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University Students Intention to Continue Using Online Learning Tools and Technologies: An International Comparison

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Abstract: In recent years, universities have put enormous efforts to promote the use of online learning among students and lecturers. Despite this, little is known about the intention of students to use online learning. The objective of this research is to study the continuance intention of online learning in the post-COVID-19 period in higher education. The research focuses on online learning tools and technologies by applying a modified Expectation-Confirmation Model (ECM) developed from earlier theoretical models, including three new constructs: the self-management of learning, computer anxiety, and habit. The international research compares three countries—Spain (Europe), Chile (Latin America), and Jordan (Asia)—which differ economically and culturally. The Partial Least Squares approach (PLS-SEM) was used to test the research model. As a conclusion of the study, the relationships of the proposed model's constructs vary among the three countries, given their socioeconomic, technological, and cultural differences. Interestingly, self-management learning is a key factor that has a significant positive influence on continuance intention for the three countries, especially in Jordan. This study makes an interesting contribution to existing research in education and discusses how learning can be made more sustainable in complex settings.

Keywords: anxiety; continuance intention; habit; higher education; online courses; self-management learning

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1. Introduction

In recent years, technological advances, such as tablets, chrome books, student response systems (clickers), and smartphones, have been progressively incorporated into education, gaining relevance and importance in the learning process [1]. Universities have made enormous efforts to promote the use of online learning among students and lecturers. According to Lee [2], it is known that the initial incorporation of online learning by students is important in achieving success. Likewise, the continuity in the use of online learning environments by students is necessary to achieve learning in these environments [3]. There exist studies on the acceptance, adoption, and use of these technologies as an innovation, and they analyze their use and adoption in a very short term. However, none of the theories or models of the acceptance and adoption literature has predicted the intention to continuity in the use of various learning settings. One of the theories most used to measure the continuance in the use of technologies is based on the Expectation-Confirmation Model (ECM) by Bhattacherjee [4].

Some studies have found that the extent to which users perceive some technology to be useful positively affects their Continuance Intention (CINT) [4–8]. ECM is also widely used to explain and predict the CINT of learners [9] and is used with the incorporation of different educational factors, such as the inclusion of tutors [10–12], learning materials [13], learning processes [12,14], massive open online courses (MOOCs) [15], and task technology fit [9].

In general, studies on the use of online learning tools and technologies have been performed under a voluntary scheme by university students [16]. However, the COVID-19 pandemic has become a global issue with a broad impact, especially in educational settings [17,18], adding enormous pressure to higher education [19]. That situation has forced higher education institutions to reevaluate existing processes and organizations to adapt their activities [20]. Face-to-face teaching and learning processes have had to be transformed into an online learning context using online education technology, including Google Classroom, WhatsApp groups, Moodle platforms, and Zoom meetings [21]. Chen et al. [22] show that students had a poor attendance rate and continuous intention and found an important influence of performance expectancy, social influence, and effort expectancy. Wang et al. [9] included in their ECM model the technical support (task-technology fit) and showed that when university students verified that online learning was useful to them, they were more interested in continuing with this learning modality.

The year 2020 has witnessed a radical change in higher education around the world [19], including in countries such as Chile, Jordan, and Spain. One reason is that online learning activities were implemented rapidly and will probably continue in the future, even after the COVID-19 crisis. Therefore, in light of today's complex scenarios, this study extends the ECM model to explain the CINT of usage of online learning tools and technologies by university students. In line with Daghan and Akkoyunlu [3], it is believed that determining variables that affect the continued use of online learning tools and technologies will contribute to more effective online learning success. This study is interested in analyzing the perceptions of university students in three countries—Chile, Jordan, and Spain—to visualize this phenomenon in different geographical areas that are culturally different. The COVID-19 context was one of mandatory online education, and the proposed model in this study will analyze three variables that have been studied before, but in a voluntary context: Self-Management of Learning (SML) [23], Anxiety (ANX) [24], and Habit (HAB) [25].

This study makes three main contributions, which correspond to the three central objectives of this research. First, it contextualizes the ECM to online learning by including three new context-specific factors, namely, SML, ANX, and HAB. It is expected that this would lead to a better understanding of the main factors that influence the university student's intention to continue using online learning tools and technologies. Second, most of the studies have been conducted in North America, Europe, and East Asia; to date, to the best of our knowledge, few studies have been conducted in Africa [26] or Latin America [27]. Furthermore, there is a low number of comparative online learning-related studies that include three different countries that are culturally different. This study offers empirical evidence comparing three countries from three different global regions: Latin America (Chile), Asia (Jordan), and Europe (Spain). Third, this study makes a practical contribution, offering useful implications for policymakers in higher education institutions for the successfully continuous use of online learning. Furthermore, our results can improve the teaching–learning process in online mode by considering the factors that influence the CINT of online courses in a higher education environment.

The article is structured as follows. After the introduction, the next section presents the theoretical review and hypotheses development. The third section describes the methodology and the fourth section presents the results, followed by the discussion. It finishes with the conclusions, the implications of our findings, and further research guidelines.

2. Literature Review

Many scholars have proposed psychological models to explain and predict the behavior of users towards the adoption of new technologies at the individual level [28]. In recent years, the number of studies about CINT using technologies has grown tremendously and now covers several subjects such as CINT in mobile banking services, mobile payment, e-learning, social networking, health applications, e-government, and mobile commerce, among others [27]. The most popular theoretical models used to predict the intention of adoption and continuity of technology are discussed in [4,29]. They were based on the theory of reasoned action [30], a theory of behavioral intention that has been widely used for decades. This theory focuses on the initial acceptance of technologies, considers that their use is directly determined by the intention to perform the behavior and, in turn, is motivated by the attitude of the user towards the use of the technology. The theory of planned behavior (TPB) of Ajzen [31] incorporated perceived control into the analysis. In contrast, the ECM seeks to understand users' CINT to use technologies and explain the enablers of its usage continuity once there is already experience with its use. The theoretical foundation of this study is based on the ECM model.

2.1. Expectation-Confirmation Model (ECM)

ECM has three key constructs that explain CINT: Satisfaction (SA), Perceived Usefulness (PU), and Confirmation (CO).

1. Satisfaction (SA) refers to an individual's post-consumption evaluation of a specific transaction [32]. Lee and Chung [33] found that SA was the strongest predictor for driving users' CINT.
2. Perceived Usefulness (PU) was adopted from TAM. This construct is a cognitive belief that it is important to use technologies [27] and considers the definition of expectation. At the initial point of using the technologies, there is low PU, and such PU might be modified based on the outcomes of the CO [34].
3. Finally, CO could be used to adjust the technologies' PU, especially when doubt and uncertainty about what to expect from technologies usage overshadow the consumers' initial PU [4]. More specifically, CO increases the degree of PU and vice versa [35].

According to ECM, when using any technology, users evaluate performance perception with their initial expectation and then decide the level of CO [36]. Following users' usage experience and CO of expectations level, users develop a post-acceptance (usefulness perception). Such perceptions of usefulness may be different from or aligned with their initial prospects. Then, CO of expectations and PU result in developing SA. Finally, satisfied users form a CINT.

2.2. ECM Extensions to Online Learning

Several studies have related the CINT of online learning using the ECM model. Table 1 shows some of them, with different extensions of the ECM basis. Lee [2] affirms that adult learners being satisfied with the Information Systems (IS) use play a vital role in forming the continuance intent of online learning. Ho [37] demonstrated that PU, user SA, and attitudes could significantly predict users' online learning CINT. Wang et al. [38] found that computer self-efficacy and enjoyment significantly predict CINT to use cloud e-learning applications, while PU, perceived ease of use and user perception were not significant. Huang [39] obtained that PU positively affects students' continuous usage intention of online learning platforms. Almahamid and Rub [40] showed that to increase users' SA with an online learning system, the university has to maintain a high level of system quality, service quality, and perceived internet self-efficacy, among others, in order to ensure continuous intention to use it. Roca et al. [41] found that PU has the most significant effect on continuous intention and that some demographic variables existed. In brief, these studies have validated the relevance of some constructs of the ECM in this context.

Table 1. Main research on continuance intention (CINT) of online learning tools and technologies.

Authors	Research Contexts	Constructs	Fundamental Theories
Cheung and Limayen [25]	Continued Use of Advanced Internet-Based Learning Technologies	Confirmation, perceived usefulness, satisfaction, continuance intention and habits.	ECM

Table 1. *Cont.*

Authors	Research Contexts	Constructs	Fundamental Theories
Ho [37]	Continuance intention of e-learning platform	Confirmation, perceived usefulness, satisfaction, perceived ease of use, attitude, autonomy, competence, relatedness, and continuance intention.	ECM-TAM-COGM
Lee [2]	Continuance intention of e-learning	Confirmation, perceived usefulness, satisfaction, perceived ease of use, attitude, subjective norms, perceived behaviour control, perceived enjoyment, concentration and continuance intention.	ECM-TAM-TPB
Daghan and Akkoyunlu [3]	Continuance usage intention of online learning environments	Confirmation, satisfaction, information quality, system quality, service quality, perceived value, utilitarian value, perceived usability, outcome expectations and continuance intention.	ECM-ISSM
Yimei et al. [42]	Continued intention of online self-regulated learning	Confirmation, perceived usefulness, satisfaction, perceived ease of use, attitude, and continuance intention.	ECM-TAM
Wang et al. [38]	Continuance of intention to use cloud e-learning application	Computer self-efficacy, enjoyment, perceived ease of use, perceived usefulness, user perception and continuance intention	ECM-TAM-MT
Huang [39]	Continuous usage intention of online learning platforms	Perceived usefulness, perceived easy, social interaction ties, shared language, shared vision, trust, norms of reciprocity, identification and continuance intention.	ECM-SCT-TAM
Wang et al. [9]	Online learning during COVID-19 pandemic	Confirmation, perceived usefulness, satisfaction, task-technology fit and continuance intention.	ECM

COGM, cognitive model; ECM, Expectation-Confirmation Model; ISSM, information system success model; MT, motivation theory; SCT, social capital theory; TAM, technology acceptance model; TPB, theory of planned behavior.

3. Research Model and Hypotheses

Next, we explain the research model and hypotheses, the data, the instrument and measurement scale, and the estimation and statistical validation.

3.1. The Research Model and Hypotheses

As mentioned in the introduction, one of the contributions of this research refers to conducting an empirical study on the extension of the ECM. Higher education students who have had to change their in-person courses to an online format have considered continuing the use of digital learning platforms for the next few months.

Figure 1 shows all the hypotheses in the proposed model of this study to explain the university student's intention to continue using online learning tools and technologies.

The first group of hypotheses intends to verify whether the variables of the ECM model explain the intention of university students to continue using technology. Considering that the results are quite controversial in general, even though the ECM has shown considerable consistency, the following hypotheses are proposed for each of the three countries in the study:

Hypothesis 1a (H1a). *Satisfaction (SA) has a positive influence on Continuance Intention (CINT) towards online courses.*

Hypothesis 1b (H1b). *Perceived Usefulness (PU) has a positive influence on Satisfaction (SA) with online courses.*

Hypothesis 1c (H1c). *Perceived Usefulness (PU) has a positive influence on Continuance Intention (CINT) towards online courses.*

Hypothesis 1d (H1d). *Confirmation (CO) has a positive influence on the Perceived Usefulness (PU) of online courses.*

Hypothesis 1e (H1e). *Confirmation (CO) has a positive influence on Satisfaction (SA) with online courses.*

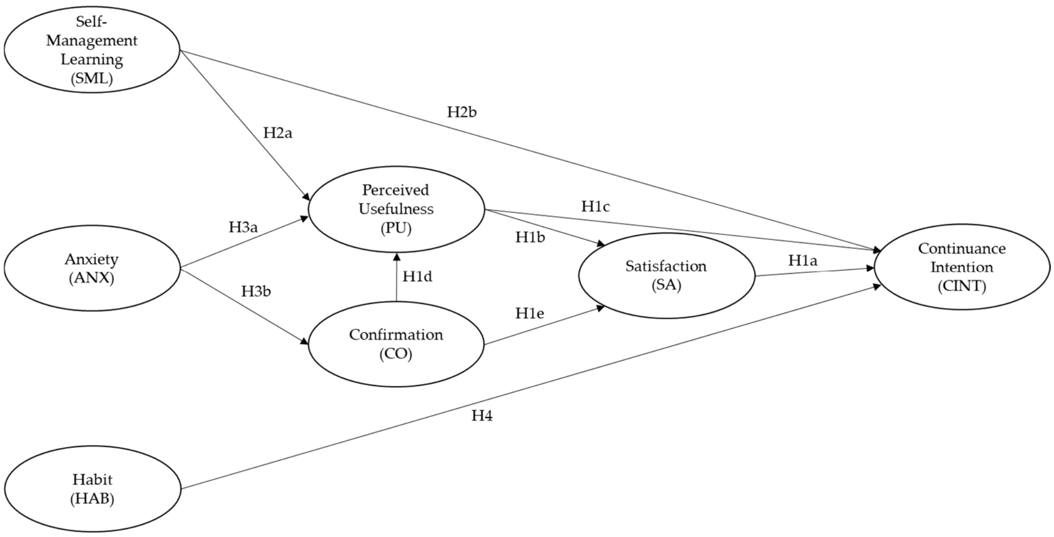

Figure 1. Research model.

Many researchers regard that the explanation of users' continued intention only from ECM and PU is insufficient [42]. Thus, three new constructs have been added to consider the unique features focused on online learning tools and technologies that university students use. These constructs include, namely: SML, ANX and HAB. SML is seen as a core competency that students need to master in an online learning environment. In addition, computer anxiety is deemed a key issue that hinders the usage of e-learning systems as it has a diverse effect on user interaction with technology such as e-learning systems. The use of habit in this study signifies the importance of students' beliefs that they need to use the system frequently and automatically during their online learning.

3.1.1. Self-Management of Learning (SML)

According to Smith et al. ([43], p.60), SML is defined as "the degree to which an individual perceives self-discipline and can engage in autonomous learning". SML reflects the extent to which students consider themselves self-disciplined and are capable of being involved in a highly autonomous learning environment [44]. In online settings, students are physically separated from their instructors and classmates, which entails them managing and controlling their own learning activities independently [45]. Self-management, an important element of online learning, is recognized as one of the critical factors in the educational environment due to its key role in allowing affirmative learning performance. It acts as a major determinant of learning outcomes and achievement [46,47]. It has been suggested that SML boosts self-directed, autonomous, and independent learning [48,49].

Al-Adwad et al. [50] point out that self-regulated students are those who are behaviorally and cognitively active contributors to their own education and learning processes without being reliant on others (e.g., instructors). Self-directed learning necessitates that students acquire systematic behaviors and cognitions to attain learning goals [51]. The skills of SML are positively associated with educational outcomes and lead to positive beliefs towards online learning and perceptions of the usefulness of the collaborative activities of online learning [23]. In an online learning environment, students are away from their peers and instructors and are therefore required to possess effective self-regulated learning strategies to manage and succeed in their own learning [44,46]. Thus, compared to students' low autonomous learning abilities, students with a high-level self-management of learning are inclined to continue using online learning systems as they have autonomous learning abilities that enable them to effectively manage their own learning. Furthermore, it has been noted that students with high levels of self-regulated abilities realize the usefulness of e-learning systems [50]. On the other hand, students who lack self-management learning are inclined to recognize the e-learning system as not useful.

Hence, based on this argument, the following hypotheses are proposed for university students for each of the countries in the study. A direct and positive relation between SML and PU and CINT is expected.

Hypothesis 2a (H2a) . *Self-Management of Learning (SML) has a positive influence on the Perceived Usefulness (PU) of online courses.*

Hypothesis 2b (H2b) . *Self-Management of Learning (SML) has a positive influence on Continuance Intention (CINT) towards online courses.*

3.1.2. Anxiety (ANX)

Anxiety can also be considered a part of normal human reactions to stressful situations [52]. Nevid et al. [53] define ANX as "an emotional state that is characterized by unpleasant feelings of tension and is related to negative events that may come". According to Lazar et al. [54], the concept of technology anxiety suggests that it is shaped as a reply to perceived threats from technology that may be too hard to use, with the performance benefits of usage outweighed by their effort.

ANX plays a crucial role in the adoption of technology. Individuals who are anxious or disturbed about using technology are more likely to be reluctant to use technologies. Additionally, ANX negatively affects the intention of long-term use of complex technology [55]. Past research has shown that computer ANX is negatively related to PU [24]. Other studies have found no effect of technology or computer ANX on PU [56]. Chou et al. [55] found that the individual factors that affect behavior in the use of IS include beliefs (usefulness), positive affect (enjoyment from the use of technology), or negative affect (ANX). Bai et al. [57] found that ANX negatively and directly influences teachers' CINT towards the adoption of information and communication technology in their teaching practices. Although ANX has been studied extensively to explain behavior related to technology, there is little research on the direct effect of technology ANX on the CINT of online course adoption in higher education. In online learning, students are mainly required to interact with the e-learning system to learn and perform their tasks. High levels of computer anxiety can lead to a decrease in students' perception of the e-learning system's ease of use, and consequently its usefulness. When students are anxious using the e-learning systems, they are prevented from benefiting from many important features of the system, which, in turn, affect their learning. Accordingly, computer nervousness is viewed as a major inhibitor of e-learning systems adoption.

Based on the above arguments, we propose the following hypothesis for a negative influence between ANX and PU. Likewise, a negative influence between ANX and CO is anticipated.

Hypothesis 3a (H3a) . *Anxiety (ANX) has a negative influence on the Perceived Usefulness (PU) of online courses.*

Hypothesis 3b (H3b) . *Anxiety (ANX) has a negative influence on the Confirmation (CO) of online courses.*

3.1.3. Habit (HAB)

To gain a better understanding of factors influencing students' continued usage of learning technology, there is strong support that HAB is an influential factor that impacts the relationship between intentions and continued behavior [25]. Venkatesh et al. [58] extended the Unified Theory of Acceptance and Use of Technology (UTAUT2), incorporating three factors: HAB, hedonic motivation, and price value. Venkatesh et al. [59] added the impact of HAB on behavioral intention and technology use. They also indicate that this new relationship opens an opportunity for future research.

In their study on the continuance usage of internet-based learning technologies, Limayem and Cheung [7] integrated the HAB variable into the TCM model and tested this extended theory using a sample of 303 university students. The study concluded that HAB, CINT, SA, and prior behavior could affect the continuance usage of internet-based learning technologies. Interpersonal behavior habit strength has been measured using the number of times the act has already been performed by the person [60]. Most scholars consider past experience (or usage) to be a good predictor of future behavior because, with repeated performance, the behavior becomes routine and executes with minimal conscious control [61]. When learning behaviors become habit-oriented, people do not consider their behavior too much, i.e., it becomes natural [62]. Mahasneh [63] mentioned that habits need to be learned and are a reaction based on individual past experiences. According to Lai et al. [64], habit is an important factor that influences a user's CINT. Venkatesh et al. [58] examined the effects of habit on user behavior and found that it has a significant effect on consumer behavior regarding the use of technology.

As a result, the following hypothesis is proposed to measure the positive effect of HAB on the CINT of university students towards using online learning tools and technologies.

Hypothesis 4 (H4) . *Habit (HAB) has a positive effect on Continuance Intention (CINT) behavior for online courses.*

3.1.4. The International Comparison

Various studies have investigated, using different models and factors, the CINT to use online learning. However, in the literature, there are few studies that compare differences among countries with different cultures, economics, and background ([40] only for Jordan and [18] only for Spain). Therefore, this study aims to analyze not only CINT, but also the differences among the three countries included (Chile, Jordan, and Spain), with different traditions, economies, and social environments. Chile is a developing country in Latin America, in position 61 (USD 14,772) in GDP per capita (nominal), with a population of almost 19 million, and a mobile cellular subscription (per 100 people) of 132.8. Jordan is an Asian developing country, at position 85 (USD 7661), with a population of almost 6.7 million, and a mobile cellular subscription of 61.8 per 100 people. Finally, Spain is a developed European country in position 32 (USD 29,993), with a population of 47 million, and a mobile cellular subscription of 118.3 per 100 people.

Considering these three countries, this study seeks various insights regarding university students in the COVID-19 crisis. Analyzing the factors that affect the intention of university students to continue taking their courses online may result in differences across countries. Based on the above arguments, the following hypothesis is proposed:

Hypothesis 5 (H5) . *There are significant differences between the proposed paths based on the responses from Chile, Spain, and Jordan.*

3.2. Data

The sample was 969 university students of administrative sciences and related subjects, who are currently studying in undergraduate universities from three countries: Chile, Jordan, and Spain. In the case of Chile, the students were from the Universidad Catolica del Norte, the main university in the north of Chile, from campuses of Coquimbo and Antofagasta. For Spain, the surveys were collected mainly from the Universidad Complutense de Madrid and the Universidad Autonoma de Madrid, which are the main public universities of Spain. In Jordan, the sample was obtained from students from the Al Ahliyya Amman University, which is the first private university in Jordan, located in Amman city. An online questionnaire hosted by Google was used to collect the data between June and December 2020.

The sampling method was non-random, with questionnaires distributed to students by e-mail (Google forms). Table 2 shows that the proportions of male and female students in the sample are quite similar in Chile and Spain, while in Jordan, the vast majority are men (70%). Regarding the areas of study, those who study business predominate, although, in Chile, most of the participants are engineering students. Regarding whether they shared their computer with other family members during the first months of the COVID-19 crisis, Spain stands out, since almost 71% of students have never had to share their computer, from which it can be inferred that it is mainly a device for their personal use. This is probably due to Spain's higher level of income. In the case of Chile and Jordan, this is not so clear, since the proportion of those who shared it 'sometimes' is similar to the proportion of 'never' having shared their computer. Finally, regarding the quality of the internet connection, the great difference was reflected in the opinions of Chilean students, who mostly indicated that the quality was very bad, bad, or regular. In contrast, in Spain and Jordan, the students reported mostly good or very good internet quality.

Table 2. Characteristics of the sample of undergraduate students by country.

		Chile	Spain	Jordan	Total
Gender	Female	244 (53.98%)	163 (52.24%)	59 (29.5%)	466 (48.34%)
	Male	206 (45.58%)	147 (47.12%)	140 (70%)	493 (51.14%)
	Prefer not to indicate	2 (0.44%)	2 (0.64%)	1 (0.5%)	5 (0.52%)
	Total	452 (100%)	312 (100%)	200 (100%)	964 (100%)
Area of study	Accounting	18 (32.73%)	4 (7.27%)	33 (60%)	55 (100%)
	Business	137 (27.4%)	255 (51%)	108 (21.6%)	500 (100%)
	Economics	67 (58.77%)	26 (22.81%)	21 (18.42%)	114 (100%)
	Engineering	230 (89.49%)	27 (10.51%)	0 (0%)	257 (100%)
	Tourism	0 (0%)	0 (0%)	38 (100%)	38 (100%)
	Total	452 (46.89%)	312 (32.37%)	200 (20.75%)	964 (100%)
Share PC	Never	190 (37.92%)	221 (44.11%)	90 (17.96%)	501 (100%)
	Sometimes	185 (56.23%)	63 (19.15%)	81 (24.62%)	329 (100%)
	Always	77 (57.46%)	28 (20.9%)	29 (21.64%)	134 (100%)
	Total	452 (46.89%)	312 (32.37%)	200 (20.75%)	964 (100%)
Internet Connection Quality	Bad or very bad	73 (60.33%)	21 (17.36%)	27 (22.31%)	121 (100%)
	Regular	225 (61.98%)	85 (23.42%)	53 (14.6%)	363 (100%)
	Good or very good	154 (32.08%)	206 (42.92%)	120 (25%)	480 (100%)
	Total	452 (46.89%)	312 (32.37%)	200 (20.75%)	964 (100%)

3.3. Instrument and Measurement Scale

The items of this study's questionnaire are borrowed from previous research (see Table 3. A five-level Likert-type scale is used to measure the seven constructs, where 1 corresponds to Strongly Disagree, 2 to Disagree, 3 to Neither Disagree nor Agree, 4 to Agree, and 5 to Strongly Agree.

Table 3. Questionnaire items.

Construct	Abbrev.	Items	Reference
Anxiety (ANX)	ANX_1	I am apprehensive about taking online courses.	Venkatesh et al. [65]
	ANX_2	I hesitate with online courses for fear of making mistakes that I cannot correct.	
	ANX_3	Online courses are somewhat intimidating for me	
Confirmation (CO)	CO_1	Overall, most of my expectations of taking my regular university courses online were confirmed	Bhattaherjee [4]
	CO_2	My experience taking my regular university courses online was better than what I expected	
	CO_3	The service level provided taking my regular university courses online was better than what I expected	
Continuance Intention (CINT)	CINT_1	I intend to continue taking regular university courses online instead of discontinuing it.	Bhattaherjee [4]
	CINT_2	My intentions are to continue taking my regular university courses online instead of any alternative means	
	CINT_3	If I could, I would like to discontinue taking my regular university courses online	
	HAB_1	Using online courses has become a habit for me.	
Habit (HAB)	HAB_2	I am addicted to online courses.	Venkatesh et al. [58]
	HAB_3	I must take online courses.	
	HAB_4	Using online courses has become second nature to me.	
Perceived Usefulness (PU)	PU_1	Taking my regular university courses online improves my learning performance.	Bhattaherjee [4]
	PU_2	Taking my regular university courses online increases my learning productivity.	
	PU_3	Taking my regular university courses online enhances my learning process.	
	PU_4	Overall, taking my regular university courses online is useful to my learning process	
Satisfaction (SA)	SA_1	In my overall experience, taking my regular university courses online, I feel very pleased.	Bhattaherjee [4]
	SA_2	In my overall experience, taking regular university courses online, I feel very satisfied.	
	SA_3	In my overall experience, taking regular university courses online, I feel absolutely delighted.	
Self Management Learning (SML)	SML_1	I have high expectations for doing well in my studies.	Al-Adwan and Khdour [47]
	SML_2	I set up my learning goals and study plan independently.	
	SML_3	I manage my studies according to my study plan.	
	SML_4	I am independent in seeking resources and completing my learning tasks.	

3.4. Estimation and Statistical Validation

The partial least squares approach (PLS-SEM or path model) was used to test the research model [66]. This includes a two-steps analysis, namely: (1) the structural or inner model, which describes the relationships between the latent variables; and (2) the measurement models, which describe the relationships between the latent variables and their measures (indicators). Data analysis was performed using SmartPLS software [67], which is a second-generation technique in multivariate methods. Furthermore, Stata software [68] was used for descriptive statistics.

Reliability was analyzed by evaluating whether the scales exhibit internal consistency through Cronbach's alpha and the composite reliability. Values greater than 0.7 were considered acceptable [66].

For convergent validity, the factor loadings were verified to be greater than 0.708, and the Average Variance Extracted (AVE) was calculated for every latent construct (acceptable threshold is ≥ 0.5). For discriminant validity, according to the Fornell–Larcker criterion, the square root of the AVE of the dimensions should be greater than the correlations with other dimensions in the model, thereby confirming the independence of the latent variables [66].

Regarding the structural model, the presence of collinearity among the predictor constructs was examined by evaluating the Variance Inflation Factor (VIF) by bootstrapping for each independent variable, which should be <5 [69]. To evaluate the structural model, we use two criteria: the analysis of the path coefficient and the coefficient determination (R^2).

Finally, multi-Group Analysis (MGA) was employed to test if the predefined three data groups (the three countries) had significant differences in their group-specific parameter estimates [69,70]. For this, the outer weights, outer loadings, and path coefficients using bootstrapping results from estimations for every country were used.

4. Results

Next, we show the results of the measurement model assessment, the structural model assessment, and summary of results by hypothesis.

4.1. Measurement Model Assessment

Table 4 reports the main outputs from the estimations. Regarding the test performed to assess the validity and reliability of the reflective indicators, all the values meet the requirements, except for HAB (Chile: $\alpha = 0.682$) and CO (Spain: $\alpha = 0.662$). The composite reliability indicators are all over 0.8, indicating that almost all constructs have adequate reliability. Furthermore, the values obtained for loadings exceed the minimum required (0.708) for all the items (indicator variables, Table 3) except Habit2 and Sml4 (Chile and Spain, respectively). The confidence level for each construct's AVE surpasses the acceptable value of 0.5. This result confirmed convergent validity for the dataset. Table 4 shows the results for the three countries.

Table 4. Reliability and validity evaluation.

		ANX	CO	CINT	HAB	PU	SA	SML
Chile	Cronbach's Alpha	0.872	0.766	0.71	0.682	0.88	0.794	0.771
	Composite Reliability	0.921	0.865	0.837	0.809	0.918	0.88	0.839
	ρA	0.903	0.769	0.722	0.76	0.889	0.815	0.856
	AVE	0.796	0.681	0.632	0.532	0.737	0.71	0.568
Jordan	Cronbach's Alpha	0.828	0.886	0.879	0.876	0.918	0.903	0.864
	Composite Reliability	0.897	0.929	0.925	0.913	0.942	0.939	0.907
	ρA	0.841	0.888	0.884	0.909	0.92	0.907	0.874
	AVE	0.743	0.814	0.805	0.725	0.804	0.838	0.71
Spain	Cronbach's Alpha	0.804	0.662	0.733	0.73	0.894	0.812	0.763
	Composite Reliability	0.88	0.813	0.846	0.833	0.927	0.889	0.84
	ρA	0.868	0.781	0.777	0.719	0.899	0.836	0.85
	AVE	0.712	0.606	0.648	0.558	0.762	0.728	0.569

As Table 5 shows, the Fornell–Larcker test confirms the presence of discriminant validity.

Table 5. Tests of discriminant validity: Fornell and Larcker criterion.

	ANX	CO	CINT	HAB	PU	SA	SML
Chile							
Anxiety (ANX)	0.892						
Confirmation (CO)	−0.193	0.825					
Continuance Intention (CINT)	−0.225	0.433	0.795				
Habit (HAB)	−0.085	0.440	0.461	0.729			
Perceived Usefulness (PU)	−0.200	0.509	0.513	0.625	0.859		

Table 5. *Cont.*

	ANX	CO	CINT	HAB	PU	SA	SML
Satisfaction (SA)	−0.238	0.690	0.558	0.523	0.603	0.842	
Self-Management Learning (SML)	−0.166	0.470	0.560	0.449	0.523	0.484	0.754
Jordan							
Anxiety (ANX)	0.862						
Confirmation (CO)	−0.271	0.902					
Continuance Intention (CINT)	−0.175	0.215	0.897				
Habit (HAB)	−0.654	0.647	0.389	0.852			
Perceived Usefulness (PU)	−0.591	0.645	0.330	0.845	0.897		
Satisfaction (SA)	−0.338	0.787	0.259	0.669	0.591	0.915	
Self-Management Learning (SML)	−0.165	0.181	0.735	0.384	0.340	0.232	0.842
Spain							
Anxiety (ANX)	0.844						
Confirmation (CO)	−0.154	0.778					
Continuance Intention (CINT)	−0.141	0.393	0.805				
Habit (HAB)	−0.093	0.344	0.407	0.747			
Perceived Usefulness (PU)	−0.170	0.471	0.454	0.617	0.873		
Satisfaction (SA)	−0.270	0.729	0.496	0.355	0.569	0.853	
Self-Management Learning (SML)	−0.125	0.474	0.582	0.453	0.541	0.486	0.754

To confirm the discriminant validity obtained in Table 5, the heterotrait–monotrait ratio test was performed. In Table 6, all values were ≤0.85 for all samples with only four exceptions (CO-SA for the three countries and PU-HAB for Jordan); thus, the results discriminant validity were confirmed. The bootstrapping procedure showed that none of the confidence intervals included the value 1, with the only exception of Spain for SA-CO (0.840, 1.026). Some relationships that seemed invalid, with values HTMT > 0.85, now yielded acceptable confidence intervals, as the case of Chile for SA-CO (0.813, 0.932), and Jordan for SA-CO (0.800, 0.942) and PU-HAB (0.894, 0.984). In summary, all measures of the three samples demonstrated satisfactory validity and reliability.

Table 6. The Heterotrait–Monotrait ratio of correlations (HTMT test).

	ANX	CO	CINT	HAB	PU	SA	SML
Chile							
Anxiety (ANX)							
Confirmation (CO)	0.232						
Continuance Intention (CINT)	0.290	0.584					
Habit (HAB)	0.142	0.602	0.643				
Perceived Usefulness (PU)	0.226	0.618	0.645	0.799			
Satisfaction (SA)	0.294	0.874	0.742	0.698	0.712		
Self-Management Learning (SML)	0.156	0.531	0.654	0.539	0.542	0.510	
Jordan							
Anxiety (ANX)							
Confirmation (CO)	0.314						
Continuance Intention (CINT)	0.206	0.240					
Habit (HAB)	0.758	0.738	0.420				
Perceived Usefulness (PU)	0.671	0.715	0.360	0.943			
Satisfaction (SA)	0.387	0.876	0.286	0.751	0.648		
Self-Management Learning (SML)	0.193	0.201	0.828	0.421	0.367	0.254	
Spain							
Anxiety (ANX)							
Confirmation (CO)	0.218						
Continuance Intention (CINT)	0.175	0.555					

Table 6. *Cont.*

	ANX	CO	CINT	HAB	PU	SA	SML
Habit (HAB)	0.257	0.491	0.523				
Perceived Usefulness (PU)	0.190	0.596	0.550	0.765			
Satisfaction (SA)	0.331	0.930	0.631	0.453	0.662		
Self-Management Learning (SML)	0.140	0.560	0.659	0.578	0.590	0.501	

Additionally, it is important to analyze whether there is collinearity between the independent variables. High correlations may cause many problems in the interpretation of the results and in the model fit indices. Table 7 shows that this is confirmed, as the VIFs for all the constructs for the three different models are below the cut-off value of 5.

Table 7. Collinearity test: Variance Inflation Factor (VIF).

Dependent Variable	Independent Variable	Chile	Jordan	Spain
Continuance Intention (CINT)	Habit (HAB)	1.768	4.287	1.672
	Perceived Usefulness (PU)	2.113	3.513	2.206
	Satisfaction (SA)	1.744	1.820	1.587
	Self-Management Learning (SML)	1.493	1.176	1.568
Confirmation (CO)	Anxiety (ANX)	1.000	1.000	1.000
Perceived Usefulness (PU)	Anxiety (ANX)	1.046	1.096	1.028
	Confirmation (CO)	1.307	1.102	1.305
	Self-Management Learning (SML)	1.294	1.050	1.294
Satisfaction (SA)	Confirmation (CO)	1.349	1.714	1.286
	Perceived Usefulness (PU)	1.349	1.714	1.286

4.2. Structural Model Assessment

A path analysis was performed to examine the proposed hypotheses for each country separately.

4.2.1. Chile

Figure 2 presents the results for the estimation of the research model for Chile. The results are somewhat like those for Spain. While the effect of ANX on PU is insignificant ($\beta = -0.078$, *p*-value = 0.077), ANX has a negative and significant effect on CO ($\beta = -0.193$, *p*-value = 0.000). CO is reported to have positive significant effects on PU ($\beta = 0.326$, *p*-value = 0.000) and SA ($\beta = 0.517$, *p*-value = 0.000). PU is found to be a significant enabler of SA ($\beta = 0.340$, *p*-value = 0.000) and CINT ($\beta = 0.113$, *p*-value = 0.03), as it has a significant positive effect on both. In addition, SA was found to be a key determinant of CINT ($\beta = 0.284$, *p*-value = 0.000). Similar to the results of Jordan and Spain, SML in Chile is found to have positive significant effects on CINT ($\beta = 0.319$, *p*-value = 0.000) and PU ($\beta = 0.357$, *p*-value = 0.000). With respect to HAB, like the results from Jordan, but in contrast to those from Spain, HAB is found to have an insignificant effect on CINT in Chile ($\beta = 0.099$, *p*-value = 0.055). ANX explained only a total variance of 3.7% ($R^2 = 0.037$) in CO. The total variance explained in PU was 36.8% ($R^2 = 0.368$) and was generated from the effects of SML, ANX and CO. PU and CO explained a total variance of 56.2% ($R^2 = 0.562$) in SA. Finally, Self-Learning of Management, HAB, PU, and SA explained a total variance of 44% ($R^2 = 0.44$).

4.2.2. Jordan

The results for Jordan are shown in Figure 3. They indicate that ANX has significant effects on both PU ($\beta = -0.427$, *p*-value = 0.000) and CO ($\beta = -0.271$, *p*-value = 0.001). CO shows strong significant positive effects on PU ($\beta = 0.497$, *p*-value = 0.000) and SA ($\beta = 0.694$, *p*-value = 0.000). While PU has a positive significant effect on SA ($\beta = 0.143$, *p*-value = 0.039), surprisingly, its effect on CINT is found to be insignificant (β = −0.037, *p*-value = 0.696). SML has positive significant effects on PU (β = 0.180, *p*-value = 0.000) and CINT (β = 0.688, *p*-value = 0.000). Unexpectedly, the effect of SA on CINT is found to be insignificant (β = 0.031, *p*-value = 0.640). Similarly, HAB has an insignificant effect on CINT (β = 0.135, *p*-value = 0.203). The percentage of total variance explained (R^2) in PU by ANX, CO, and SML is 63.4% (0.634). ANX explains a total variance of 7.3% (R^2 = 0.073) in CO. Both PU and CO explain a total variance of 63.1% (R^2 = 0.631) in SA. Collectively, HAB, SML, PU, and SA explain 55.4% (R^2 = 0.554) of the variance in CINT.

4.2.3. Spain

The results for Spain are presented in Figure 4. They demonstrate that while the effect of ANX has a negative and significant effect on CO (β = −0.154, *p*-value = 0.010), its effect on PU is insignificant (β = −0.078, *p*-value = 0.118). CO has positive significant effects on PU (β = 0.268, *p*-value = 0.000) and SA (β = 0.593, *p*-value = 0.000). Furthermore, the results show that PU has a significant positive effect on SA (β = 0.290, *p*-value = 0.000) and an insignificant effect on CINT (β = 0.021, *p*-value = 0.778). Additionally, SA has a significant positive influence on CINT (β = 0.248, *p*-value = 0.000). As anticipated, SML is found to have a positive significant effect on CINT (β = 0.391, *p*-value = 0.000) and PU (β = 0.405, *p*-value = 0.000). HAB is seen as an enabler of CINT with a positive significant effect (β = 0.129, *p*-value = 0.019). The total variance explained (R^2) in PU by ANX, CO, and Self-Learning of Management is 35.8% (R^2 = 0.358). ANX explains only 2.4% (R^2 = 0.024) of the variance in CO. Both PU and CO jointly explain a total variance of 59.7% (R^2 = 0.597) in SA. The total variance explained in CINT is 41.3% (R^2 = 0.413); this percentage is generated from the participation of PU, CO, HAB, and SML.

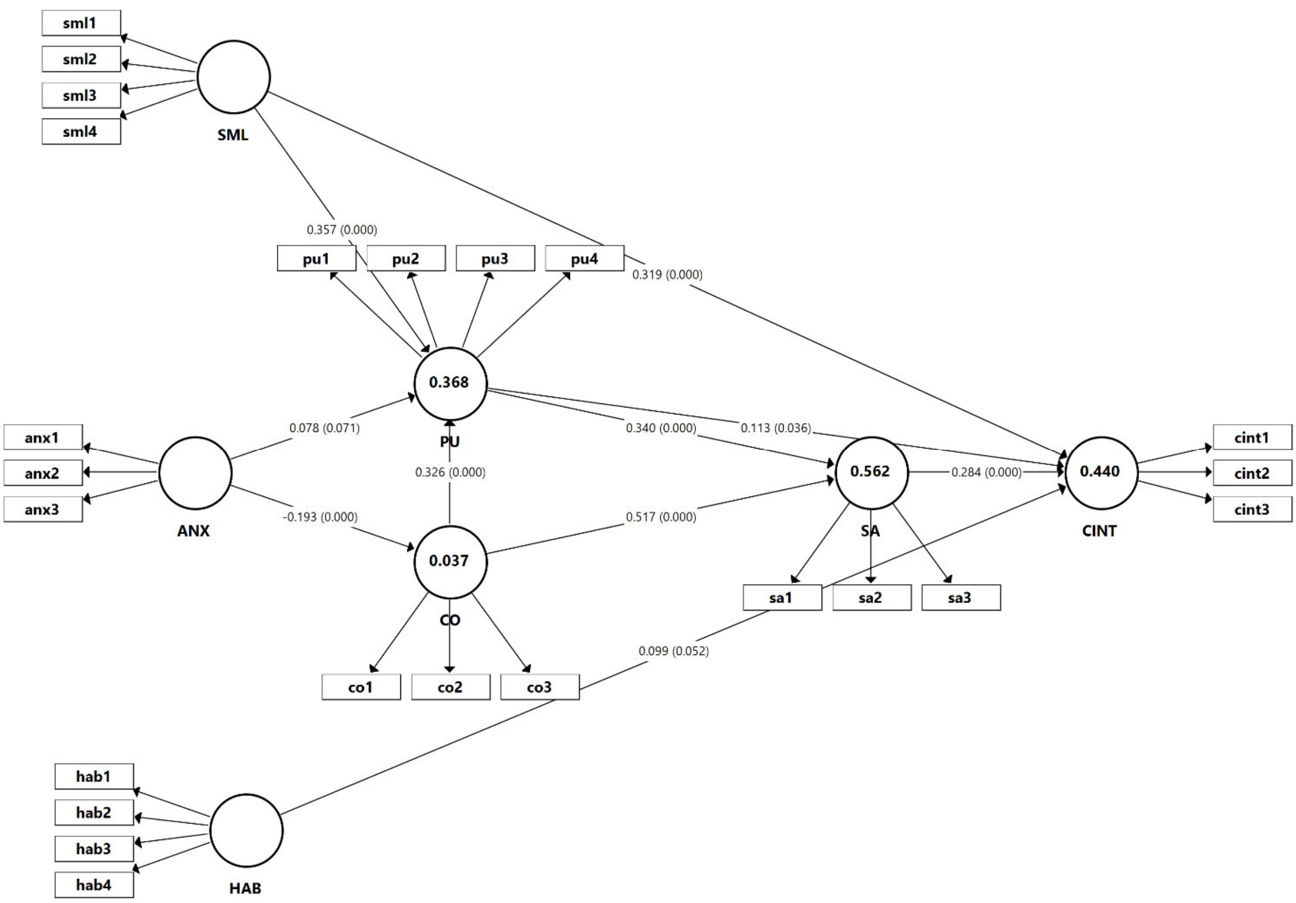

Figure 2. Estimation of the structural model: Chile. Path coefficient and *p*-value in parentheses.

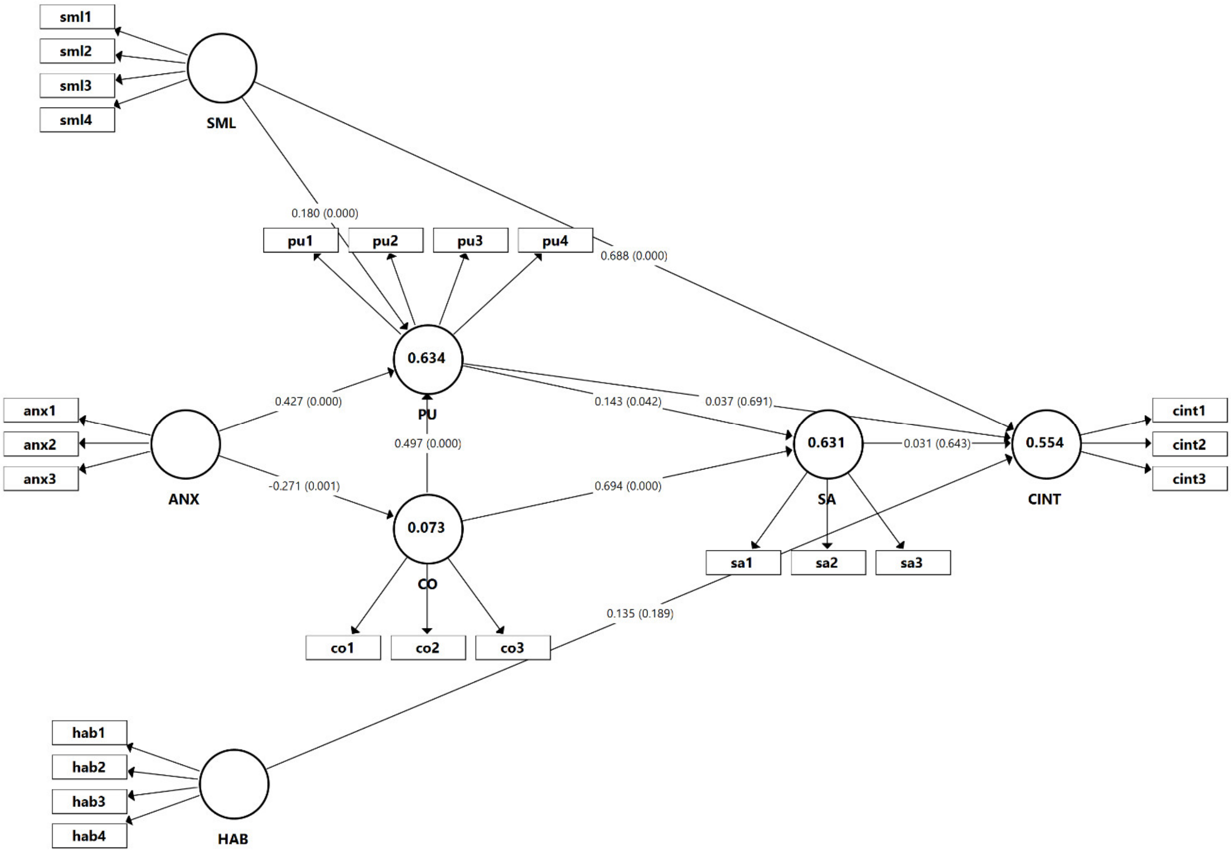

Figure 3. Estimation of the structural model: Jordan. Path coefficient and *p*-value in parentheses.

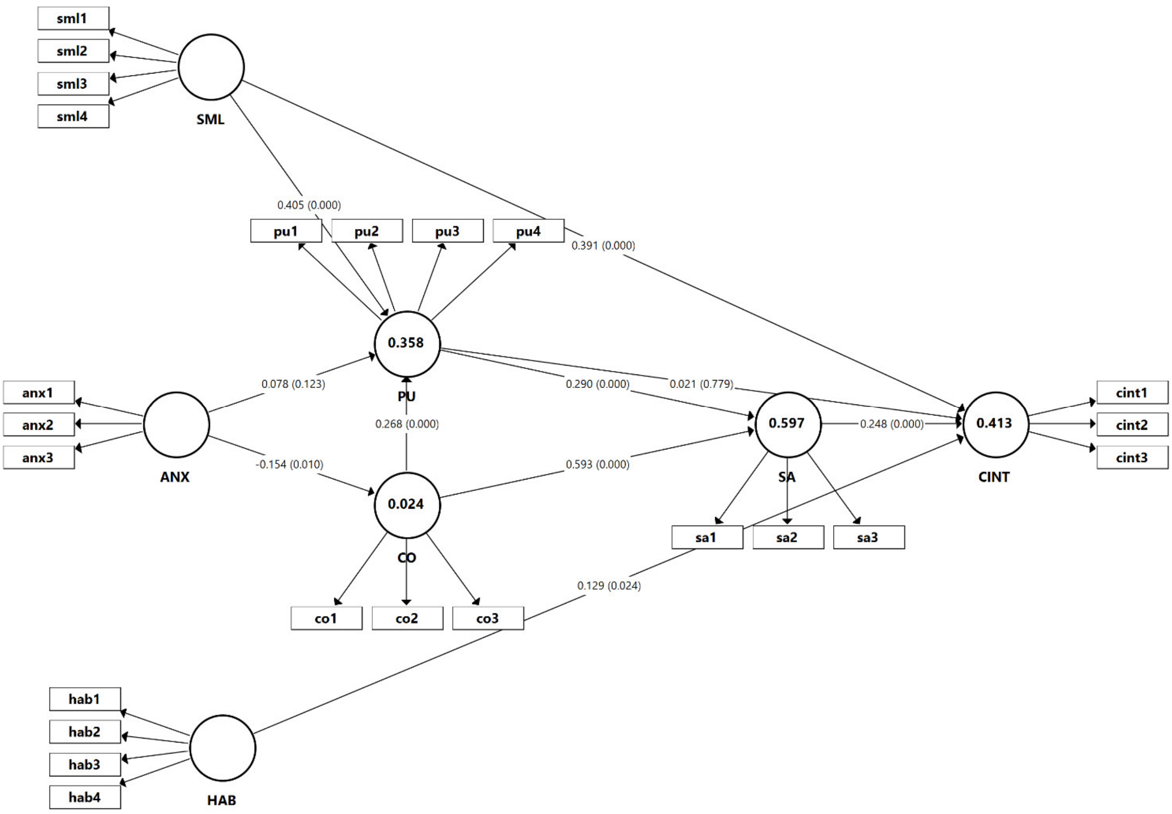

Figure 4. Estimation of the structural model: Spain. Path coefficient and *p*-value in parentheses.

Table 8 presents a summary of the results of evaluating the path coefficients and their corresponding *p*-value and percentile confidence intervals for each sample.

Table 8. Path coefficient, *p*-value, and confidence intervals.

	Chile				Jordan				Spain			
Relationship	Path Coeff.	*p*-Value	Low 2.5%	Upp 97.5%	Path Coeff.	*p*-Value	Low 2.5%	Upp 97.5%	Path coeff.	*p*-Value	Low 2.5%	Upp 97.5%
SA -> CI	0.284	0.000	0.189	0.378	0.031	0.640	−0.098	0.161	0.248	0.000	0.139	0.362
PU -> SA	0.340	0.000	0.258	0.420	0.143	0.044	0.028	0.304	0.290	0.000	0.198	0.382
PU -> CINT	0.113	0.031	0.015	0.222	−0.037	0.693	−0.211	0.160	0.021	0.779	−0.125	0.174
CO -> PU	0.326	0.000	0.223	0.421	0.497	0.000	0.370	0.611	0.268	0.000	0.163	0.374
CO -> SA	0.517	0.000	0.434	0.590	0.694	0.000	0.530	0.815	0.593	0.000	0.492	0.669
SML -> PU	0.357	0.000	0.268	0.438	0.180	0.000	0.079	0.281	0.405	0.000	0.303	0.488
SML -> CI	0.319	0.000	0.232	0.398	0.688	0.000	0.587	0.774	0.391	0.000	0.269	0.495
ANX -> PU	−0.078	0.077	−0.158	0.009	−0.427	0.000	−0.554	−0.300	−0.078	0.123	−0.168	0.034
ANX -> CO	−0.193	0.000	−0.291	−0.091	−0.271	0.001	−0.422	−0.111	−0.154	0.009	−0.256	−0.027
HAB -> CINT	0.099	0.053	−0.007	0.191	0.135	0.191	−0.086	0.330	0.129	0.019	0.012	0.232

Furthermore, the procedure of PLS prediction was performed to evaluate the predictive power for each country. Most of the endogenous factors had a lower prediction error for the research model than LM. Such results are associated with the positive Q2 values for all these indicators except for CO_1 for Spain, demonstrating that the research model possesses medium to high predictive power. (See Appendix A).

4.2.4. Multigroup Analysis

Table 9 presents the results of the multigroup analysis and demonstrates that the differences are insignificant for any of the proposed paths based on the responses from Chile and Spain. However, the results show significant differences among some path coefficients based on responses from Jordan and Chile (*p*-values <0.05). Specifically, ANX has a much stronger and more significant effect on PU in Jordan than in Chile. Furthermore, PU is deemed to be more important in forming SA in Chile than in Jordan, regarding the sign of the coefficient. Similarly, respondents from Chile place more value on the role of SA in developing CINT beliefs than in Jordan. SML plays a more critical role in determining PU in Jordan than in Chile. Two significant differences are found between respondents from Jordan and Spain: CO is viewed as being more important in Jordan than in Spain in terms of building PU; and SML has a more significant influence on CINT in Jordan than in Spain. In brief, H5 is partially fulfilled.

Table 9. Results for multigroup analysis.

	Chile vs. Jordan				Chile vs. Spain				Jordan vs. Spain			
Path	Path Coeff. Diff	*p*-Value	P-v. Param. Test	P-v. Welch-Satt.	Path Coeff. Diff	*p*-Value	P-v. Param. Test	P-v. Welch-Satt.	Path Coeff. Diff	*p*-Value	P-v. Param. Test	P-v. Welch-Satt.
ANX -> CO	0.078	0.204	0.391	0.406	−0.038	0.687	0.621	0.623	−0.117	0.878	0.241	0.248
ANX -> PU	0.349	0.000	0.000	0.000	0.000	0.496	0.998	0.998	−0.349	1.000	0.000	0.000
CO -> PU	−0.171	0.984	0.046	0.032	0.058	0.216	0.434	0.426	0.229	0.003	0.006	0.005
CO -> SA	−0.178	0.977	0.024	0.032	−0.076	0.893	0.223	0.218	0.102	0.117	0.211	0.235
HAB-> CINT	−0.036	0.618	0.728	0.757	−0.030	0.657	0.697	0.692	0.006	0.485	0.959	0.963
PU -> CINT	0.149	0.080	0.136	0.162	0.092	0.161	0.302	0.320	−0.058	0.683	0.633	0.632
PU -> SA	0.197	0.013	0.012	0.016	0.051	0.210	0.430	0.424	−0.146	0.951	0.074	0.086
SA -> CINT	0.253	0.001	0.003	0.002	0.036	0.316	0.637	0.636	−0.217	0.994	0.015	0.013
SML -> CINT	−0.369	1.000	0.000	0.000	−0.073	0.846	0.298	0.310	0.297	0.000	0.000	0.000
SML -> PU	0.177	0.004	0.015	0.008	−0.048	0.770	0.461	0.454	−0.225	0.999	0.002	0.001

4.3. Summary of Results by Hypothesis

Table 10 shows the results associated with the other ten hypotheses: six were accepted for the three countries, three were not accepted for at least two countries (H1c, H3a, and H4), and only one hypothesis was not accepted for Jordan while being accepted for the other two countries (H1a). Hypothesis H1a is not supported for Jordan, and hypothesis H1c is not supported for Jordan and Spain. Hypothesis 3a is not accepted for Chile and

Spain; finally, hypothesis 4 is not fulfilled for Chile and Jordan. According to the results, Chile is the country in which the traditional ECM theoretical model is fully met (H1a, H1b, H1c, H1d, and H1e), followed by Spain and then Jordan.

Table 10. Results by hypothesis and path analysis.

		Chile			Jordan			Spain		
Hypothesis	**Relationship**	**Path Coefficient**	***p*-Value**	**Remarks**	**Path Coefficient**	***p*-Value**	**Remarks**	**Path Coefficient**	***p*-Value**	**Remarks**
H1a	SA -> CINT	0.284	0.000	Supported	0.031	0.640	Not Supported	0.248	0.000	Supported
H1b	PU -> SA	0.340	0.000	Supported	0.143	0.044	Supported	0.290	0.000	Supported
H1c	PU -> CINT	0.113	0.031	Supported	−0.037	0.693	Not Supported	0.021	0.779	Not Supported
H1d	CO -> PU	0.326	0.000	Supported	0.497	0.000	Supported	0.268	0.000	Supported
H1e	CO -> SA	0.517	0.000	Supported	0.694	0.000	Supported	0.593	0.000	Supported
H2a	SML -> PU	0.357	0.000	Supported	0.180	0.000	Supported	0.405	0.000	Supported
H2b	SML -> CINT	0.319	0.000	Supported	0.688	0.000	Supported	0.391	0.000	Supported
H3a	ANX -> PU	−0.078	0.077	Not Supported	−0.427	0.000	Supported	−0.078	0.123	Not Supported
H3b	ANX -> CO	−0.193	0.000	Supported	−0.271	0.001	Supported	−0.154	0.009	Supported
H4	HAB -> CINT	0.099	0.053	Not Supported	0.135	0.191	Not Supported	0.129	0.019	Supported

5. Discussion

In the case of Chilean students, the ECM of [4] fits completely. The three variables (PU, CO, and SA) show the relationships as significant at more than 99% to explain the CINT of university students in taking their regular courses online. These results are coincident with those obtained by [71] and [36]. The empirical correlation between PU and SA could be accredited to the fact that when an m-learning system enhances students' performance, they generally exhibit high levels of SA [72]. This result agrees with the outcomes observed in previous studies [9,73,74].

For Chile, there is sufficient research reported in other countries that CINT is significantly influenced by PU [74] and SA [74,75]. In the case of Jordan, the findings in this study suggest that these two factors are not predictors of CINT. These findings were strange but coincident with those of [72], who studied the CINT of using mobile learning by postgraduate students from the United Arab Emirates. This discrepancy between the countries in this study and those reported in previous studies might be due to the students' preferences and cultural differences. Further research is highly encouraged to examine this phenomenon in Asia.

Regarding the variables included as an extension of the model, the most relevant is SML. The effect on PU and CINT is significant at more than 99%, even the β that is achieved between SML and PU is the second-highest among all those analyzed (0.357, 0.405, and 0.180 for Chile, Jordan, and Spain, respectively). These results coincide with [23] but are contrary to the results obtained by [47], who found a negative influence of SML on PU for massive open online courses (MOOCs). This implies that the lower the level of students' SML, the less they will recognize the usefulness and functionality of MOOCs.

Likewise, SML has one of the greatest effects on our variable to explain CINT, with $\beta = 0.319$, $\beta = 0.688$, and $\beta = 0.391$ for Chile, Jordan, and Spain, respectively. These results coincide with those of the study carried out by [76] for MOOCs. However, these results are contrary to the results obtained by [44] and [47]. They found a direct and negative relation between SML and behavioral intention for MOOCs. Our results indicate that students with high learning skills will facilitate CINT for online classes. This requires students to be willing to engage with a highly autonomous learning environment and places much responsibility for controlling the learning process onto the students [47].

For the case of ANX, the results show an important effect towards CO for the three groups of students. The relationship is negative, which implies that in the case of Chilean, Jordanian, and Spanish students, ANX makes CO difficult. These results are in line with what was found by [77], who revealed that both social anxieties (general and online) are negatively associated with CINT to sustain participation in the social network of Facebook.

The ANX of all analyzed students acts as a disincentive regarding the positive expectations, experience, and service level associated with taking university courses in an online system.

In relation to the effects of ANX on PU for Chilean and Spanish students, they are similar to those reported by [56], who found that, of seven studies, only two show that ANX has a negative and significant effect on PU. The results for Jordanian students are coincident with those found by [24], who demonstrated that computer ANX has a significant negative effect on PU. This implies that the greater the level of ANX, the lower the level of PU towards behavioral intention to use online learning systems (portal for banking). They also are similar to the results of Lazar et al. [54] and Tick [78], who found that computer ANX has a direct and negative effect on PU but not an indirect and negative effect on CINT towards digital tools for undergraduate students of psychology. This new online learning environment can make Jordanian students feel more uncomfortable due to the learning tradition that embraces face-to-face lecture and teacher-centered learning, and the prior preparation to use educational technology for learning purposes.

The findings of the direct and significant effect of HAB on CINT for Spanish students are in line with [64]. They analyzed CINT using a meta-analysis with a structural equation model and concluded that HAB had a significant positive effect on CINT. Amoroso and Lim [79] incorporate it in their study of consumer CINT, highlighting that consumers can enhance their level of SA by developing a HAB, which is a stronger predictor of consumer intention than SA. Moghavvemi et al. [80] also considered HAB as a direct determinant of behavior, concluding that HAB and facilitating conditions all positively affected students' use of online learning via Facebook. Wu and Perng [81] also reached the same conclusions: study habits reveal remarkably positive correlations with continuous learning. In general, this variable adds value to the models, since when a person practices repetitive behavior after the adoption of technology, reflective cognitive processing diminishes over time, leading to non-reflective and routinised behavior [82]. Corresponding to Cheung and Limayen [25], system designers and instructors should exhibit the usefulness of online learning by facilitating the learning process. Therefore, when students gain more experience with the system, there is a shift to habitual behavior. Thus, instructors should try to get students into the HAB of using technology.

The results concerning the students from Chile and Jordan show an insignificant relationship between HAB and CINT. These findings are more related to those of [73], who conclude that, among other variables, HAB is a determinant of the intention to change to online methodology, although negatively. If one has already experienced in-person classroom settings, there is an inertia that negatively influences switching to online learning. In other words, when users develop inertia [83], they have less intention to switch behavior to the online channel. This result corresponds with those of past studies [84,85]. Most likely, the obligatory change in the study routine has opened the minds of Spanish students to new methodologies. In other words, it seems that in Spain, students accepted new habits more easily than in Jordan and Chile. HAB for Chilean students significantly affects CINT. These results coincide with those obtained by [65], who analyze CINT using a meta-analysis with a structural equation model, concluding that HAB had a significant positive effect on CINT.

6. Conclusions

Given the current environment of the coronavirus pandemic, it is critical to study students' CINT to use online learning. As a summary of the results, it is confirmed that PU, CO, and SA are positively related to CINT in the three countries under study. Therefore, online practitioners should focus on maximizing students' CO of expectations, as well as their PU to increase their SA. However, there are estimates from our model that were statistically different for each region, suggesting that there is evidence that each country has its own particularities that explain the intention of university students to continue using online learning.

The proposed extension of the original ECM presented in this study suggests three context-specific variables that contribute to determining the Continuous Intention of online learning, namely, ANX, SML, and HAB. The proposed model is empirically tested and validated by university students in Spain, Jordan, and Chile. The results show that the relationships of the proposed model's constructs vary among the three countries, given their socioeconomic, technological, and cultural differences. SML was found to be a key factor that has a significant positive influence on CINT for the three countries, especially Jordan. Furthermore, while ANX is found to have a negative influence on CO for all contexts, it has a negative influence on PU only in the Jordanian context. The effect of the construct HAB on CINT is found to be significant only for Spanish students. Surprisingly, the effect of PU on CINT is found to be insignificant in both the Jordanian and Spanish contexts.

6.1. Theoretical and Practical Implications

From the perspective of university management, the online learning environment under emergency circumstances has been a good turning point in promoting the development of online learning [9]. The pandemic has changed learning modes, focused on teaching materials and improved learning tasks. Therefore, the CINT of students using online learning in the future can also be increased.

The various contexts of technology have different context-specific factors that influence the CINT to use it. This study extends the ECM to online learning by incorporating a set of context-specific factors that influence students' CINT to use online learning. The extension of the ECM model is validated, given the impact of incorporating SML, HAB, and ANX. Furthermore, this study investigates the differences in patterns of CINT behavior between three countries. This would lead us to identify the impact of cultural differences on CINT.

Considering our findings, acquiring proper technical skills, allocating adequate technical support, and possessing higher self-efficacy favors continuity in the use of online learning by students. It can be inferred that it is advisable to strengthen the teaching and employment of technology before and during university education. This can open doors not only to the use of new teaching methodologies but also to better preparation for professional careers. The relevance of the SML suggests that universities should encourage instructors in Spain, Chile, and Jordan to promote autonomous development that favors and facilitates learning in online environments. In the Jordanian context, it is important to increase students' technical skills and encourage instructors to support students to increase their confidence regarding the use of information technology for their learning. Such actions would reduce ANX and enhance the recognition of IT as a useful learning tool. Finally, the results also suggest that the use of technology for academic purposes must be enhanced both in Jordan and Chile to make it an essential part of the learning experience. This would also diminish the degree of ANX when using online learning systems. Chen et al. [23] suggest that in order to improve the learners' expectations and the perception of course quality, some auxiliary learning tools (that enhance learners' willingness to continuous use) are indispensable. Thus, instructors and institutions must pay attention to the ease of use of learning tools, to the interaction and communication between students (social capital) and the participation in teamwork. Instructors should implement pedagogical interventions in online learning to improve learning outcomes [86].

Based on our findings, the relevance of SML suggests that universities may encourage teachers to promote autonomous development that favors and facilitates learning in online environments. University professors and university authorities can improve the learning process of students by assigning adequate technical support. Having greater self-efficacy favors the continuity in the use of online learning. This would decrease the degree of ANX of the students when using online learning systems. In addition, this virtual reality can open doors not only to the use of new teaching methodologies but also to better prepare the future professional performance of students in this increasingly virtual world. Researchers may use different theories related to exploring students' CINT after more than a year of the pandemic. Understanding the factors that may affect the usage of technology could increase the motivation for its use and the students' learning and teaching process.

6.2. Limitations and Future Research

This study had a few limitations. The moderating effects of demographics (i.e., age and gender) and culture-related factors (i.e., uncertainty avoidance) were not examined in this study. Future research can consider the moderating effect of demographic and cultural factors. Likewise, this study examines the CINT of online learning systems from the students' perspective in three countries. A similar study could be conducted on the perceptions of instructors. It would be beneficial to explore the main factors influencing instructors' perceptions to continue the use of online learning systems.

Future research can consider the moderating effect of demographic and cultural factors. Additionally, a mixed method using quantitative and qualitative perspectives could be employed. In-depth interviews or focus groups could be applied to validate quantitative results or explore new variables that have not been discovered or analyzed yet for CINT of online learning.

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Appendix A

Table A1. Predict assessment.

Construct	Item	$RMSE_{PLS}$	$Q^2\_predict_{PLS}$	$RMSE_{LM}$	$RMSE_{PLS} < RMSE_{LM}$	Predictive Power
Chile Continuance Intention (CINT)	CINT_1	1.045	0.284	1.206	YES	High
	CINT_2	1.159	0.198	1.280	YES	
	CINT_3	1.262	0.150	1.347	YES	
Confirmation (CO)	CO_1	0.921	0.012	0.904	NO	Low
	CO_2	1.020	0.038	0.998	NO	
	CO_3	1.033	0.012	0.990	NO	
Perceived Usefulness (PU)	PU_1	0.994	0.181	1.061	YES	High
	PU_2	1.028	0.156	1.095	YES	
	PU_3	0.948	0.216	1.047	YES	
	PU_4	0.944	0.204	1.023	YES	
Satisfaction (SA)	SA_1	0.936	0.118	0.970	YES	High
	SA_2	0.923	0.114	0.926	YES	
	SA_3	0.890	0.073	0.892	YES	
Jordan Continuance Intention (CINT)	CINT_1	0.869	0.501	1.197	YES	High
	CINT_2	0.980	0.448	1.317	YES	
	CINT_3	1.084	0.325	1.310	YES	

Table A1. *Cont.*

Construct	Item	$RMSE_{PLS}$	Q^2_predict$_{PLS}$	$RMSE_{LM}$	$RMSE_{PLS}$ < $RMSE_{LM}$	Predictive Power
Confirmation (CO)	CO_1	1.063	0.054	0.943	NO	Low
	CO_2	1.142	0.037	1.057	NO	
	CO_3	1.139	0.050	1.068	NO	
Perceived Usefulness (PU)	PU_1	1.031	0.295	1.134	YES	Medium
	PU_2	1.071	0.270	1.065	NO	
	PU_3	0.911	0.365	1.036	YES	
	PU_4	0.994	0.325	1.111	YES	
Satisfaction (SA)	SA_1	1.117	0.059	1.078	NO	Low
	SA_2	1.039	0.112	1.016	NO	
	SA_3	1.069	0.096	1.025	NO	
Spain Continuance Intention (CINT)	CINT_1	0.966	0.346	1.139	YES	High
	CINT_2	1.175	0.198	1.294	YES	
	CINT_3	1.270	0.096	1.316	YES	
Confirmation (CO)	CO_1	0.979	-0.008	0.971	NO	Low
	CO_2	1.091	0.026	1.039	NO	
	CO_3	1.106	0.002	1.057	NO	
Perceived Usefulness (PU)	PU_1	0.941	0.233	1.005	YES	High
	PU_2	1.047	0.191	1.105	YES	
	PU_3	0.978	0.195	1.040	YES	
	PU_4	0.975	0.221	1.055	YES	
Satisfaction (SA)	SA_1	1.006	0.086	1.021	YES	Medium
	SA_2	0.940	0.138	0.936	NO	
	SA_3	0.901	0.085	0.890	NO	

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