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Résumé de l'article

The global pandemic caused by the SARS-CoV-2 virus brought about a true revolution in the predominant teaching–learning processes (i.e., face-to-face environment) that had been implemented up to that point. In this regard, virtual teaching–learning environments (VTLEs) have gained unprecedented significance. The main objectives of our research were to define an explanatory theoretical model and to test a multiple serial mediation model with four variables in series (one independent variable plus three mediators) to relate perceived utility (independent variable) in the use of a VTLE and perceived learning (dependent or criterion variable) in such contexts, taking into account the mediation of subjective norm (mediator 1), ease of use (mediator 2), and intention to use behavior (mediator 3), and using the extended technology acceptance model as the theoretical framework. Additionally, we aimed to analyze the direct and indirect relationships and effects among the variables that constituted the proposed model. Methodologically, the research can be classified as a cross-sectional causal ex post facto design. A representative sample of students enrolled in higher education institutions in the Dominican Republic was used as the research population, and a standardized Likert scale was administered to measure the five dimensions of the proposed model. Finally, it is worth noting that the obtained results indicate that all direct and indirect effects considered in the model were statistically significant, except for the indirect effect, where the four predictor variables were arranged in series to verify their influence on the criterion variable: perceived learning.

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Abstract

The global pandemic caused by the SARS-CoV-2 virus brought about a true revolution in the predominant teaching–learning processes (i.e., face-to-face environment) that had been implemented up to that point. In this regard, virtual teaching–learning environments (VTLEs) have gained unprecedented significance. The main objectives of our research were to define an explanatory theoretical model and to test a multiple serial mediation model with four variables in series (one independent variable plus three mediators) to relate perceived utility (independent variable) in the use of a VTLE and perceived learning (dependent or criterion variable) in such contexts, taking into account the mediation of subjective norm (mediator 1), ease of use (mediator 2), and intention to use behavior (mediator 3), and using the extended technology acceptance model as the theoretical framework. Additionally, we aimed to analyze the direct and indirect relationships and effects among the variables that constituted the proposed model. Methodologically, the research can be classified as a cross-sectional causal ex post facto design. A representative sample of students enrolled in higher education institutions in the Dominican Republic was used as the research population, and a standardized Likert scale was administered to measure the five dimensions of the proposed model. Finally, it is worth noting that the obtained results indicate that all direct and indirect effects considered in the model were statistically significant, except for the indirect effect, where the four predictor variables were arranged in series to verify their influence on the criterion variable: perceived learning.

Keywords: virtual teaching–learning environment, extended technology acceptance model, higher education, information and communications technology

Perceived Utility and Learning by Dominican University Students in Virtual Teaching–Learning Environments: An Analysis of Multiple Serial Mediation Based on the Extended Technology Acceptance Model

Virtual teaching–learning environments (VTLEs) have become an established reality that has been further reinforced by the COVID-19 pandemic and new educational needs (Adov & Mäeots, 2021; Herrador-Alcaide et al., 2019; Kortemeyer et al., 2023; Williamson et al., 2020) that have emerged in this new context. This is the starting point of our research, which aims to complement the existing scientific literature on VTLEs, but within the context prompted by the COVID-19 crisis among students enrolled in higher education in the Dominican Republic. Formally, these teaching–learning environments can be classified within a broader context known as *blended learning* (Hrastinski, 2019)—a broad term that refers to a continuum ranging from traditional face-to-face teaching–learning processes to innovative online teaching–learning processes (Garrison & Kanuka, 2004). In the context of VTLEs, learning management systems (LMSs) are valuable for supporting students' teaching–learning process (Araka et al., 2021; Bansah & Agyei, 2022).

However, at this point, it is worth asking to what extent the teaching–learning process based on these virtual environments can influence perceived learning outcomes among students. With this aim in mind, this research proposal emerged, grounded in a set of hypotheses related to specific variables (perceived usefulness, subjective norm, ease of use, and intention to use) and their influence on perceived learning within VTLE contexts. Thus, conducting a study of this nature and with these characteristics would seek to generate an explanatory theoretical model based on the technology acceptance model (TAM) and subsequent variations as a cornerstone for new pedagogical models and methodologies within VTLEs. Some current references on the practical utility of these models include Martín-García et al. (2019), Schimidthuber et al. (2020), and Ranellucci et al. (2020); the levels of satisfaction of students immersed in these VTLEs are also emphasized (Hamutoglu et al., 2020).

Theoretical Support

The field of educational practice and research is not immune to the new demands and innovations being developed to provide a rapid and accurate response to each situation that arises. All these changes share a common denominator: the exponential increase in new technologies and digital devices. As a result, a new way of understanding teaching–learning processes is emerging, where students are assuming an increasingly active role as they progress through educational levels, eventually reaching higher education (Gallego-Gómez et al., 2021; Quevedo-Arnaiz et al., 2021).

There are studies that demonstrate this paradigm shift, where new methodologies and active learning are gaining prominence—notably, Mohamed (2021), Rodríguez-Sabiote et al. (2020) Roitsch et al. (2021), and Tan et al. (2021). However, due to the COVID-19 pandemic, the global population was forced to endure periods of confinement. Specifically in the field of education, face-to-face classroom instruction in elementary schools, high schools, universities, and other educational centers had to be replaced with virtual classrooms and environments. Undoubtedly, education has undergone rapid changes in a very short period, and it is not surprising that various difficulties have arisen, such as dealing with misinformation in the media, maintaining the level of engagement in the teaching–

learning process, and managing anxiety toward these accelerated changes (Martin et al., 2022; Unger & Meiran, 2020). Thus, processes that were already underway were accelerated, and many changes and innovations that were introduced due to the new reality have ultimately become permanent. In this new context, students and teachers have been compelled to adapt to online learning and distance education in a short time, giving rise to a new model in education in the so-called post-COVID era (Lockee, 2021).

In this context, VTLEs gain significant strength and presence. VTLEs are understood as virtual environments that facilitate pedagogical communication among participants in an educational process, whether fully online, face to face, or in a blended nature that combines both modalities in varying proportions (Weller, 2007). Therefore, VTLEs can be considered as highly potential and functional alternatives that effectively combine technology and pedagogy, enabling the execution of learning activities and tasks across different subjects in virtual environments or classrooms, where both students and teachers can visualize and access various educational resources (Baez-Estrada & Ossandón Núñez, 2015). Furthermore, VTLEs promote collaborative learning, where the teacher acts as a mediator in the learning construction process and students are the protagonists of their own development (Huang et al., 2010). They foster social interaction in the teaching–learning process (Hernández-Sellés, 2021; Limniou & Smith, 2010; Uzunboylu et al., 2011), which is considered one of the main pillars of these platforms and tools.

All of this originates from the TAM proposed by Davis (1989) and from subsequent extended and adapted models (Abdullah & Ward, 2016). The purpose of this model is to explain the factors that determine the use of information and communications technology (ICT) by a significant number of users, suggesting that perceived usefulness and perceived ease of use are determinants of a user's intention to use a system. This predictive model of ICT use is based on two main variables:

1. perceived usefulness (PU): the user's perception of how adopting the technology would enhance their performance or productivity.

2. perceived ease of use (PEoU): the user's perception of how effortless it is to use the technology.

Following the TAM, there are external variables that can directly influence PU and PEoU (Yong-Varela et al., 2010). These external variables indirectly influence attitude toward use, behavioral intention to use, and actual behavior. PEoU has a causal effect on PU, and PU significantly affects an individual's attitude toward using a particular system, which can be either favorable or unfavorable. Among the external variables that have been studied with great interest in the scientific literature over the years (Bueno & Salmerón, 2008; Huffman & Huffman, 2012; Ngai et al., 2007; Venkatesh, 2000), five can be highlighted: social influence, technological support, cooperation among organization members, academic success, and knowledge need.

Objectives and Hypotheses

The first objective was to define an explanatory theoretical model (extended technology acceptance model) as tested by Urquidi Martín et al. (2019) and to confirm it through a multiple serial mediation model with three mediating variables to relate perceived usefulness (PU) derived from the use of VTLE and perceived learning (PL) in these contexts, taking into account the mediation of subjective norm (SN), perceived ease of use (PEoU), and behavioral intention to use (BIU). The second objective was to

analyze the relationships and the given direct, indirect, and total effects among the variables comprising this model. Based on these research objectives, a series of hypotheses were derived. These hypotheses are based on model 6 proposed by Hayes (2022) within the mediation models, which will be discussed in detail in the methodology section. The following hypotheses are enumerated accordingly.

Hypotheses With a Single Mediator

The following hypotheses were derived from the indirect effects of the predictor (x = PU) on the criterion (y = PL) modulated by a single mediator (indirect effect of x on y through only $m_i = a_i b_i$):

hypothesis 1: greater PU derived from the use of a VTLE, along with a stronger SN imposed within this environment, enhance PL: Ind_1 = PU→SN→PL or, alternatively, *m1* SN ~ PU.

hypothesis 2: greater PU derived from the use of a VTLE, combined with a higher PEoU, increase PL: Ind_2 = PU→PEoU→ PL or, alternatively, *m2* PEoU ~ PU.

hypothesis 3: greater PU derived from the use of a VTLE, coupled with a higher BIU, enhance PL: Ind_3 = PU→BIU→PL or, alternatively, *m3* BIU ~ PU.

Hypotheses With Two and Three Mediators

The following hypotheses were derived from the indirect effects of the predictor (x = PU) on the criterion (y = PL) modulated by two or three mediators (indirect effect of x on y through *m1*, *m2*, *m3* in serial):

hypothesis 4: greater PU derived from the use of a VTLE, along with a stronger SN imposed within this environment, as well as a higher PEoU within the same environment, enhance PL: Ind_1 = PU→SN→PEoU→PL.

hypothesis 5: greater PU derived from the use of a VTLE, coupled with a stronger SN imposed within this environment, as well as a higher BIU within the same environment, enhance PL: Ind_2 = PU→SN→BIU→ PL.

hypothesis 6: greater PU derived from the use of a VTLE, along with a higher PEoU and a higher BIU within the same environment, enhance PL: Ind_3 = PU→PEoU→BIU→PL.

hypothesis 7: greater PU derived from the use of a VTLE, combined with a stronger SN imposed within this environment, associated with a higher PEoU within the same environment, as well as a higher BIU, enhance PL: Ind_4 = PU→SN→PEoU→BIU→PL.

Methodology

Study Variables

The study considers five distinct variables, which are actually latent dimensions formed by grouping observable variables (scale items) of the proposed model: PU, SN, PEoU, BIU, and PL. The role and definition of each variable in the proposed model are as follows (Urquidi Martín et al., 2019, p. 6):

- PU: the perception held by students receiving their classes in a VTLE regarding the usefulness of an innovation in improving their learning competence. ROLE→ (*x*: independent).

- SN: the set of social pressures exerted by relevant individuals on students receiving their classes in a VTLE, with the aim of influencing these users to perform a specific action or behavior. ROLE→ (*m1*: mediator 1).

- PEoU: the degree to which a student considers the use of a particular innovation to be free of additional effort. ROLE→ (*m2*: mediator 2).

- BIU: the perception held by students receiving their classes in a VTLE regarding their future employment of an innovation. ROLE→ (*m3*: mediator 3).

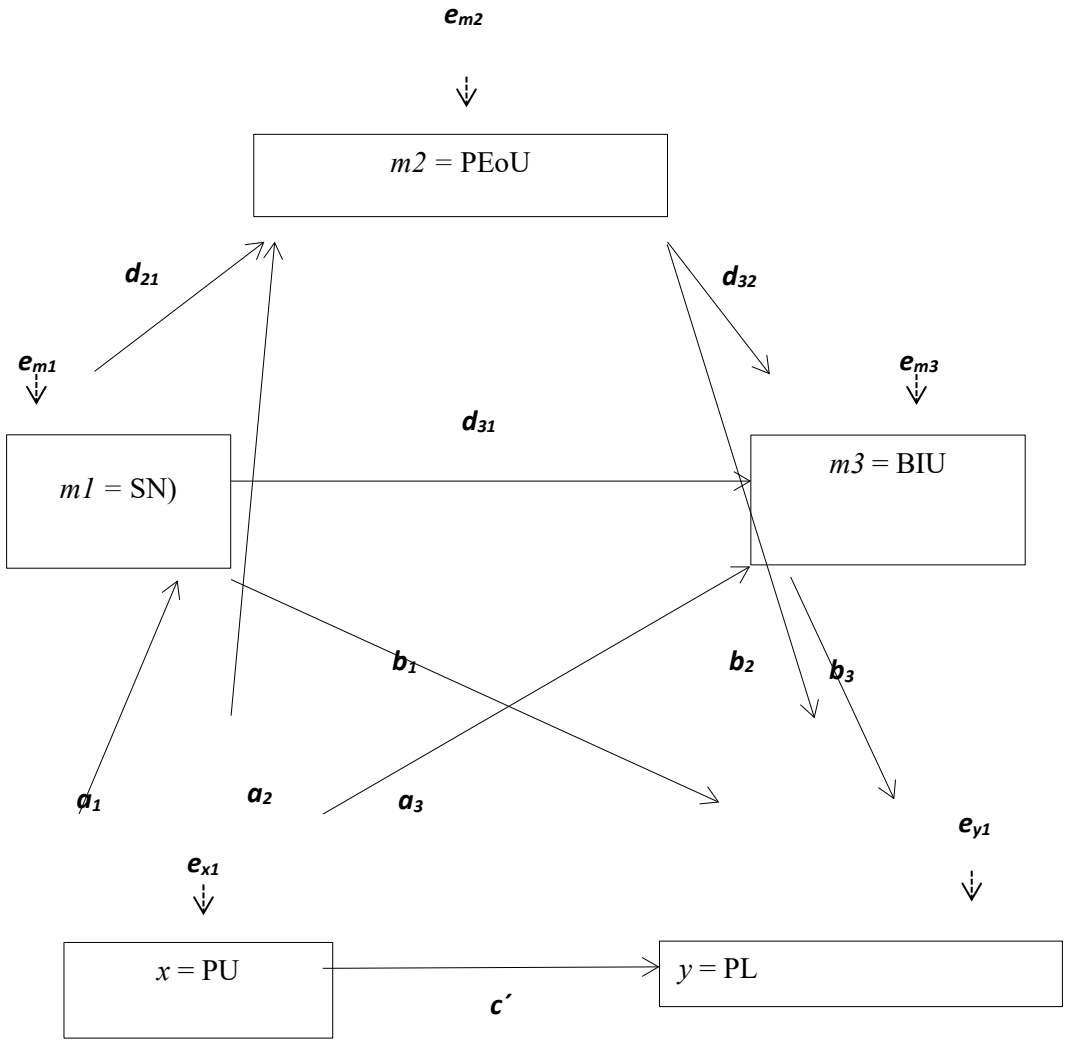
- PL: the relationship between the use of an innovation by students receiving their classes in a VTLE and the improvement they could achieve in their learning. ROLE→ (*y*: dependent).

Methodological Design

The methodology used in the research follows an ex post facto correlational-predictive design of a cross-sectional nature, characterized by establishing relationships of covariation and regression among variables of different nature—namely, independent, dependent, and mediator variables—aiming to confirm a specific mediation model. The model being tested is model 6 proposed by Hayes (2022). This model is a mediation model that involves a criterion or dependent variable *y* = PL, an independent variable *x*= PU, and three sequential or serial mediator variables, namely, *m1* = SN, *m2* = PEoU, and *m3* = BIU. Conceptually, it can be referred to as a multiple mediation model with three variables in a series. The model can be represented schematically using a statistical diagram, where, in addition to the five variables, each of the regression coefficients (β) or standardized/unstandardized slopes corresponding to the regression equations that make up the model are represented by letters (Figure 1). In our case, we would have the following regression coefficients: *a1, a2, b1, b2, b3, d21, d31,* and *c´*, along with an overall coefficient *c* (total effect not shown in the diagram), as well as different errors (e_n) associated with the different regression coefficients.

Figure 1

Statistical Diagram (Model 6 With Three Mediators)



Note. PEoU = perceived ease of use; SN = subjective norm; BIU = behavioral intention to use; PU = perceived usefulness; PL = perceived learning; indirect effect of x on y through m_i only = a_ib_i (a_1b_1, a_2b_2, and a_3b_3); indirect effect of x on y through $m1$ and $m2$ in serial = $a_1d_{21}b_2$; indirect effect of x on y through m_1 and m_3 in serial = $a_1d_{31}b_3$; indirect effect of x on y through $m2$ and $m3$ in serial = $a_2d_{32}b_3$; indirect effect of x on y through $m1$, $m2$, and $m3$ in serial = $a_1d_{21}d_{32}b_3$; direct effect of x on y = $c´$.

Data Collection

Instrument

For data collection, a single instrument was used: the measurement scale of the extended technology acceptance model (MSETAM) by Urquidi Martín et al. (2019). There are three reasons for using a single instrument. The first is that it is properly standardized in terms of reliability, internal consistency, and concurrent and construct criterion validity (Urquidi Martín et al., 2019). It also has content validity, as

it was developed by adapting several previously standardized instruments. The sources of the dimensions and items that constitute the instrument are presented in Table 1.

Table 1

Sources of the Dimensions of the Instrument

Scale dimension	Sources
PU	Arteaga Sánchez & Duarte Hueros (2010); Davis (1989); Islam (2013); Premkumar & Bhattacherjee (2008)
SN	Sánchez-Prieto et al. (2017)
PEoU	Arteaga Sánchez & Duarte Hueros (2010); Davis (1989); Islam (2013); Premkumar & Bhattacherjee (2008)
BIU	Arteaga Sánchez & Duarte Hueros (2010); Davis (1989); Islam (2013); Premkumar & Bhattacherjee (2008)
PL	Islam (2013)

Note: PU = perceived usefulness; SN = subjective norm; PEoU = perceived ease of use; BIU = behavioral intention to use; PL = perceived learning. Adapted from "Entornos virtuales de aprendizaje: modelo ampliado de aceptación de la tecnología [Virtual Learning Environments: Extending the Technology Acceptance Model]," by A. C. Urquidi Martín, M. S.Calabor-Prieto, & C. Tamarit-Aznar, 2019, *Revista Electrónica de Investigación Educativa*, *21*, p. 6 (https://doi.org/10.24320/redie.2019.21.e22.1866). Copyright 2019 by the Revista Electrónica de Investigación Educativa.

The second reason for using a single instrument is that the scale consists of 20 items (5 items for each included dimension), making it a short and easy-to-complete scale. The third reason is that the instrument is structured around the dimensions that will constitute the mediation model being tested. The MSETAM used in this study is composed of five dimensions, PU, SN, PEoU, BIU, and PL, each consisting of four items. The response format is a Likert-type scale ranging from 1 to 5 (1 = strongly disagree; 5 = strongly agree). The scale was administered online.

Sample

The sample size of this research was 407 students from 15 public and private universities or higher education institutions in the Dominican Republic. Of these, 108 were male and 299 were female, with ages ranging from 17 to 54 years (M = 25.86, SD = 7.35). No specific sampling technique was used, as the instrument was made available to the target population in an online format. The population from which the sample was drawn was approximately 580,000 individuals (i.e., students enrolled in higher education in the Dominican Republic during the 2020–2021 academic year, the latest year for which data were available). For this particular study, the sample size was determined based on the following parameters: significance level (1-α) = 0.95, sampling error = ±4.8%, and unknown proportions (p = q = 0.5). Once the sample size was calculated to be approximately n = 471, the instrument was administered online. Sample attrition amounted to 64 participants (13.58%), which was not a cause for concern, as the focus was on the proportion of participants per variable (subject to variables [STV]). The resulting STV ratio was 20.35 (407/20). While the minimum value for STV is relative and varies depending on the consulted author, a minimum value of 10 is recommended (Garson, 2008). Our value

was comfortably above this threshold (20.35 > 10). The data collection process is described in more detail in the procedure section.

Reliability and Validity of the Data Collection Instrument

The scale used in our study has been properly standardized and demonstrates the necessary psychometric properties, including content and construct validity. We will now present the results obtained for the complete scale and the various subscales in terms of reliability (internal consistency) and concurrent criterion validity in the context of our particular study.

For internal consistency reliability, we calculated Cronbach's alpha (α) coefficient and McDonald's omega (ω) coefficient after a single administration of the instrument. For concurrent criterion validity, we calculated the corrected item-total correlation. The results for both aspects are presented in Table 2 and discussed below.

Table 2

Scale and Subscales Reliability Statistics

Scale/subscale	Cronbach's α	McDonald's ω
Subscale PU (4 items)	0.838	0.844
Subscale SN (4 items)	0.877	0.878
Subscale PEoU (4 items)	0.705	0.725
Subscale BIU (4 items)	0.891	0.894
Subscale PL (4 items)	0.849	0.853
Full scale (20 items)	0.950	0.954

Note. PU = perceived usefulness; SN = subjective norm; PEoU = perceived ease of use; BIU = behavioral intention to use; PL = perceived learning.

The results for the reliability coefficients, Cronbach's α and McDonald's ω, indicate high internal consistency for the evaluated subscales, except for the isolated case of the PEoU subscale, which shows slightly lower internal consistency. Notably, the overall scale demonstrated high internal consistency with α = 0.950 and ω = 0.954. In conclusion, moderately high α and ω values were obtained, indicating good internal consistency of the scale as a whole (Zumbo et al., 2007), with slightly lower consistency for the PEoU subscale.

Regarding criterion validity, we calculated the corrected item-total correlation or item-rest correlation, which represents the correlation between each item and the total score of the scale after removing that particular item. In most cases, the reported correlations were $r > 0.65$, suggesting that most items in the scale accurately measured the same construct as the total scale (internal consistency criterion).

Data Analysis

To test the proposed mediation hypotheses, we employed the PROCESS macro for SPSS v4.0 (Hayes, 2022) using the bootstrapping method. This strategy is advantageous for addressing violations of parametric assumptions such as normality and small sample sizes (although this is not the case in our

study). It is considered a more robust approach Hayes & Rockwood, 2020) than, for example, jackknifing method or permutation tests. The bootstrapping method is based on repeated random sampling with replacement from the data set to calculate the desired statistic for each resample, in our case with 10,000 bootstrap samples. Its major advantage over the initial methods used in sequential mediation models (e.g., Baron & Kenny, 1986) and the Sobel test (Preacher & Hayes, 2004) is its ability to provide point estimates and confidence intervals. With the help of these confidence intervals, we can assess whether the mediation effect is statistically significant (Igartura & Hayes, 2021).

Table 3

Regression Analysis and Total, Direct, and Indirect Effects of x on y

Outcome variable: Subjetive Norm (SN)

Model summary

R	R-sq	MSE	F	df1	df2	P
.73	.53	6.75	456.29	1	405	.000***
Model	**Coeff.**	**Se**	**T**	**p**	**LLCI**	**ULCI**
constant	3.34	.55	6.04	.000***	2.25	4.42
PU	.76	.04	21.36	.000***	.69	.83

Standardized coefficient PU= .73 (a_1)

Outcome variable: Perceived Easy Use (PEOU)

Model summary

R	R-sq	MSE	F	df1	df2	p
.67	.45	5.50	162.70	2	404	.000***
Model	**Coeff**	**Se**	**T**	**p**	**LLCI**	**ULCI**
constant	5.12	.52	9.83	.000***	4.10	6.14
PU	.47	.05	9.96	.000***	.37	.56
SN	.14	.04	3.07	.000***	.05	.23

Standardized coefficients PU= .54 (d_{21}); SN =.14(a_2)

Outcome variable: Behavioural Intention Use(BIU)

Model summary

R	R-sq	MSE	F	df1	df2	p
.86	.74	3.83	391.86	3	403	.000***
Model	**Coeff**	**Se**	**T**	**p**	**LLCI**	**ULCI**
constant	.99	.48	2.05	.04*	.04	1.94

PU	.32	.04	7.38	.000***	.24	.41
SN	.55	.04	14.64	.000***	.48	.63
PEoU	.13	.04	3.17	.000***	.05	.21

Standardized coefficients PU= .30 (a_3); SN =.54(d_{31}); PEOU=.11(d_{32})

Outcome variable: Perceived Learning(PL)

Model summary

R	**R-sq**	**MSE**	**F**	**df1**	**df2**	**p**
.86	.69	3.99	224.98	4	402	.000***
Model	**Coeff**	**Se**	**T**	**p**	**LLCI**	**ULCI**
constant	1.74	.50	3.51	.000***	.76	2.71
PU	.18	.04	7.38	.000***	.09	.27
SN	.30	.04	14.64	.000***	.21	.39
PEoU	.26	.04	3.17	.000***	.18	.34
BIU	.20	.05	4.01	.000***	.10	.30

Standardized coefficients PU= .18 (c´); SN =.32 (b_1); PEOU=.23 (b_2); BIU=.22 (b_3)

TOTAL EFECT MODEL

Outcome variable: Perceived Learning (PL)

Model summary

R	**R-sq**	**MSE**	**F**	**df1**	**df2**	**p**
.73	.54	5.94	486.93	405	1151	.000***
Model	**Coeff.**	**Se**	**T**	**p**	**LLCI**	**ULCI**
constant	4.91	.52	9.48	.000***	3.89	5.93
PU	.72	.03	21.65	.000***	.66	.79

Standardized coefficient PU= .73 (a_1)

TOTAL AND DIRECT EFECT OF *X* ON *Y*

Total effect of X on Y

Effect	**Se**	**t**	**P**	**LLCI**	**ULCI**	**c_ps**	**c_cs**
.72	.03	21.65	.000***	.66	.79	.20	.73

Standardized coefficient PU= .73 (a_1)

Direct effect of X on Y

Effect	Se	t	P	LLCI	ULCI	c_ps	c_cs
.18	.05	3.81	.000***	.09	.27	.05	.18
Standardized coefficient PU= .18 (total)							

*Note. *p<.05, **p<.01, ***p<.001.*

Level of confidence for all confidence intervals in output: 95%

Number of bootstrap samples for percentile bootstrap confidence intervals: 10000.

After applying the PROCESS program, the results regarding the various regression equations that statistically support model 6 are presented. In this regard, we can observe the different regression analyses developed as follows:

1. $x \rightarrow m1$ (coeff. a1) $y = \alpha + \beta 1\ (a_1)$, where the variable x (PU) acts as the sole predictor of mediator 1 (SN). All parameters were statistically significant ($p < 0.001$).

2. $m1, x \rightarrow m2$ (coeff. d21, a2) $y = \alpha + \beta 1\ (d_{12}) + \beta 2\ (a_2)$, where both mediator 1 (SN) and the main predictor (PU) act as predictors of moderator 2 (PEoU). All parameters were statistically significant ($p < 0.001$).

3. $m1, m2, x \rightarrow y$ (coeff. $b_1, b_2, c´$) $y = \alpha + \beta 1\ (b_1) + \beta 2\ (b_2) + \beta 3\ (c´)$, where the two mediators, 1 and 2 (SN and PEoU), along with the main predictor (PU), act as predictors of the criterion or dependent variable (PL). All parameters were statistically significant ($p < 0.001$).

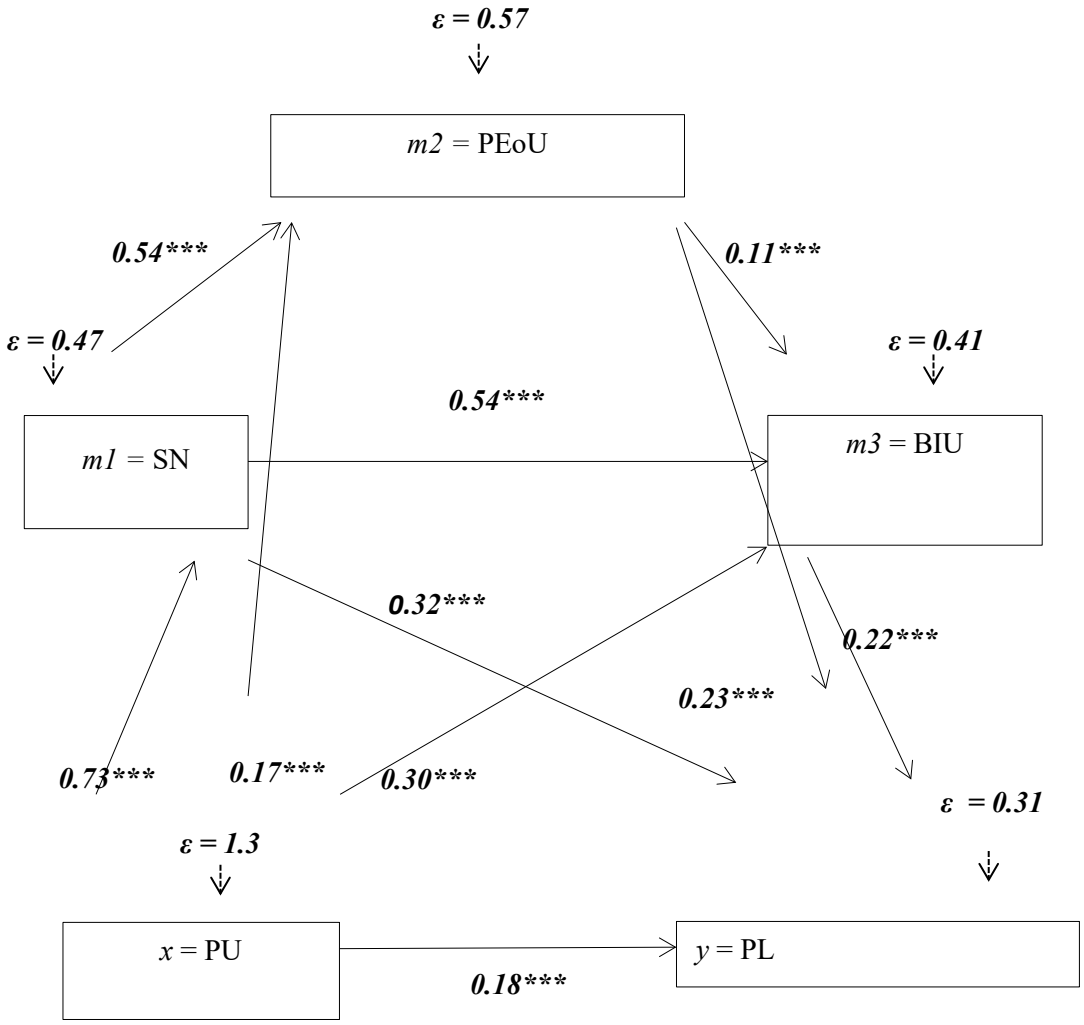
4. $m1, m2, m3, x \rightarrow y$ (coeff. $b_1, b_2, b_3, c´$) $y = \alpha + \beta 1\ (b_1) + \beta 2\ (b_2) + \beta 3\ (b_3) + \beta 4\ (c´)$, where the three mediators (SN, PEoU, and BIU), along with the main predictor (PU), act as predictors of the criterion or dependent variable (PL). All parameters were statistically significant ($p < 0.001$).

5. Finally, both the total effect $\beta\ (c) = 0.72$ ($p < 0.001$) and the direct effect $\beta\ (c´) = 0.18$ ($p < 0.001$) were statistically significant.

Empirical confirmation seems to support the relevance and possibility of including the main predictor (PU) and its mediators (SN, PEoU, and BIU) as variables that can help predict PL. Figure 2 presents a diagram of the inferred model with the calculated parameters.

Figure 2

Statistical Diagram With Coefficients (Model 6 With Three Mediators)



Note. PEoU = perceived ease of use; SN = subjective norm; BIU = behavioral intention to use; PU = perceived usefulness; PL = perceived learning. Indirect effect of x on y through m_i only = $a_i b_i$ ($a_1 b_1$, $a_2 b_2$, and $a_3 b_3$). Indirect effect of x on y through $m1$ and $m2$ in serial = $a_1 d_{21} b_2$. Indirect effect of x on y through m_1 and m_3 in serial = $a_1 d_{31} b_3$. Indirect effect of x on y through $m2$ and $m3$ in serial = $a_2 d_{32} b_3$. Indirect effect of x on y through $m1$, $m2$, and $m3$ in serial = $a_1 d_{21} d_{32} b_3$. Direct effect of x on y = $c´$. Betas are completely standardized.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Second, we present the results concerning the mediating indirect effects, as well as the comparison between them using binomial tests to either accept or reject each of the seven hypotheses proposed (Table 4).

Table 4

Completely Standardized Indirect Effect(s) of x on y

Types of effects	Effect	Boot_SE	Boot_LLCI	Boot_ULCI
Total	0.55	0.04	0.47	0.63
Ind_1^	0.23	0.04	0.15	0.32
Ind_2^	0.12	0.03	0.07	0.18
Ind_3^	0.07	0.02	0.03	0.11
Ind_4^	0.03	0.01	0.01	0.05
Ind_5^	0.09	0.03	0.04	0.14
Ind_6^	0.01	0.01	0.01	0.03
Ind_7	0.00	0.00	0.00	0.01
Specific indirect effect contrast definition(s)				
C_1 (Ind_1 vs. Ind_2)	0.11	0.06	0.00	0.23
C_2 (Ind_1 vs. Ind_3)^	0.16	0.06	0.06	0.27
C_3 (Ind_1 vs. Ind_4)^	0.20	0.05	0.11	0.29
C_4 (Ind_1 vs. Ind_5) ^	0.14	0.06	0.02	0.26
C_5 (Ind_1 vs. Ind_6) ^	0.22	0.05	0.13	0.31
C_6 (Ind_1 vs. Ind_7) ^	0.23	0.04	0.14	0.31
C_7 (Ind_2 vs. Ind_3)	0.06	0.04	−0.02	0.13
C_8 (Ind_2 vs. Ind_4) ^	0.10	0.04	0.04	0.16
C_9 (Ind_2 vs. Ind_5)	0.04	0.04	−0.05	0.12
C_{10} (Ind_2 vs. Ind_6) ^	0.11	0.03	0.05	0.17
C_{11} (Ind_2 vs. Ind_7) ^	0.12	0.03	0.06	0.18
C_{12} (Ind_3 vs. Ind_4)	0.04	0.02	−0.01	0.09
C_{13} (Ind_3 vs. Ind_5)	−0.02	0.02	−0.06	0.01
C_{14} (Ind_3 vs. Ind_6) ^	0.05	0.02	0.02	0.10
C_{15} (Ind_3 vs. Ind_7) ^	0.06	0.02	0.03	0.11
C_{16} (Ind_4 vs. Ind_5)	−0.06	−0.03	−0.12	0.00
C_{17} (Ind_4 vs. Ind_6)	0.01	0.01	−0.01	0.04
C_{18} (Ind_4 vs. Ind_7) ^	0.02	0.01	0.01	0.04
C_{19} (Ind_5 vs. Ind_6)	0.07	0.02	0.03	0.12
C_{20} (Ind_5 vs. Ind_7) ^	0.08	0.03	0.04	0.14
C_{21} (Ind_6 vs. Ind_7)	0.01	0.00	0.00	0.02

Note. LLCI = lower limit confidence interval; ULCI = upper limit confidence interval; PU = perceived usefulness; SN = subjective norm; PL = perceived learning; PEoU = perceived ease of use; BIU = behavioral intention to use. ^confidence interval (boot LLCI–boot ULCI) does not cover the value 0 → statistically significant. Indirect effect key: Ind_1 PU → SN →PL; Ind_2 PU → PEoU → PL; Ind_3 PU → BIU → PL; Ind_4 PU → SN → PEoU → PL; Ind_5 PU → SN → BIU → PL; Ind_6 PU → PEoU → BIU → PL; Ind_7 PU → SN → PEoU → BIU → PL.

As can be seen from the seven direct effects, six were statistically significant, considering that at a 95% confidence level, confidence intervals (boot LLCI–boot ULCI) have been estimated that do not include the value 0 (Hayes, 2022). Specifically, the statistically significant indirect effects include all but one, which is the indirect effect 7 (Ind_7). In this effect, we obtained a standardized coefficient $\beta = 0$, associated with a standard error boot = 0, which, considering a 95% confidence level, yields a confidence interval of 0.00–0.01, where the value 0 is indeed included, indicating the non significance of the contemplated effect (Hayes, 2022).

Another relevant aspect, once the indirect effects have been examined, is to determine which are more significant and whether there are statistically significant differences among them (post hoc contrasts). For this procedure, the seven indirect effects were compared using binomial tests. In this way, a total of 21 comparisons were conducted, corresponding to the combinations of seven elements taken two at a time ($C_2^7 = 7! / 2! \times [7 - 2]!$). Out of these 21 comparisons, 12 were statistically significant, meaning that their confidence intervals (boot LLCI–boot ULCI) did not include the value 0. In more detail, the indirect effects with statistically significant differences when compared to each other are comparisons 2, 3, 4, 5, 6, 8, 10, 11, 14, 15, 18, and 20. On the other hand, the remaining comparisons—1, 7, 9, 12, 13, 16, 17, 19, and 21—were not statistically significant, as they included the value 0 in the confidence intervals (boot LLCI–boot ULCI).

Furthermore, the comparisons that showed the greatest differences among the indirect effects were those with higher standardized effects β, which corresponded to the comparisons involving the indirect effect 1 (Ind_1 = PU → SN → PL) with the other indirect effects.

Discussion and Conclusions

The results obtained regarding the three initial hypotheses (hypotheses 1, 2, and 3) indicate that PU is a good predictor of PL when mediated by each mediator individually, namely SN, PEoU, and BIU.

As a result, we can conclude that higher PU derived from the use of a VTLE in the teaching and learning process, along with a stronger subjective norm imposed within this environment, increases PL. Additionally, higher PU derived from the use of a VTLE, coupled with a greater PEoU, enhances PL. Finally, higher PU resulting from the use of a VTLE, combined with a greater BIU, increases PL.

Furthermore, regarding hypotheses with two mediators (hypotheses 4, 5, and 6) and three mediators (hypothesis 7) in series, we also observed that PU is an excellent predictor of PL when mediated by SN and PEoU in series, when mediated by SN and BIU in series, and when mediated by PEoU and BIU in series. However, no empirical evidence was found to conclude that PU is a good predictor of PL when mediated by SN, PEoU, and BIU, all in series.

Based on these findings, we can conclude that higher PU derived from the use of a VTLE, along with a stronger SN imposed within this environment, as well as a greater PEoU within the same environment, increases PL. Similarly, higher PL derived from the use of a VTLE, coupled with a stronger SN imposed within this environment, and a greater BIU, also enhance PL. Finally, we can also conclude that higher PU derived from the use of a VTLE, along with a greater PEoU and a higher BIU, increases PL. However, we cannot conclude that higher PU when using a VTLE, combined with a stronger SN imposed within this environment, a greater PEoU within the same framework, and a higher BIU, increases PL.

Furthermore, the total and direct effects of the model were also found to be statistically significant. Therefore, it can be concluded that PU is a good predictor of PL in VTLE, both when it directly influences learning and when it does so through the mediation of subjective norm, ease of use, and intention to use.

When comparing our conclusions with those of other studies, we found a solid agreement with the findings obtained from other research. Considering the specific characteristics and specific approaches of the different studies selected for this comparative purpose, we observe that they indeed bear a considerable resemblance to our conclusions. However, we do note a difference with some of these studies. For example, in the work of Urquidi Martín et al. (2019), PEoU did not prove to be an influential variable in PL. On the other hand, we highlight the works of Baez-Estradas and Ossandón Núñez (2015), Calderón et al. (2020), Islam (2013), Montagud Mascarell and Gandía Cabedo (2014), Hernández-Sellés (2021), Ranellucci et al. (2020), Talantis et al. (2020), Severt et al. (2020), Schepers and Wetzels (2007), Şimşek and Ateş (2022), Tırpan and Bakirtas (2020), and Wismantoro et al. (2020), whose findings are more in line with those obtained in the present research. All these findings propose the TAM model and its different variants as a robust reference model for determining the effectiveness of VTLE and LMS as environments where certain mediating variables can determine PL (Murillo et al., 2021).

Limitations

This study has several limitations, primarily related to methodological aspects. For instance, the sample size, although adequate, could be larger in future explorations to ensure greater representativeness by including more private and public institutions in the Dominican Republic. Another concern is the imbalance of gender representation among study participants. In this case, female participants accounted for nearly 75% of the total sample, which led the researchers in a previous study (Rodríguez-Sabiote et al., 2023) to conduct a confirmatory factor analysis on the administered scale, examining gender invariance. The results indicated that the factorial structure is similar for men and women. Therefore, it can be concluded that the scale is consistent, valid, and invariant in determining PL in VTLEs within the extended TAM in the Dominican context. Another limitation encountered in this study was the difficulty comparing the conclusions with previously published research in the scientific literature, as very few studies consider PL as a criterion variable within the extended acceptance model of learning.

Implications

The use of VTLEs in distance education, research, and practice has a number of implications. Some of the most relevant ones are as follows. Regarding education, we highlight global access, time flexibility, interactivity, and multimedia. For research, we highlight access to global resources, remote data collection, and international collaboration. Finally, for practice, distance education can be useful for teleworking, lifelong learning, cost reduction, and improved work–life balance.

Data Availability Statement

The authors will provide the raw data on which the conclusions of this article are based without any reservations.

Ethics Statement

The study conducted adhered to all necessary ethical aspects. In this regard, the Ethics Committee of the "Higher Institute of Teacher Training Salomé Ureña (ISFODOSU)" ensured the anonymity of the participants, and it was ensured that none of the items on the administered scale posed a threat to the physical, psychological, and/or social profiles of the participants.

Author Contributions

Clemente Rodríguez-Sabiote analyzed and interpreted the data. Álvaro Úbeda-Sánchez, Roberto Batista-Almonte and Ana Teresa Valerio-Peña contributed to the development of the theoretical framework and data collection. All authors made significant contributions to the development and writing of this article and have conceived and designed the work.

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Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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