a mixed delivery type due to their different time restrictions. They preferred convenience at their pace, which was still able to result in positive academic output and achievement. The study results showed that the students chose the mixed delivery type of learning due to different priorities and goals. Another study by Ong [13] showed that senior high school students' choice of either mixed or asynchronous classes would either not affect or have no significance on their learning process. This indicates that online learning is efficient for students. However, students must be responsible for their time management in education.

Despite challenges, Ong [13] indicated that students are willing to pursue education through online learning despite difficulties relating to the setting. However, as the COVID-19 pandemic is nearing an end, schools are now being reopened and catering to traditional or face-to-face learning, fully online learning, and blended learning. The challenge of adapting to the different learning modes has still been underexplored. It was indicated by Bast [14] that receptiveness to online learning had been a challenge in developing countries such as India. With the usability issue in online learning evident during the COVID-19 pandemic, Pal and Vanijja [15] expounded on learning consumption, stating that there are no significant differences in utility. However, they highlighted that individual differences in utility, acceptance of technology, and learners' perspectives on online learning were minimal [15,16]. Thus, the need to assess behavioral aspects of adaptation and the learner's perspective is needed to evaluate available learning modes at the end of the COVID-19 pandemic. The results would enable schools and universities, especially in developing countries, to provide insights, motivation, and a foundation for preplanning and implementing the available learning modes developed before and during the lockdown.

The different behavioral aspects of the adaptation to online learning (despite the availability of traditional learning or blended learning) could be evaluated using several theories. One of these theories is the self-determination theory (SDT) established by Ryan and Deci in 1977, which is inspired by Bandura's work [13] and focuses on delivering satisfaction of the basic psychological needs of learners and teachers in terms of education. It also measures students' autonomy, relatedness, and competency [17]. Chiu [18] conducted an application for online learning using the SDT. Their study showed how the SDT could measure student satisfaction and engagement in online learning. Another theory that could be utilized is the theory of planned behavior (TPB) established by Ajzen in 1991 from the theory of reasoned action by Fishbein and Ajzen in 1975 [19], which covers important individual beliefs, such as subjective norms (SNs), attitudes towards behavior (AB), and perceived behavioral control (PBC), that affect positive or negative intention behaviors towards other people [19,20]. The TPB was used in a study by Mouloudj et al. [21] which showed that both positive AB and SNs significantly influenced the student to continue with the intention to use online learning. Evidence of PBC was found to have the most substantial influence, which indicated that students with higher confidence are more likely to be confident in online learning.

In addition, Ong [13] explained how both the SDT and TPB could be integrated, similar to the study of Hollett et al. [22] which demonstrated how the integrated theories would be able to holistically measure both the behavioral aspect and cognitive aspects of a student in terms of their behavioral intention. Since the COVID-19 pandemic has continued for almost three years, fully online learning has been administered, and students have now experienced both online and traditional education. Students expect different understandings, which can be assessed by the expectation–confirmation theory (ECT). This theory, which was established by Bahattacherjee in 2001, shows that expectations of perceived performance affect satisfaction [23,24]. Positive or negative confirmation between expectations and performance serves as a medium for this effect [23]. In a study by Wang et al. [24], the ECT was used to study the factors that affect satisfaction and the continuous behavior of students in online learning.

This study aimed to evaluate factors affecting behavioral intention when adapting to online learning despite the availability of traditional learning during the near end of the COVID-19 pandemic. Specifically, the SDT, TPB, and ECT were integrated to measure the behavioral, psychological, and cognitive aspects completely. This would be considered one of the first studies to integrate the three theories and measure behavioral intention holistically regarding different online learning modes at the near end of the pandemic. The study results can benefit fellow researchers, academicians, and the educational sector regarding plans for additional modes of learning, continuous online learning, and the perceived effectiveness of suitable learning modes for students. The findings can also contribute to verifying the effectiveness of the use of online learning or blended learning after the pandemic.

2. Related Studies and Conceptual Framework

2.1. Behavioral Theories and Related Studies

Figure 1 represents the ECT originated by Oliver [25]. The ECT is a framework utilized to measure consumers' relationships with information systems, specifically continued use based on their acceptance and behavior [26]. Bhattacherjee [27] stated that it is used in the literature regarding consumer behavior to analyze consumer satisfaction, behavior, and service marketing. In the ECT, expectations act as the baseline on which consumers compare actual performance and make a confirmation decision—presenting a direct effect. According to the theory, confirmation influences satisfaction—presenting the direct effect, with positive confirmation resulting in satisfaction and negative confirmation resulting in dissatisfaction [23].

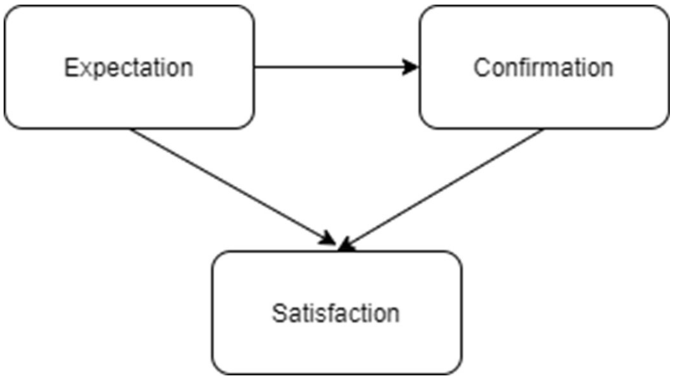

Figure 1. Expectation–confirmation theory.

An individual consumer forms an initial expectation of a product/service before its purchase or usage [28]. However, the ECT lacks other important factors crucial in decision making as it only focuses on the attitude formed by individual consumers, particularly in an online setting. Factors such as social influence and perceptions of how easy or difficult performing those behaviors is seen to be undermined. Previous research depicted important consumer behavior factors in the TPB [29]. These free factor affects intention, leading to an effect on behavior as indicated by the arrows. With this, a study in Korea by Kim [30] focused on the intention to continue using mobile services in Korea by integrating the ECT and TPB. Their study justified the mishap of using the ECT as a framework alone to assess information system-related studies. On the other hand, the TPB alone intends to explain consumer acceptance, which was criticized for not accurately representing consumers' continuance behavior [31]. A study by Thanasarnaksorn and Suntrayuthb [29] considered integration of the ECT and TPB for the analysis of continuous usage of information systems. The framework for the TPB is presented in Figure 2.

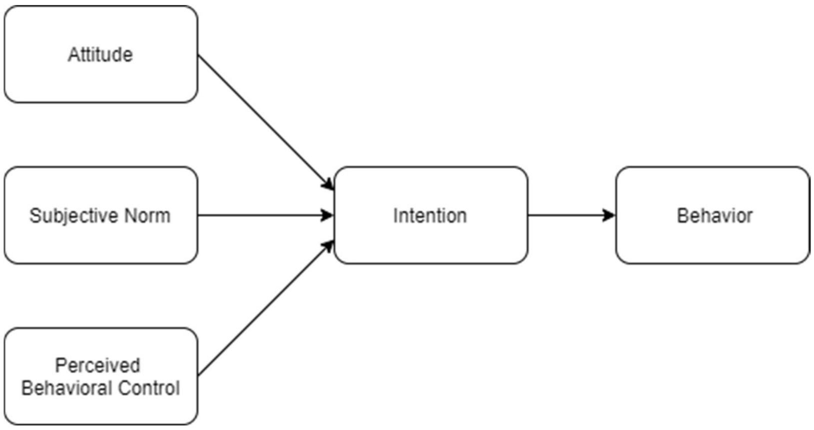

Figure 2. Theory of planned behavior.

The TPB is widely utilized to assess the behavioral aspects of consumers holistically. This model represents three variables: attitude, subjective norms, and perceived behavioral control towards the behavior that affects consumers' intentions. A study by Hollett et al. [22] explained lecture attendance behavior with the SDT and the TPB. Their study showed that the TPB alone could not assess the behavioral aspect and cognitive aspects of a student holistically in terms of behavioral intentions. In addition, it was explained how the TPB does not define most of the behavioral variation among students. Thus, integration of the SDT was considered. The SDT framework, with factors such as autonomy, relatedness, and competency, is presented in Figure 3—three domains as affecting self-determination. Similarly, Ong [13] utilized the SDT, which was integrated with the TPB, to assess students' overall behavioral intentions regarding enrolling in chemistry-related courses. Despite their positive results, it expounded on the limitations of how other latent variables or theories may be applied to consider the holistic measurement of students' intentions.

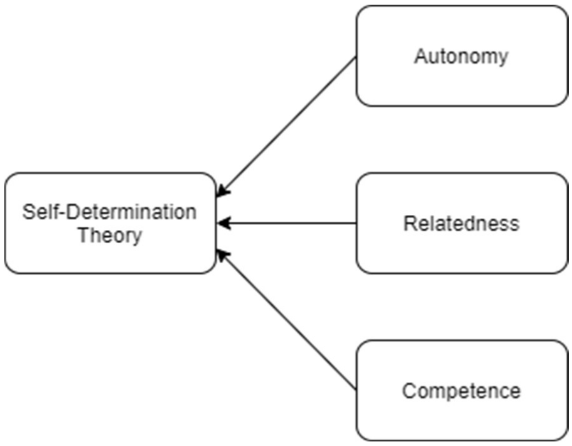

Figure 3. Self-determination theory.

2.2. Hypotheses Building and Conceptual Framework

In accordance, Ong [13] claimed that many arguments were observed regarding the preparedness of online learning setups for developing countries during the COVID-19 pandemic. It was posited that universities in the Philippines were not ready to shift into a relatively new mode of learning, now commonly known as online learning [32]. However, three years have passed since the implementation of the online learning setup, and universities worldwide are implementing traditional learning, online learning, or blended learning [33,34]. To assess the behavior intentions of students to accept the continuous implementation of online learning in developing countries despite the transition to traditional education, the conceptual framework utilized in this study integrated the expectation–confirmation theory, theory of planned behavior, and self-determination theory, as presented in Figure 4.

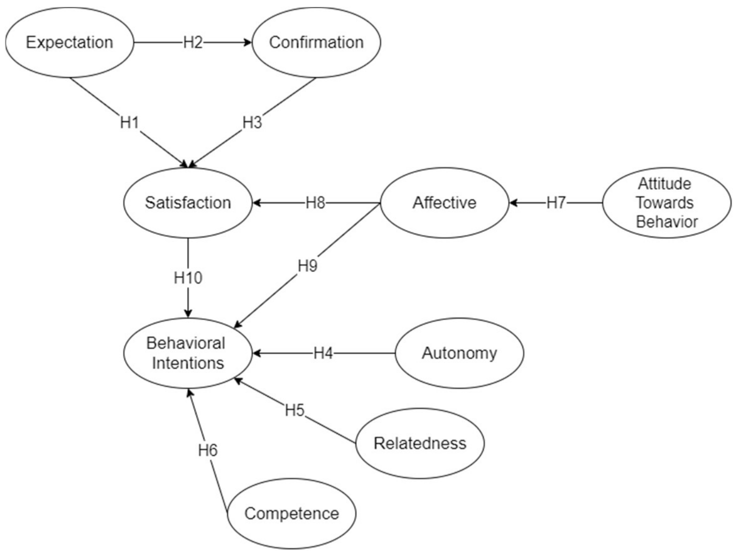

Figure 4. Conceptual framework.

The purpose of integrating the three theories was based on the disadvantages presented by the individual theories that, upon integration, would explain a holistic measurement of the expectations, cognitive aspects, and behavioral aspects of students towards the intention to consider online learning rather than the traditional face-to-face setting. From the conceptual framework, it was seen that twelve hypotheses were built based on the different relationships from the integrated model.

According to the ECT, expectation and perceived performance lead to satisfaction. In a study by Rajeh et al. [35], students' satisfaction and continued intention towards e-learning concluded that expectation significantly affects medical students' confirmation, influencing satisfaction and the desire to continue to engage in e-learning. Expectations showed a significant direct relationship with student satisfaction as they are the main factor for predicting the student's intention to use e-learning. Chou et al. [36] also confirmed that expectation significantly affects confirmation. Their study posited that the expectation of continuing to use e-learning influenced satisfaction. Related research affirmed that e-learning in relation to medical professionals' confirmation significantly impacts satisfaction [37]. Furthermore, the higher the confirmation, the higher the student satisfaction [24]. With the supporting studies, the following hypotheses were formed:

Hypothesis H1. *Expectation has a significant direct positive effect on satisfaction.*

Hypothesis H2. *Expectation has a significant direct positive effect on confirmation.*

Hypothesis H3. *Confirmation has a significant direct positive effect on satisfaction.*

The SDT is extensively used to comprehend and predict motivation in the educational sector. This theory enhances motivation when autonomy, competence, and relatedness are highly optimistic [38]. Autonomy refers to individuals thinking freely and hence being responsible for their behavior. Competence is an individual's interactions with their environment, while relatedness is an individual's sense of belonging to their environment [39]. In a study by Raman et al. [40], autonomy and competence significantly affected behavioral intentions in postgraduate schools; 2000 students registered in 2020–2021 participated in the study. A study by Racero et al. [41] showed how SDT latent variables were a combined construction of factors that significantly affect behavioral intention. Moreover, autonomy, competence, and relatedness were significant in terms of behavioral intention, which was shown in the study through investigation of the effects of the SDT on the intended users of interaction technology [42]. Therefore, the following hypotheses were created:

Hypothesis H4. *Autonomy has a significant direct positive effect on behavioral intention.*

Hypothesis H5. *Relatedness has a significant direct positive effect on behavioral intention.*

Hypothesis H6. *Competence has a significant direct positive effect on behavioral intention.*

The TPB asserts the relationship between perceived behavioral control, subjective norms, and attitude towards an individual's intention [43]. Attitude towards the behavior describes how positively or adversely a person judges the target behavior [44]. A study by Patterson [45] demonstrated that the attitude towards behavior is the most significant determinant of behavioral intention. The study by Ong [13] considered that affective behavior is an emotion or feeling towards something, subsequently relating the person's attitude with affective behavior. However, as evident in a study by Ong [13], the subjective norm under the TPB was not considered due to the relatedness factor from the base framework of the SDT. Similarly, autonomy, expectation, and confirmation reflect their behavioral control [46]. Du et al. [47] demonstrated that other factors such as affective behavior relate to the control of an individual. Thus, this online study considered attitude, which is hypothesized as follows:

Hypothesis H7. *Attitude towards behavior has a significant direct positive effect on affective behavior.*

As mentioned, affective behavior can have a positive or negative effect on the behavior of a student [13]. With the TPB proposed by Azjen [44], behavioral intention is a motivational factor influencing overall behavior, and affective behavior is a reaction towards an object, person, or subject. Results have shown that the teacher's affective behavior correlates with and has a positive intention towards research [48]. The study by Du et al. [47] proved that affective behavior influences the individual's feelings, moods, and attitudes, significantly affecting consumer satisfaction. Findings in a study by Geier [49] showed that the affective behavior of teachers, such as feedback, encouragement, understanding, and their performance, significantly affects student satisfaction. Therefore, the following hypotheses were created:

Hypothesis H8. *Affective behavior has a significant direct positive effect on satisfaction.*

Hypothesis H9. *Affective behavior has a significant direct positive effect on behavioral intentions.*

Understanding learners' attitudes is essential in an online learning setting when seeking to improve its usage and impact. Satisfaction is the usual evaluation of the success or failure of a system and its use, which is usually characterized by an individual's comfort level with the tool [50]. In the tourism field, a study by Baker and Crompton [51] showed the significant effect of satisfaction on behavioral intention. Chao [52] presented influential factors affecting users' behavioral intentions regarding educational settings using mobile learning. It suggested that satisfaction is the most crucial factor, with a significant direct effect on behavioral intentions. Zhou and Duangekanong's [53] study deduced that satisfaction positively affects behavioral intention. This means that students were willing to fully adopt the online learning system since students were satisfied with the opportunity to develop their creative learning environment, such as the environment of a group activity conducted through an online class. Therefore, the following was hypothesized:

Hypothesis H10. *Satisfaction has a significant direct positive effect on behavioral intentions.*

3. Methodology

3.1. Data Gathering and Participants

Following the suggestion of Hair et al. [54], frameworks with more than eight latent variables should consider at least 500 respondents for generalizability. In the study of German et al. [55] with 62.6 million Filipinos, the sample size was calculated using the Yamane Taro formula, as seen in Equation (1). At 95% accuracy, 400 respondents would suffice to generalize the public. With that, this study aimed to collect at least 500 respondents.

$$n = \frac{N}{1 + N\,(e)^2} \tag{1}$$

Due to the COVID-19 pandemic and strict lockdown implementation, an online self-administered survey was distributed through social media platforms such as Facebook, Twitter, Instagram, and Viber to collect various samples using the convenience sampling approach. Convenience sampling was used, which is a nonprobability method that is considered easy and cost-efficient [56,57]. The target samples were easily accessible, available at a given time, in geographical proximity, and willing to participate in the study. Moreover, there are fewer complications between the researcher and respondents when using this method [56]. In a survey by Haba and Dastane [57], convenience sampling was also used to analyze behavioral studies using structural equation modeling (SEM).

Aligned with this study, an introductory section was placed alongside a confirmation tab for those who were willing to participate. This section was presented as a platform for the current study to clearly explain the background and aim of the study and how the current intended measures would be utilized. After agreeing to these terms, participants could proceed with the survey items, with respondents allowed to cancel at any time. In addition, the caption underneath where the survey link was posted in social media sites also showed introductory information so participants would be able understand the aim of the survey before beginning.

Table 1 shows the demographic statistics of the respondents. In total, 500 students voluntarily participated in the survey questionnaire administered using Google Forms. Based on the results, 55.4% of the participants were female students, while 44.6% were male students. Most respondents were aged 16–22 years old (88.8%), which also indicates most of the students (462) were at the college level (92.4%), with 27 (5.4%) high school students and 11 (2.2%) master's degree students also participating. Overall, 438 (87.6%) were from private universities/schools, while the remaining 62 (12.4%) students studied at public universities/schools. In terms of access to the internet, more than half, 292 (58.4%), had moderate access, 186 students, about 37.2%, had strong access, while the remaining 22 (4.4%) had weak internet access. Since the majority of the participants were in college, 76% of students' allowances were less than PHP 15,000, with 13% having PHP 15,000–30,000, 4.8% having PHP 30,000–45,000, 3.8% having more than PHP 75,000, 2% having PHP 45,000–60,000, and 0.4% having PHP 60,000–75,000 in monthly salary/allowance. More than half of the participants (56.8%) were located or residing in the National Capital Region (NCR), followed by 123 (24.6%) from Region IV-A (Calabarzon) and 68 (13.6%) from Region III (Central Luzon), with the rest of the participants from different regions. Moreover, 88.2% (441) of the participants had experienced both traditional and online learning in the past two years, with only 59 (11.8%) not experiencing both modalities. Lastly, 60.4% of students intended to consider online learning over traditional face-to-face classes.

Table 1. Demographic profile of respondents (n = 500).

Characteristics	Category	N	%
Gender	Male	223	44.6%
	Female	277	55.4%
Age	16–22 years old	444	88.8%
	23–29 years old	53	10.6%
	30–36 years old	3	0.6%
	37–43 years old	0	0
	44–50 years old	0	0
	51–60 years old	0	0
Educational level	High school	27	5.4%
	College	462	92.4%
	Master's degree	11	2.2%
	PhD	0	0
Type of university/school	Private	438	87.6%
	Public	62	12.4%
Access to the Internet	Weak	22	4.4%
	Moderate	292	58.4%
	Strong	186	37.2%
Monthly salary/allowance	Less than PHP 15,000	380	76%
	PHP 15,000–30,000	65	13%
	PHP 30,000–45,000	24	4.8%
	PHP 45,000–60,000	10	2%
	PHP 60,000–75,000	2	0.4%
	More than PHP 75,000	19	3.8%

Table 1. *Cont.*

Characteristics	Category	N	%
Location	Region I (Ilocos Region)	2	0.4%
	Region II (Cagayan Valley)	4	0.8%
	Region III (Central Luzon)	68	13.6%
	Region IV-A (Calabarzon)	123	24.6%
	Region IV-B (Mimaropa)	6	1.2%
	Region V (Bicol Region)	4	0.8%
	CAR (Cordillera Administrative Region)	3	0.6%
	NCR (National Capital Region)	284	56.8%
	Region VI (Western Visayas)	2	0.4%
	Region VII (Central Visayas)	4	0.8%
	Region VIII (Eastern Visayas)	0	0
	Region IX (Zamboanga Peninsula)	0	0
	Region X (Northern Mindanao)	0	0
	Region XI (Davao Region)	0	0
	Region XII (Soccsksargen)	0	0
	Region XIII (Caraga)	0	0
	BARMM (Bangsamoro)	0	0
Have you experienced both traditional face-to-face classes and fully online classes for at least two years each?	Yes	441	88.2%
	No	59	11.8%
Do you have the intention to consider online classes rather than face-to-face classes?	Yes	302	60.4%
	No	198	39.6%

3.2. Questionnaire

An online survey was developed to determine factors affecting students' intention to pursue online learning despite the availability of traditional modes of education during the near end of the COVID-19 pandemic and was distributed to different social media platforms through Google Forms. The participants were encouraged to respond to the adapted questions using their knowledge and experience as thoroughly as possible. Table 2 represents the measured items, which were divided into three sections in the survey. All factors were covered with a total of 42 questions that were adapted from various studies as indicated. To evaluate the constructs, the survey utilized a 5-point Likert scale (5 = strongly agree, 1 = strongly disagree) [10–13].

Table 2. Questionnaire.

Theory	Construct	Items	Measure	References
Theory of Planned Behavior	Affective	AF1	I find studying online easier than face-to-face learning.	[58]
		AF2	I find learning online interesting.	[59]
		AF3	I am willing to spend more time learning online than in traditional face-to-face learning.	[59]

Table 2. *Cont.*

Theory	Construct	Items	Measure	References
		AF4	I find online learning to be more comfortable than traditional face-to-face learning.	[60]
		AF5	I find learning online to be the same as traditional face-to-face learning.	
		AF6	I feel as though I get the same quality of education when learning online compared to traditional face-to-face learning.	
	Attitude towards Behavior	AB1	I enjoy learning online more than traditional face-to-face learning.	[61]
		AB2	I find myself having more of an urge to learn when studying with the online setup.	[13]
		AB3	I feel more confident learning online.	
		AB4	I find it more comfortable participating online than in face-to-face learning.	[60]
		AB5	I look forward to learning online more than learning in traditional face-to-face classes.	
Self-Determination Theory	Autonomy	AU1	I like learning online as it helps me understand the lessons more.	[13]
		AU2	If I have the choice, I will choose online learning rather than face-to-face learning.	[59]
		AU3	I find myself engaging more in online learning discussions.	[62]
		AU4	I contribute more when using the online learning setup.	
		AU5	I always want to do better in online learning than in face-to-face classes.	[59]
	Relatedness	RS1	My parents want me to choose online learning rather than traditional face-to-face classes.	[63]
		RS2	My friends' preference in choosing learning online affects my decision.	[63]
		RS3	My preferred course is available through online learning.	[63]
		RS4	My preferred school offers online learning.	[63]
		RS5	People who are important to me want me to use the online learning setup.	

Table 2. *Cont.*

Theory	Construct	Items	Measure	References
	Competency	C01	I find it easy to participate and share my thoughts during online learning.	[64]
		C02	I consider learning online because it will help me in my future career.	[58]
		C03	I feel as though learning online helps me better manage my time than face-to-face classes.	
		C04	I have the ability to use devices applicable for online learning.	
Expectation Confirmation Theory	Expectation	EX1	My skills can be improved in online learning.	[35]
		EX2	Online learning can increase my knowledge.	[35]
		EX3	I find online learning very useful to me.	[35]
		EX4	I find that learning online is the same as learning in a traditional face-to-face setup.	
	Confirmation	CF1	Learning online was better than I expected.	[35]
		CF2	I find that online learning provides a better learning atmosphere for me.	[65]
		CF3	I find that online learning meets the demand of delivering a quality learning experience.	[65]
		CF4	The service of learning online is the same as face-to-face learning.	[65]
	Satisfaction	SF1	I find satisfaction in learning through an online setup.	[35]
		SF2	I find satisfaction in the experience of online learning.	[35]
		SF3	I think my course was well delivered through online learning.	
		SF4	I think I am satisfied with my performance with online learning.	[35]
		SF5	I am satisfied with the knowledge I gained through the online learning setup.	
	Behavior Intentions	BI1	I intend to use online learning to assist me in my studies.	[66]
		BI2	I intend to use online learning as a learning tool.	[66]

Table 2. *Cont.*

Theory	Construct	Items	Measure	References
		BI3	I plan to use online learning in the future.	[21]
		BI4	I predict that I will choose online learning rather than traditional face-to-face classes.	[21]

3.3. Structural Equation Modeling

Structural equation modeling (SEM) is a multivariate analysis tool used to determine complex hypotheses and the relationships between the different latent variables considered in a framework [67]. SEM differs from other analyses as it can determine the relationship while distinguishing measurement errors [68]. According to Behjati et al. [69], SEM is used in the study of behavioral intention as it allows for multiple iterations when identifying an explanatory variable's direct and indirect effect on the dependent variable. AMOS 24 and SPSS 25 were both utilized to analyze SEM. Several studies concerning online learning have utilized SEM to determine influential factors affecting behavioral intentions among students. In a survey by Kucuk and Richardson [70], the SEM method was used to determine the structural relationship between the community of inquiry framework, four components of engagement (agentic, behavioral, cognitive, and emotional), and the satisfaction of students. Zhao et al. [71] also used SEM to analyze the variables and develop their relationships with factor analysis, determining the factors related to students' satisfaction with STEM education. Another study utilized SEM to compare emerging models, satisfaction's relationship to attitude and behavioral intentions, and the direct relationship between attitude and satisfaction and behavioral intention [72].

4. Results

In the SEM analysis, the model was developed using AMOS 24, with all the relationships built from the conceptual framework created in the initial model (Figure 4). SEM used the bootstrapping method and employed relative iterations at a 95% confidence level [73]. The threshold set by Hair [73] was adopted for item measures and relationships. Removal of non-significant items and relationships was then performed, and the final model was run to check the fit of the model. Modification indices were considered for the different relationships to present a model with better fit for the final SEM.

Figure 5 shows the initial SEM for evaluating factors related to students' intentions to pursue online learning. As shown in Figure 5, six (6) out of ten (10) hypotheses were validated for acceptance since the relationships had p-values of less than 0.50 [54]. Therefore, Figure 6 demonstrates the final SEM findings for determining factors related to students' intentions to pursue online learning. The modified model (Figure 6) presents coefficients that signify the relationship of the latent variables. The higher the β values, the higher the relationship between the variables [73]. The expectation variable was seen to have no significant relationship to satisfaction, affective behavior, autonomy, or relatedness to behavioral intentions. On the other hand, the relationship between expectations and confirmation was significant (β = 0.924 and p = 0.018). Confirmation was also substantially related to satisfaction (β = 0.813 and p = 0.028). Attitude towards behavior and affective behavior were also significantly related (β = 0.974 and p = 0.011). A significant relationship also exists between affective behavior and satisfaction (β = 0.217 and p = 0.010), satisfaction and behavioral intention (β = 0.708 and p = 0.007), and behavioral intention and competence (β = 0.457 and p = 0.006).

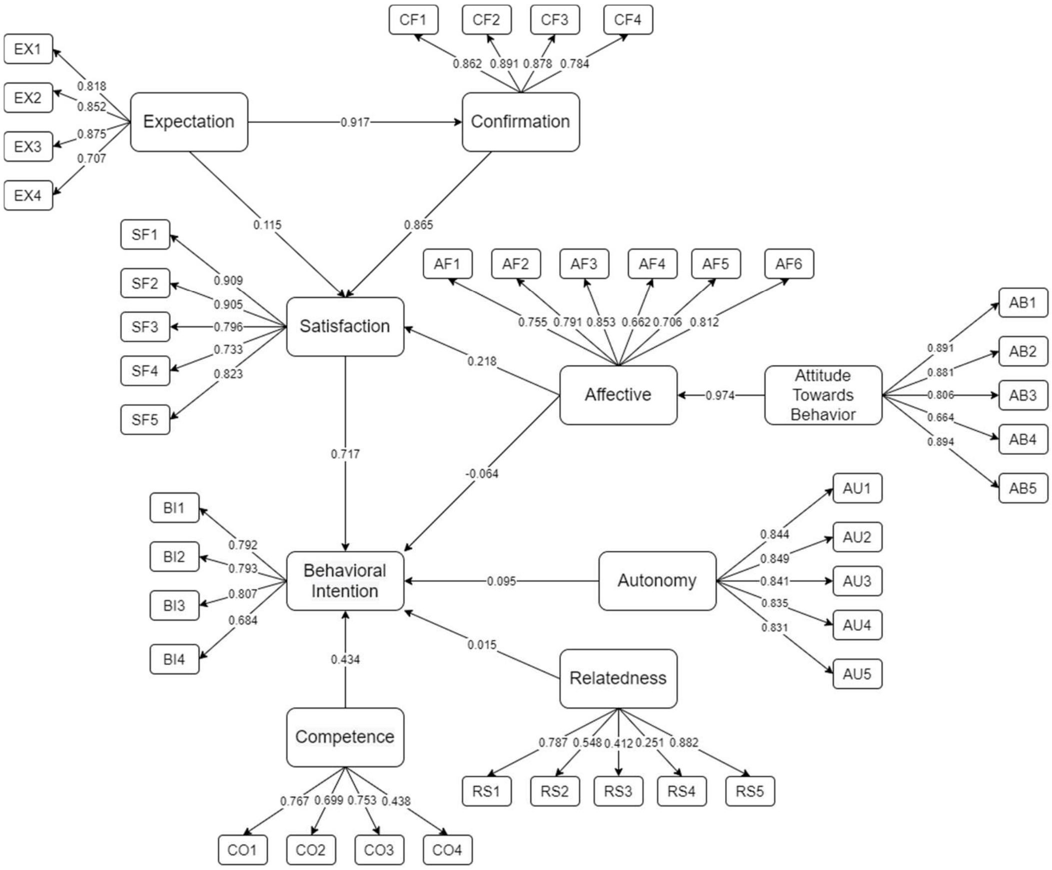

Figure 5. Initial model.

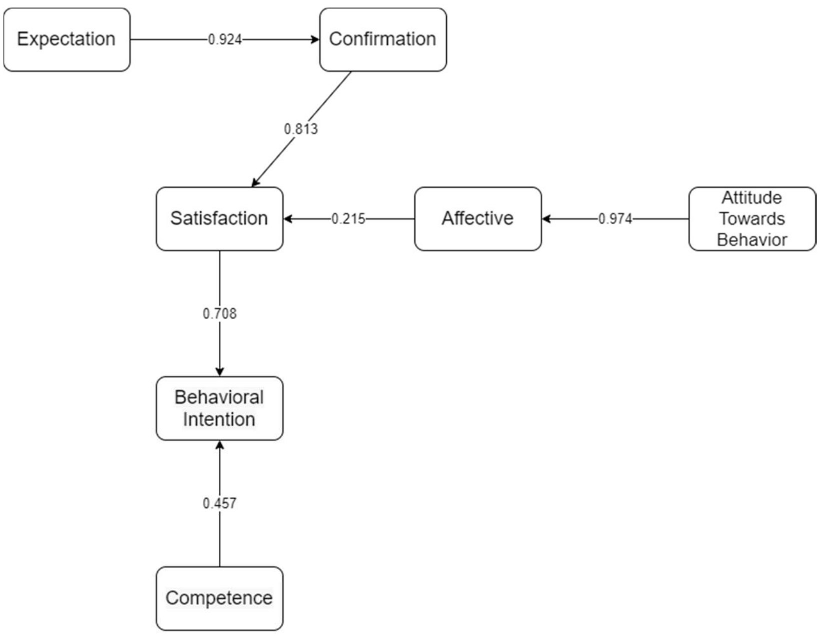

Figure 6. Final model.

Table 3 demonstrates the statistics for the indicators utilized in the model. The table shows the factors, mean, standard deviation, and initial and final factor loadings. Values more than 0.50 are regarded acceptable for these construct variances representing the model's latent variables [73].

Table 3. Descriptive statistical results.

Factors	Items	Mean	Standard Deviation	Factor Loadings	
				Initial	Final
Affective	AF1	4.3320	1.64535	0.755	0.755
	AF2	4.3200	1.60959	0.791	0.792
	AF3	4.0200	1.71391	0.853	0.853
	AF4	4.8620	1.73233	0.662	0.663
	AF5	3.2680	1.85447	0.706	0.705
	AF6	3.3460	1.89459	0.812	0.811
Attitude towards Behavior	AB1	3.8260	1.73948	0.891	0.891
	AB2	3.7360	1.83112	0.881	0.881
	AB3	4.0940	1.89112	0.806	0.805
	AB4	4.4660	1.82524	0.664	0.664
	AB5	3.7840	1.82757	0.894	0.894
Autonomy	AU1	3.9580	1.70706	0.844	-
	AU2	3.9500	1.90651	0.849	-
	AU3	3.9820	1.79670	0.841	-
	AU4	4.1780	1.76310	0.835	-
	AU5	4.0320	1.77010	0.831	-
Relatedness	RS1	3.8300	2.00927	0.787	-
	RS2	3.5960	2.03398	0.548	-
	RS3	4.8460	1.80355	0.412	-
	RS4	5.2940	1.74518	0.251	-
	RS5	3.9220	1.85979	0.883	-
Competency	C01	4.3720	1.84836	0.767	0.767
	C02	3.7340	1.79267	0.699	0.699
	C03	4.6080	1.93541	0.753	0.751
	C04	5.5840	1.46944	0.538	0.609
Expectation	EX1	4.2640	1.66006	0.818	0.818
	EX2	4.5360	1.55742	0.852	0.851
	EX3	4.5640	1.58459	0.875	0.874
	EX4	3.3540	1.89522	0.707	0.709
Confirmation	CF1	4.2380	1.71091	0.862	0.862
	CF2	3.9720	1.80714	0.891	0.889
	CF3	3.8060	1.77388	0.878	0.875
	CF4	3.3540	1.85677	0.784	0.783
Satisfaction	SF1	3.9660	1.76041	0.909	0.910
	SF2	4.0160	1.76123	0.905	0.905
	SF3	3.7620	1.86341	0.796	0.796
	SF4	4.3600	1.83115	0.733	0.733
	SF5	4.0160	1.82713	0.823	0.824
Behavior Intentions	BI1	4.6260	1.67084	0.792	0.800
	BI2	4.6920	1.67534	0.793	0.802
	BI3	4.3620	1.79259	0.807	0.812
	BI4	3.7780	1.94944	0.684	0.690

Table 4 demonstrates the reliability and validity of the study. Average variance extracted (AVE) values of greater than 0.50 indicate the validity of the constructs, while Cronbach's α and composite reliability (CR) values of higher than 0.70 signify the consistency of items for each variable [73]. Table 5 shows the IFI, TLI, CFI, GFI, AGFI, and RMSEA values. Gefen et al. [74] and Steiger [75] demonstrate in their studies that IFI, TLI, CFI, GFI, and AGFI should have values greater than 0.80, while RMSEA should have a value of less than 0.70 to indicate good model fit. As seen in Table 5, acceptable measures are evident for the model.

Table 4. Reliability and validity.

Factor	Cronbach's *a*	Average Variance Extracted (AVE)	Composite Reliability (CR)
Affective	0.892	0.587	0.894
Attitude towards Behavior	0.917	0.692	0.917
Competency	0.755	0.503	0.801
Expectation	0.872	0.665	0.888
Confirmation	0.914	0.728	0.914
Satisfaction	0.938	0.699	0.920
Behavior Intentions	0.902	0.605	0.859

Table 5. Model fit.

Goodness of Fit Measures of SEM	Parameter Estimates	Minimum Cut-Off	Suggested by
Incremental Fit Index (IFI)	0.887	≥0.80	[74]
Tucker Lewis Index (TLI)	0.862	≥0.80	[74]
Comparative Fit Index (CFI)	0.879	≥0.80	[74]
Goodness of Fit Index (GFI)	0.816	≥0.80	[74]
Adjusted Goodness of Fit Index (AGFI)	0.824	≥0.80	[74]
Root Mean Square Error of Approximation (RMSEA)	0.063	<0.07	[75]

5. Discussion

This study integrated the expectation–confirmation theory (ECT), the self-determination theory (SDT), and the theory of planned behavior (TPB) to evaluate the factors affecting students' intentions to pursue online learning despite the availability of traditional modes of learning. An SEM tool was used in the study to determine the correlation of factors such as affective behavior (AF), attitude towards behavior (AB), autonomy (AU), relatedness (RS), competency (CO), expectation (EX), confirmation (CF), satisfaction (SF), and behavioral intentions (BI).

As a result, the highest direct effect was seen in the relationship between attitude towards behavior and affective behavior (β = 0.974 and $p = 0.010$). From the indicators, it was evident that students enjoy learning online more than the traditional face-to-face setup. They find themselves more inclined to learn online, feel more confident about online learning, are more comfortable participating, and look forward to learning online more than learning in a traditional setup. It was seen that a positive attitude was instilled among students throughout the experience of learning online over the past three years. At the same time, their experience in traditional education could suggest that students prefer online learning more due to adaptation. In a study by Amir Rad et al. [76], students and instructors were able to fully adapt to online learning despite the rapid transition from face-to-face to fully online delivery due to the experiences that were developed. Online teaching has continued, and despite minor inconveniences, students and instructors value its efficiency since it saves time and energy, leading them to having a greater work–life balance amid the pandemic. This finding correlates to another study conducted by Zheng et al. [77], which showed that students have had more positive perceptions of online learning than the traditional face-to-face setup during the pandemic. It has been said that online learning helps students feel more comfortable, with options such as typing questions in a chat box making them feel less intimidated than speaking in class.

These findings also showed the significant positive effect of expectations on confirmation (β = 0.924 and $p = 0.011$). The indicators that emphasized expectation included the following statements: skills can be improved in online learning; it can increase knowledge; online learning is very useful; and it is the same as the traditional face-to-face setup. Furthermore, indicators that highlighted confirmation included the following statements:

learning online was better; it provides a better learning atmosphere; it meets the demands of delivering a quality learning experience; and the service of online learning is the same as the traditional setup. Based on the findings, students prefer online learning as it delivers the same quality as a traditional face-to-face setup. Students also report that online learning has increased their knowledge and skills. A study about the perception of students and faculty during the pandemic highlights that, according to students, online learning is an open and productive source of knowledge that provides them with 24 h access to learning materials at any time of the day, thus encouraging students to engage in self-learning and seek out new experiences [78]. In contrast, a study by Gumasing and Castro [4] provided insights into environmental effects impacting student attitudes towards online learning. As indicated by their results, control of background noise, lighting, and atmosphere should be applied to achieve satisfaction during online learning. Another study showed that only minor differences are seen between online and traditional learning; thus, the assessment indicates that both online and classroom learners perform on the same level, with factors such as class rank seeing no significant differences whether learning takes place online or face-to-face [79]. Moreover, previous research found more satisfaction in face-to-face learning than online learning in terms of social presence, social interaction, and satisfaction; however, a study by Bali and Liu [80] identified that there is no significant perception of online learning and traditional classroom setups among different levels within the university (freshman, sophomore, junior, and senior).

Thus, the relationship between expectations and satisfaction shows no significant direct effect on students pursuing online learning. Although students find a similar understanding when learning online or face-to-face and having seen almost no difference in the quality of delivery, gaining knowledge, and new experiences, they were not satisfied with online learning and pursued it throughout their course. A study shows that online and on-campus takers perform well on given exams; however, online takers have lower exam scores than on-campus takers. Analyzing the feedback from the study, results showed that online learners have less satisfaction than on-campus takers [81]. Students are now more familiar with the use of technology and online learning platforms than they were pre-pandemic. Interaction, communication, and other technical difficulties may have hindered them from expressing positive satisfaction with online learning. Elshami et al. [82] pointed out that students were satisfied with the flexibility and affordability of online learning; thus, interaction, specifically collaborative activities, and technology itself were the most significant challenges during online learning.

Satisfaction was also seen to positively affect behavioral intention ($\beta = 0.708$ and $p = 0.012$). The indicators of satisfaction highlight where students find satisfaction in learning through online setups. The experience of online learning, whether the course was well delivered, online performance, and the knowledge gained in online learning were significant. Behavioral intention was the student's intent to use online learning to assist in their studies, to use it as a learning tool, to use online learning in the future, and to choose online learning over traditional face-to-face classes. As the findings indicate, student satisfaction could lead to future intentions to use online learning in their studies and pursue this mode of education rather than traditional face-to-face methods even though it is now being offered. According to an article released by *Forbes*, a survey by Learning House Inc. showed that 85% of students who previously enrolled in both face-to-face classes and online learning felt that learning online is either the same or better than the traditional setup. Additionally, 37% also thought it was a superior experience throughout the semester [83]. A study by Ilie and Frăsineanu [84] investigated how familiar students were with e-learning and how well they could accept and adapt to it in the future with the help of a technological model. Analysis showed that most students were already familiar with e-learning; thus, when a program was introduced to them, students were able to understand how it worked. In addition, they were more willing to pursue online learning. Researchers also added that since the younger generation has already grown a connection with the internet, they feel more comfortable engaging online, bringing advantages to e-learning [4].

A significant positive effect was also seen for competence and behavioral intention ($\beta = 0.457$ and $p = 0.015$). Students find it easy to participate and share thoughts during online learning. They consider online learning to be valuable as it will help them in their future career, allows them to manage time, and can be engaged with using several types of devices. The two variables imply that students have a positive experience and are confident enough to adapt to online learning in the future. Students are willing to pursue this mode of learning as they know that distance learning can provide them with greater flexibility in terms of time management and the opportunity to do other things. Even though face-to-face classes are now being offered, students and even faculty prefer online learning for its flexibility, which is also considered the most significant advantage of this learning mode. Moreover, students do not have to commute or be physically present in the room to join the class, providing them with more time for themselves, such as longer sleep which can help with self-care and mental health [77]. Supporting these findings, Amir et al. [76] stated that students realized that distance learning offers them more time to study and assess learning materials, allowing them to do an advanced reading for their courses. Al-Saadi [85] stated that online learning could not entirely replace traditional face-to-face learning. Hence, since internet connectivity, advanced technology, and the massive market have entered the mainstream, the younger generation gives consideration to this learning mode due to its flexibility, accessibility, and affordability.

A positive direct effect was also seen between affective behavior and satisfaction ($\beta = 0.215$ and $p = 0.014$). The indicators for affective behavior were that students found it easier to study online than in face-to-face classes, that students found online learning interesting, that students were willing to spend more time when learning online, that online setups were more comfortable than traditional learning setups, that students found online learning to be the same as the traditional setup, and that it felt as though online learning and face-to-face learning provided the same quality of education; this variable pertains to the feeling of the student, their willingness, and how comfortable they are studying online. The indicators for affective behavior lead to the satisfaction of students in pursuing online learning. An article by Kelly [86] details a survey conducted by Bay View Analytics (in partnership with Cengage), in which 1469 students and 1286 faculty across 856 institutions in the United States participated in a study about changes in higher education due to COVID-19. Two-thirds of students and faculty said they would be more likely to use technology and digital technology in the teaching of course materials in the future. In addition, more than half of students felt more optimistic about online learning. It was stated that the pandemic did not threaten education but had instead opened opportunities for long-term growth, acceptance, and the desire to pursue online learning, thus improving it in the long run. A study by Zheng et al. [77] stated that most students also wanted to continue using online learning even though traditional face-to-face classes have been offered because online learning is more convenient and efficient and can help with their mental health.

Although affective behavior influences satisfaction, it does not directly affect behavioral intentions because students do not find online learning easy and comfortable, encouraging them to decide not to pursue the intention to use online learning in the future and rather choose the traditional face-to-face setup. A study by Lade and Patil [87] showed that students did not enjoy the transition from traditional learning to online learning at the very start of the lockdown. Although they were technically prepared for the sudden shift, students still preferred face-to-face learning, which is also one of the factors for why they gained interest in their courses. Moreover, they still prefer traditional learning even after the COVID-19 pandemic. A study that included students across the country also indicated that students desired a return to traditional learning now that schools and universities have reopened. A total of 54.4% of students across the country were eager to return to face-to-face classes, likely due to students seeking a better understanding of lessons, better infrastructure, and a better learning environment, concerns with teachers or the level of guidance, etc. [88].

However, it was seen that autonomy does not have a significant positive effect on behavioral intention. Autonomous behavior is a student trait related to taking responsibility for their learning or their ability to take control of it, allowing them to create a learning plan to find resources that help their learning [89]. It is not significant in terms of behavioral intention because even though they can choose between online or traditional learning, students do not intend to choose based on their emotions or personal traits. Hence, they choose according to what they see as an advantage of use in the future. In a study by Lakhal et al. [90], autonomy was shown to have no significant effect on behavioral intention, as the more autonomous the students are, the more they will accept digitalization. Hence, this factor can affect the success of the implemented distance learning approach. Roca and Gagne [91] also showed in their study that perceived autonomy has no direct effect on behavioral intention concerning the continuance of e-learning in a workplace. Relatedness was also seen not to have a significant direct impact on behavioral intention. Relatedness is the influence of parents and society or peers. Parental factors and peers are somewhat still involved in student enrollment in learning; thus, as shown in the study by Tortor et al. [92], senior high school students decide on the courses they want to take at college based on their own decisions and not those of their parents or peers. Ali and Tinggi [93] also established that the influence of parents, whether through suggestions or the influence of past achievements and parents' jobs, is insignificant to a student's choices.

5.1. Theorethical Implications

Structural equation modeling (SEM) provides an analysis of causal relationships among latent variables. It has been used to provide measures of the effects (direct, indirect, and total) of different latent variables affecting a target output. SEM is utilized in research related to behavioral intentions [69,94]. In the attempt to measure students' expectations, cognitive aspects, and behavioral aspects relating to the intent to pursue online learning despite the availability of traditional or other learning modalities, the model holistically measured students' intentions. Therefore, applying the integrated expectation–confirmation theory, self-determination theory, and theory of planned behavior benefits the educational setting. This is especially true when evaluating student perceptions when technology is involved while also considering student experiences. Universities can also benefit from this considering that it is almost the end of the pandemic, wherein schools now offer various types of learning; students can still consider and enroll in this kind of learning modality. Moreover, continuous online learning can also be beneficial to students and teachers or professors. Holistic measurement of the different factors can be justified and assessed with the established framework of this study.

5.2. Practical Implications

Since the pandemic will come to an end, universities will need to offer different types of learning modalities depending on the needs of students, as established during the peak of the COVID-19 pandemic. They currently offer online, face-to-face, blended, or hybrid forms of learning—wherein some students are on-campus and others join online. The highlight of the findings of this study is that, when it comes to fully online learning, students do consider pursuing online education even though universities now offer traditional learning. With that being said, online learning could expand and further improve to create better learning experiences for students. Teachers and professors can also consider this modality's effectiveness based on convenience or preference. Moreover, universities that offer online learning, despite the availability of face-to-face learning, would pave the way to promoting online education to students who cannot fully adapt to traditional learning due to distance, experience, or habit. With this, it provides students with convenience, flexibility, and time management opportunities so that they can do other things without sacrificing their education. Additionally, since the world is adapting to modern technology, students who engage in online learning can enhance their technology usage and adoption abilities, subsequently paving the way to professions that would improve their capabilities in different aspects.

5.3. Limitations

Despite the evident findings in the study, this paper still has limitations to acknowledge. The survey utilized items adapted from related studies that considered the same frameworks (ECT, SDT, and TPB). It is recommended that other variables be considered to understand why students intend to adopt the online learning modality despite the availability of traditional learning. It is also recommended that future research consider qualitative and quantitative methods in assessing student intentions, such as the conduction of surveys and group discussions to uncover other factors affecting student intentions. Several studies have presented the limitations of SEM, so it is suggested that machine algorithms be utilized to extend and verify the study's findings. Future researchers may consider neural networks, random forest classifiers, and even segmentations of demographic characteristics to identify students who are more likely to consider fully online learning. Lastly, the separation of private and public institutions was not considered in the study due to strict guidelines concerning the COVID-19 pandemic in the country. Since the Philippines is a country in which private and public institutions have different learning delivery styles, extending the study by comparing different types of universities is encouraged. Additionally, future researchers may also focus on the different experiences of students in terms of theoretical lectures versus practical lectures since various studies have demonstrated that students were not satisfied with online learning when it comes to the practical aspects of learning, such as conducting experiments or laboratory work.

6. Conclusions

The COVID-19 pandemic widely affected all sectors of life, especially the educational sector. Education had to continue, so schools and universities were forced to shift from a traditional learning setting to online learning. Students have adapted to online learning for almost three years so that they can continue their education. Now that we are near the end of the COVID-19 pandemic, universities are offering different learning modalities, such as fully online, fully face-to-face, and blended learning. The challenge to this is the intention of students to select online learning despite the availability of other modalities that universities offer. This study therefore gains the perspective necessary to assess intentions by utilizing three frameworks: the expectation–confirmation theory (ECT), self-determination theory (SDT), and theory of planned behavior (TPB). Structural equation modeling (SEM) was utilized to measure the causal relationships among different latent variables simultaneously (affective behavior, attitude towards behavior, autonomy, relatedness, competency, expectation, confirmation, satisfaction, and behavioral intention).

The findings demonstrate that the attitude towards behavior (AB) directly affects affective behavior (AF). Expectation (EX) has the second highest direct positive effect on confirmation (CF). Satisfaction (SF) also significantly directly affects behavioral intention (BI). The effect of competence (CO) on BI was also significantly positive. Lastly, AF had a significant positive direct effect AF on SF. With that being said, the indicators suggest that students intend to pursue online learning despite the availability of other modalities offered by universities. Students find themselves more comfortable and able to participate confidently in online rather than traditional learning. They also gain knowledge in this modality, finding it similarly helpful to the traditional face-to-face setup. Additionally, students perceive online learning to have the ability to help them manage their time and future careers. Three years removed from the start of the pandemic, universities are now offering different types of learning depending on the student's needs, indicating that the capabilities of developing countries are comparable to developed countries when it comes to technology and education alignment. Since we are now adapting to technology more, given its flexibility and convenience, students can consider and pursue online education.

Therefore, universities should also focus on improving their platforms to enhance students' online learning experience and promote the available learning modalities.

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