Reviewing ADANCO 2.3.1 for a Modern Partial Least Squares Structural Equation Model to be Used in Online Education During the COVID-19 Pandemic

Chanta Jhantasana

Faculty of Management Science, Valaya Alongkorn Rajabhat University, under the Royal Patronage, Pathum Thani 13180, Thailand

Corresponding author: Chanta@vru.ac.th

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Abstract

The current study employed a composite model to examine the factors affecting student satisfaction with online education (OE) and the relationship between it and student life quality during the COVID-19 pandemic. Additionally, the research reviewed the ADANCO 2.3.1 software for composite analysis. A sample of 257 management science students from anonymous Rajabhat University was used for this study. The findings indicate that only the factors of output and setup had a significant relationship with student satisfaction concerning OE. The relationship between student satisfaction with OE and the quality of student life was found to be significant. The ADANCO was extremely useful for doing confirmatory composite analysis (CCA) in modern partial least squares structural equation models (PLS-SEM). It was also a helpful tool for transforming latent and observable variables into emergent ones for CCA research. This study successfully resolved the standard bias method resulting in a better outcome.

Keywords: Composite model, Online education, Student quality of life, Student satisfaction

Introduction

A century ago, a statistical method known as structural equation modelling (SEM) was established (Fan et al., 2016). Most of those working in the field employ the covariance-based structural equation model (CB-SEM), which is more stable but requires a focus on modification indices, and data normalization, and can only evaluate confirmatory factor analysis (CFA). Henseler and Schuberth (2022) note that robust versions of the ML estimator and alternative estimators, such as the asymptotic distribution free estimator, were developed to deal with empirical violations of the ML estimate's assumptions. Unlike PLS-SEM, which has easy convergence and does not require normalized data, serious problems exist for both the reflective and formative models (Rönkkö & Everman, 2013). In addition, contemporary PLS-SEM exists due to the modifications made by Dijkstra and Henseler (2015 a, b); Henseler et al. (2014) to the reflective and formative models, respectively. A modern PLS-SEM may achieve the same benefits as a traditional PLS-SEM, and it can evaluate both CFA and CCA. In addition, it can use latent variable differences as an old-fashioned concept in which latent and observable indicators can be transformed into emergent variables (Hubona et al., 2021; Yu et al., 2021). This research needs to utilize latent variables that turn into emergent variables, like online education satisfaction, its dimensions, and student quality of life during the COVID-19 pandemic. To our knowledge, there are no comparable studies.

Student satisfaction with online education and quality of life are latent components typically assessed using CB-SEM and variance-based or consistent partial least squares (PLSc), which are CFA. There are numerous examples of these models in published works. Researchers can produce emergent variables from latent data using modern PLS-SEM. Research must use a mixed method to examine student quality of life and satisfaction with online education. There is various packaged software for PLS-SEM, but only ADANCO (Henseler & Dijkstra, 2017) can function efficiently with CFA and CCA; hence, we will review ADANCO in this study. This study will help people understand how to produce latent variables in composite models.

Consequently, this study's three primary aims were to review the ADANCO 2.3.1 software for emergent variables or composite models, to evaluate student satisfaction with OE, and to use a composite model to analyze the connection between student satisfaction and quality of life during the COVID-19 pandemic.

Literature review

ADANCO review for composite models

ADANCO is a graphical user interface for modeling structural equations with composites. It can implement PLS modeling, PLS-SEM modeling, and simple least squares regression utilizing sum scores. It uses consistent PLS, dominating indicators to adjust for sign uncertainty, and overall goodness-of-fit testing (Composite-modeling, 2020). PLS is a widely used technique for estimating structural equation models using latent variables. However, Rönkkö and Everman (2013) argue that PLS estimates are unreliable and that metrics such as composite reliability and average variance extracted are insufficient for detecting incorrect model specifications. Because traditional PLS-SEM models use composite variables for reflective models with no error terms in indicators, formative models use causal formative variables, and confounding interpretations have been observed (Bainter & Bollen, 2014). Dijkstra and Henseler (2015, a, b) proposed using PLSc as a latent variable measure in a reflective model utilizing the correction for measurement error attenuation to make PLS consistent (PLSc). However, PLSc only eliminates one of the two significant sources of bias in PLS that must be mitigated to reduce measurement error. However, at the same time, PLS estimates are also since they capitalize on chance; hence, finite-sample bias is inevitable (Rönkkö et al. 2015). This was put forward by Rönkkö, a Ph.D. student at the time, who identified ten top professors in this field and reported their reactions in Henseler et al. (2014). He asserts that "motivated by our critique, there have been many positive developments around PLS in recent years…" (Evermann & Rönkkö., 2021, pp124). Additionally, Rönkkö and Evermann's (2013) significant results caused a three-way split among PLS researchers

(Schuberth et al., forthcoming). The first set of scholars disregarded the problems and continued to promote and conventionally apply PLS. The second set of researchers saw no future for PLS and either discontinued its usage or strongly warned against it. A third group of academics was more positive and proposed numerous PLS advancements to address the stated problems. The first group is closely tied to the SmartPLS software (e.g., Hair, et al., 2011; Hair, et al., 2017; Sarstedt et al., 2014), while Rönkkö is the leader of the second group (e.g., Rönkkö et al., 2015; Rönkkö et al., 2016). As may be predicted, the third group includes professionals affiliated with Henseler's ADANCO program (Henseler et al., 2014; Henseler & Dijkstra, 2017). ADANCO can adequately utilize the PLSc and CCA concepts employed in PLS-SEM. However, Henseler's CCA differs significantly from a PLS-CCA (Hubona et al., 2021). As a result, SmarPLS may be more proficient in reflective techniques such as: Consistent PLS (PLSc), Weighted PLS (WPLS), Weighted OLS (WOLS), Weighted Consistent PLS (WPLSc), Confirmatory Tetrad Analysis (CTA), Importance-performance Map Analysis (IPMA), PLS Multi-Group Analysis (MGA), Finite Mixture (FIMIX) Segmentation, and Prediction-Oriented Segmentation (POS). It does not, however, contain any application-specific emergent or composite variables.

Rönkkö et al. (2016) contend that the claimed advantages of the technique are unfounded and that using PLS weights or other commonly used rules of thumb is irrational. They find that Henseler et al.'s (2014) composite factor model (CFM) is a nonsensical construct that serves no function in either methodological or practical research. Cadogan and Lee (2022) found that the PLS is incompatible with scientific realism~~,~~ but compatible with constructivism. Henseler and Schuberth (2022) contend that the various PLS types serve various purposes. These techniques can be utilized for scientific study if correctly implemented properly. Contrary to PLS advocates, PLS-SEM advocates hinder the search for truth. These proponents redefine "reflective measurement," argue against a model fit, and propose that researchers can accomplish "model confirmation". The PLSc-estimated model of Cadogan and Lee (2022) lacks a causal link between unobservable conceptual variables and data (Henseler & Schuberth, 2022).

Henseler's group work developed greater detail and advancement in CCA than in CFM (Henseler, 2017; Henseler & Schuberth., 2020; Henseler, 2021; Hubona et al., 2021; Schuberth & Henseler., 2018; Schuberth, 2021a; Schuberth et al., 2022). As for Evermann and Rönkkö (2021), they do not advocate for or against using PLS compared to other approaches. This was made evident in Rönkkö and Evermann (2013). They reviewed the current development of PLS (section 4), in which they were critical of some PLSc deficiencies. Evermann and Rönkkö (2021, p. 11) cut out see additional benefits to the PLSc, as stated in recommendation 1 that "If a researcher uses PLS for factor models (reflective), consistent PLS with measurement error correction should be used". Nevertheless, they are critical of the composite model for which Schuberth et al. (forthcoming) provided the Henseler-Ogasawara specifications (Schuberth, 2021b), allowing researchers to estimate composite models. Moreover, they agreed with Henseler (2021) that it is "a statistical method for estimating linear structural equation models" (p. 1). This viewpoint has substantial implications since it provides PLS the same status as other estimators for SEM, such as the maximum likelihood estimator (Schuberth et al., forthcoming). When all variables in a model are PLSc, confirmatory factor analysis (CFA) is possible (Henseler & Dijkstra, 2017). Additionally, in a formative model, emergent variables can be used to generate a composite model in which every construct is an emergent variable, resulting in the availability of confirmatory composite analysis (CCA) (Henseler et al., 2014).

A modern PLS exists if it can handle CFA and CCA, a feat that few software packages, including ADANCO, can accomplish. However, ADANCO is very user-friendly. The author is aware of the overall model fit that a CCA (Schuberth et al., 2022) and a CFA can yield, as well as the discriminant validity that inspired the development of the HTMT (Henseler et al., 2015) and HTMT2 (Roemer et al., 2021). ADANCO (Henseler & Dijkstra, 2017) can handle composite models, common factors, MIMIC, single-indicators, and categorical exogenous variables. Standard factor models employ mode A for weighting, while composite models use mode A, mode B, and sum scores. Mode B uses non-multicollinearity data, whereas mode A uses multicollinearity. The sum scores calculate construct scores as the total of standardized indicators multiplied by a scaling factor.

Table 1 Criteria for quality of the composite model

Model	Statistics	Criteria
Total model fit	1. SRMR, d_G, d_{ULS}	less than HI99
	Or 2. SRMR	less than 0.08
Measurement model	Nomological validity	It is valid if the model fits.
	Reliability	Equal to 1
	Weight	Sign+
		Significance (t-statistic equal or more than 1.96)
		Statistically insignificant items with values greater than 0.5 can be retained. They should be removed if the value is less than 0.5 and insignificant.
	Multicollinearity	Items with a VIF greater than 5 must be removed.
		Items with VIF of less than 5 are retained.
	Common Method of Bias	Items with VIF of less than 3.3 are retained.
Structural model	*P*-value	Less than 0.05
	t-statistics	More than 1.96
	R^2	0.25, 0.50 and 0.75 refer to weak, moderate and substantial, respectively
	f^2	0.02, 0.15 and 0.35 refer to weak, moderate and strong, respectively

Quality of Emergent Variables

Generally, the models are called confirmatory factor analysis in covariance-based structural equation models. They follow specific steps: model specification, model identification, model estimation, and model assessment which CCAs (Henseler et al., 2014; Henseler, 2017; Henseler et al., 2018; Schuberth et al., 2018) do. However, covariance-based SEM quickly recognized the importance of identified models. The applied statistical technique can generate high quality estimates for the model parameters only after the model has been identified. On the other hand, variance-based structural equation models do not have identification issues, as the existing software packages limit the models that are allowed to those that are theoretically identified (Henseler, 2017). The CCA used in this study consisted of three components: model fit index, measurement model, and structural model.

The model was fitted using a saturated and an estimated model. ADANCO 2.3.1 contains model fit tests that use bootstrapping to assess the chance of generating a high disparity between the empirical and model-implied correlation matrix for the sample in question (Dijkstra & Henseler, 2015a). All variables are orthogonalized using the model's correlation matrix. Suppose the discrepancy scores are more significant than 5%. In that case, the sample data is assumed to come from a population that behaves predictably. Hence, the model must be accepted (Henseler & Dijkstra, 2017). ADANCO generates models that are estimated and saturated. Saturated models are ones in which the analyst defines the construct measurement but allows all constructs to correlate freely; both models are equivalent if the endogenous constructs in the structural model form a complete graph. Saturated models can be used to assess the quality of measurement models, as a model mismatch is caused by the misspecification of measurement models (Henseler & Dijkstra, 2017). Gefen et al. (2011) argue that the theoretical model must be compared to the saturated model, which includes all possible paths, to confirm that (1) significant paths remain significant in the saturated model, and (2) adding paths does not significantly raise f^2. The standardized root mean squared residual (SRMR), the geodesic discrepancy (d_G), and the unweighted least squares discrepancy (d_{ULS}) are used to determine the total model fit. The SRMR is more sensitive and effective than the "goodness-of-fit" criterion (GoF,Tenenhaus et al., 2005). The quality criteria are that the value of those three parameters should be lower than the bootstrap at 95 percent (HI95) or 99 percent (HI99) or the SRMR should be less than 0.08. (Hu & Bentler, 1999).

For the measurement composite models, Muller et al. (2018); Henseler (2017) propose the following parameters for evaluating the quality of a composite model:

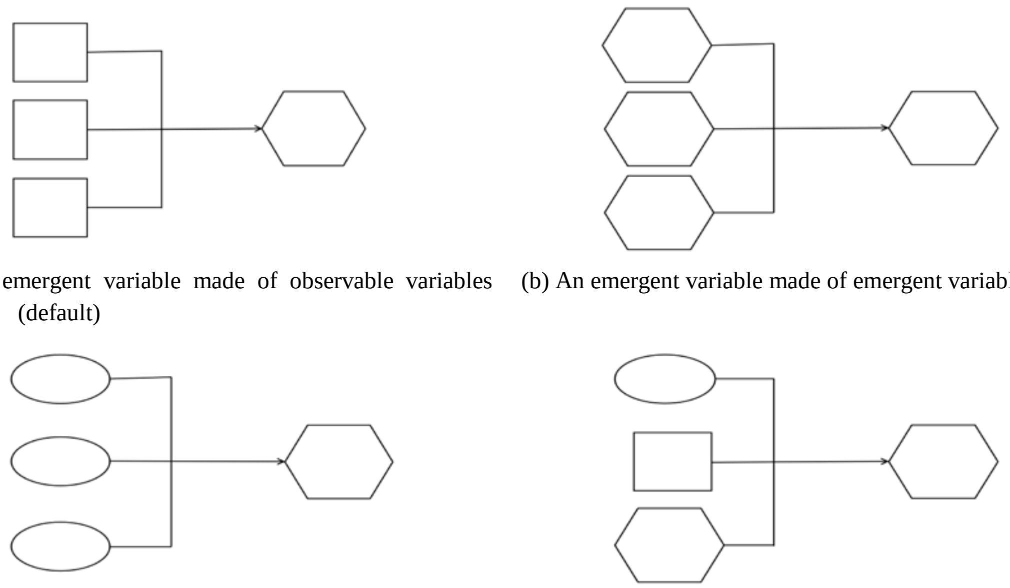
(1) Nomological validity;

(2) Reliability; and

(3) Weight (composition)

To determine nomological validity and result model fit, the composite model must have a minimum of two antecedents or consequences (Muller et al., 2018). As for reliability, ADANCO's default value is 1, although any value can be selected. However, because the composite's indicators are assumed to be measurement error-free, the composite's reliability is equal to one (Muller et al., 2018). As for weight, the significance, size, and sign of estimated weights need to be determined (Henseler, 2017). The multicollinearity of indicators within a composite model is essential since it may result in unexpected signals and large bootstrap confidence intervals when mode B is used (Muller et al., 2018). In practice, it is essential to determine whether or not to include or remove an indicator from the model. Jhantasana (2022) employed general formative criteria to identify the significance of indicator weights with t-statistics equal to or greater than 1.96. Additionally, items with loadings greater than 0.50 should be kept regardless of relevance. If the loading is less than 0.5 and statistically insignificant, it should be removed; if it is less than 0.5 but statistically significant, it should probably be removed (Russo & Stol, 2021). Another feasible method for improving model fit indices, mainly when mode B is utilized, is to investigate multicollinearity using cut-off indicators with a variance inflation factor (VIF) greater than 5. However, to account for the common method variance, the VIF must be smaller than 3.3 (Kock, 2015).

For structural models that demonstrate relationships between composite models, the most critical feature is that the path is significant, as indicated by a t-statistic greater than 1.96 or a p-value less than 0.05. R^2 values of 0.25, 0.50, and 0.75 refer to weak, moderate and substantial, respectively (Hair et al., 2011), whereas f^2 values of 0.02, 0.15, and 0.35 refer to weak, moderate, and vigorous (Cohen, 1988). Table 1 summarizes all the fit indices for the overall measurement~~,~~ and structural models. The sample size used for statistical inferences was calculated using the bootstrap method on 4,999 samples (Benitez, et al., 2020).



(a) An emergent variable made of observable variables (default)

(b) An emergent variable made of emergent variables

(c) An emergent variable made of latent variables

(d) An emergent variable made of different types of variables

Figure 1 Emergent variables made up of different components
Source: Yu et al. (2021)

How to Construct Emergent Variable

Only some scholars (She et al., 2021; Schijns, 2021) have used PLS-SEM to examine the factors determining student satisfaction with online education and its relationship to the quality of university student life. No scholar has employed a composite model. Following Hubona et al. (2021), Jhantasana (2022) created emergent variables from attitude or behavior variables. When models are sophisticated, PLS-SEM performs well with small sample numbers (e.g., Hair et al., 2017; Sarstedt et al., 2016). Jhantasana (2022) also demonstrated that when constructing a composite model using such variables, a composite model is more suitable than consistent partial least squares (PLSc), particularly for small sample sizes.

As indicated in Figure 1, emergent variables can comprise three variables: observable variables, other emergent variables, latent variables, or any combination of these (Schuberth et al., 2020; van Riel et al., 2017; Yu et al., 2021). For second-order constructions, observable and emergent variables may be used in a formative model, whereas latent variables should be used in a reflective model (Jhantasana, 2022; Schuberth et al., 2020; van Riel et al., 2017). Yu et al. (2021) encouraged additional research into emergent variable models; this should enable the examination of behavioral concepts several contexts, including latent growth curve modeling (e.g., Muthén & Curran, 1997) and multilevel modeling (e.g., Rabe-Hesketh et al., 2004).

Hierarchical Construct Model (HCM)

An HCM can be constructed using four approaches and four types of models. The approach is: repeated indicators, two-stage, hybrid, and three stage (van Riel et al., 2017). The four types are: reflective-reflective, formative-reflective, reflective-formative, and formative. The first term in an estimation type's name refers to a lower-order construct. In contrast, the final word refers to a higher-order construct. According to prior research on higher-order constructs in PLS-SEM, the reflective-reflective and reflective-formative higher-order types are prevalent across various different disciplines of study (Becker et al., 2012; Cheah et al., 2019; Ringle et al., 2012; Sarstedt et al., 2019). While the formative-formative type is less prevalent, it is used with HCM in traditional PLS-SEM with no corresponding composite model. When emergent variables are used to construct the model, a formative-formative type or composite of composite must be used (Schuberth, 2021a). Van Riel et al. (2017) used a three-stage approach to construct composite or emergent variables from a common factor (PLSc). Thus, due to the inherent nature of the variables, higher-order constructions relying on latent variables should be modeled reflectively, whereas when they rely on emergent variables, they should be modeled formatively (Henseler, 2017). The way to construct an HCM type should be based on variables that are emergent or latent (PLSc). Examples of this are provided in Figure 1. In (b), one should employ a formative-formative type, whereas in (c), one should employ a reflective-formative type. In (a), the variable acts as an emergent variable or a formative-formative type, but in (d), a mixed variable type is used. ADANCO employs a straightforward current PLS-SEM that is suitable for academic applications.

Online education satisfaction determinants

The COVID-19 pandemic has impacted world economics (Dhawan, 2020), altering several types of businesses, including higher education (Rashid & Yadav, 2020). As a result of the pandemic, 850 million children and adolescents — nearly half of the world's student population – were forced to miss school and university (UNESCO, 2020). Most educational institutes use online education (OE) platforms to maintain academic activities. However, technical constraints such as device suitability and bandwidth availability presented significant difficulties, particularly in developing countries (Muthuprasad et al., 2021). Almost all Rajabhat Universities lack a commitment to OE, rendering any OE environment ineffective. Due to the inability to construct and grow courses using OE concepts throughout the pandemic phase, this OE experience was classified as emergency remote teaching (ERT) rather than successful OE (Bond et al., 2021; Bozkurt et al., 2020; Erlam et al., 2021; Hodges et al., 2020, March 27). Eventually, global face-to-face teaching, and OE become increasingly combined (Hodges et al., 2020, March 27). Transferring face-to-face classes to online environments on a tight timeline has proven challenging for educators and students unfamiliar with these platforms (Sahu, 2020).

Both synchronous and asynchronous classrooms can use online education. Synchronous classes are delivered in real time with students and instructors from all over the world. Asynchronous classes offer a more flexible schedule because students can access course materials at different times and locations. The OE of Rajabhat University consists of synchronous classes, making it an ERT system with fewer asynchronous classes. A complex network of interacting factors in OE affects the university student's quality of life (QoL) and learning (Davy et al., 2000). QoL is one of the essential indications of effective adaptation to life and may enhance health, lifespan, and social connections (López-Ortega et al., 2016). El-Hassan (2014) stated "student perceived quality of life or life satisfaction is a component and a key indicator of a student's subjective well-being". As a result, public education, including OE efforts targeted at specific demographics, may help not just scholastic accomplishment, but also QoL for our young citizens. However, there was a lack of investigation into the variables affecting life satisfaction during the coronavirus pandemic, particularly among university students (Rogowska et al., 2021).

Universities' fundamental objective is to produce valuable products for students and to promote student satisfaction (Basuony et al., 2020). Student satisfaction is crucial and must be considered when evaluating course performance, as it correlates with improved engagement, motivation, learning, and success (Wickersham & McGee, 2008). Scholars look at a variety of indicators to determine student satisfaction with OE. Volery and Lord (2000) identified three critical criteria affecting the success of online education: 1) technological factors, including ease of access and navigation, interaction level, and interface design; 2) instructor characteristics, including attitude toward students, teaching style, technical competence, and ability to foster classroom interaction; and 3) student characteristics, including prior use of technology from the student's perspective. Sumi and Kabir (2021) assessed student satisfaction using the SERVQUAL model, reliability, responsiveness, assurance, empathy, and website design. Nashaat, et al. (2021) looked into the factors that influence student satisfaction with OE, and the relationship between student satisfaction and student commitment. Ranadeva et al. (2021) used OE efficiency to determine student satisfaction. It consisted of five determinants academic issues, accessibility issues, technological skills, mental well-being, and lecturer commitment. Concerning the influence of OE system efficacy, Alenezi (2022) separated online education quality and based it on system quality, information quality, service quality, technical support quality, course design quality, and learner quality. She et al. (2021) determined OE satisfaction with interaction, learner self-efficacy, and student engagement using a partial least square structural equation model (PLS-SEM). Elshami et al. (2021), on the other hand, assessed both student and instructor satisfaction with OE. The factors that determined student satisfaction were the instructor, the technology, the setup, the interaction, and the outcome, all of which encompass aspects of OE. Thus, the current study developed the following hypotheses;

H1: Interactions between the student and the instructor correlate positively with online education.

H2: Instructor correlates positively with online education.

H3: The output of online education correlates positively with online education.

H4: The technology of online education correlates positively with online education.

H5: The setup of online education correlates positively with online education.

Quality of life of university students & COVID-19

A complicated network of interacting variables various of detrimental effects on the quality of life and learning at a university. Accommodations, supportive relational networks, financial obligations, and various other factors positively or negatively contribute to a student's well-being and ability to cope with academic challenges (Davy, et al., 2000). The COVID-19 pandemic altered educational landscapes worldwide, with traditional education being phased out in favor of online education to prevent infectious disease transmission through social interaction. This may have affected all student scenarios, including students' lifestyles, grades, academic achievements and quality of life. Life satisfaction, self-esteem, health, and functionality are four critical components of QoL that may be defined and quantified by various methods (Vaez et al., 2004), all of which are especially relevant in light of the COVID-19 pandemic. As expected, studies conducted during the COVID-19 pandemic revealed significant declines in well-being and, in particular, life satisfaction (Aslan et al. 2020; Bodys-Cupak, 2021; Rogowska et al., 2020; Rogowska et al., 2021). In general, satisfaction with life arises from various benefits, including increased positive social interactions, social support, marital satisfaction (Pavot & Diener, 2008), job performance, career satisfaction, organizational commitment, and improved physical health. While students with higher levels of life satisfaction tend to be more satisfied with their academic experiences (Duffy et al., 2012), academic self-efficacy, perceived progress toward goals, and decreased academic stress (Ojeda et al. 2011) generally result in higher grade point averages (Rode et al., 2005). Mitreva et al., (2020) identify student life quality as a critical factor affecting students' future personal and professional achievements. Algahtani et al. (2021) used 12 items from the World Health Organization Quality of Life Instruments (WHOQoL-BREF) to assess QoL during the COVID-19 pandemic. The WHOQoL-BREF is a measurement tool used to compare health-related QoL across a wide range of disorders and illnesses and to show the effectiveness of various QoL therapies (Guyatt et al., 1993).

Scholars have examined student satisfaction with OE about a variety of variables, including internet addiction (Besalti & Satici, 2022), student commitment (Ranadeva et al., 2021), life satisfaction (Narakornwit et al., 2019), perceived student performance, engagement (Rajabalee & Santally, 2020), willingness to make recommendations (Schijns, 2021), and quality of college life (Sirgy et al., 2007). Additionally, Sirgy et al. (2007) have researched OE satisfaction and student well-being, including quality of life, satisfaction with academic elements of the institution, and satisfaction with the social aspects of the college. However, there more investigation needs to be done into the relationship between OE satisfaction and student quality of life during the COVID-19 pandemic. Thus, this study aimed was to ascertain the students' quality of life during the COVID-19 pandemic, as determined by OE satisfaction. As such, the following hypothesis was developed;

H6: Online education is related to the quality of student life during the COVID-19 pandemic.

Interactions between the students and instructors, instructors, the output of online education technology, and the setup of online education were generally positively correlated with online education. In addition, online education was connected to the quality of student life during the COVID-19 pandemic.

Rajabhat Universities

Before changing their names to Rajabhat Institutes, they were known as provincial teaching colleges. These colleges were referred to in 2005 by king Rama 9's given name, Rajabhat University. There are 38 Rajabhat Universities in Thailand, each of which is a separate legal entity. The university council administers these universities and typically has less stringent entrance requirements than other public universities. Before COVID-19, none of the Rajabhat universities was fully prepared for OE. Consequently, during the COVID-19 pandemic, all Rajabhat universities immediately transitioned to OE, employing ERT.

Conceptual framework

The study examines five determinants of student satisfaction with online education and its relationship to student quality of life during the COVID-19 pandemic by utilizing emergent variables constructed from latent variables. To our knowledge, studies have yet to be conducted incorporating emergent variables into this model. Figure 1 illustrates the method for converting latent and observable variables into emergent variables, while Figure 2 depicts the conceptual framework and hypothesis.

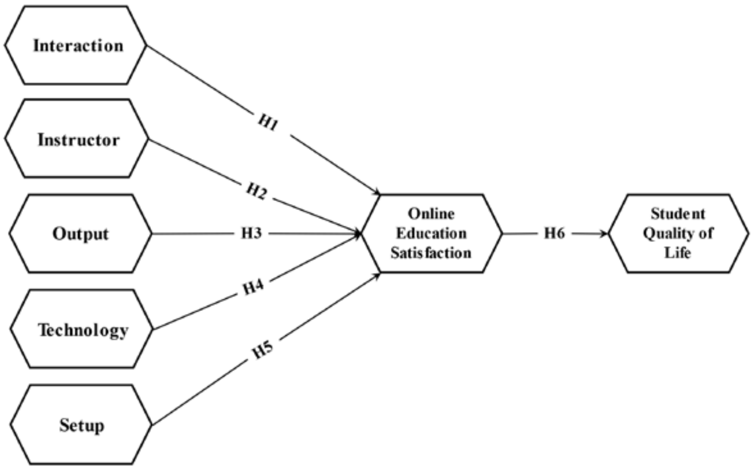


Figure 2 Hypothesis and conceptual framework

Methodology

Population & sample

The population of this study was approximately 2,350 students in the faculty of management science. The sample size was determined using the Soper (2022) method based on a webpage. This program was used to determine the sample size for a structural equation model with five parameters: effect size (0.15), statistical power (0.80), number of emergent variables (7), number of indicators (36), and probability (0.05). These parameters gave roughly 109 outcomes as a minimum sample size required for the model structure. For this study, 257 were collected via a Google form.

Questionnaire

Two authors developed the questionnaire: Elshami et al. (2021) for student satisfaction with online education and Algahtani et al. (2021) for quality of life during the COVID-19 pandemic. Elshami et al. (2021) examined the satisfaction of students and faculty members with online education. This study adapted Elshami et al. (2021)'s student questionnaire, focusing more on technology, as represented by teaching sources such as Google Class Room, Google Meet, Line, and Facebook. Quality of life during the COVID-19 pandemic examined using the Algahtani et al. (2021) questionnaire. They adopted 12 items from the World Health Organization's Instruments for Assessing Quality of Life (WHOQOL-BREF). The questionnaire employs a five-point Likert scale, with 1 indicating the most dissatisfaction, 2 indicating dissatisfaction, 3 indicating neutrality, 4 indicating satisfaction, and 5 indicating the highest level of satisfaction.

The reliability of factors instructor, technology, setup, interaction, outcomes, the total satisfaction, and quality of life questionnaires were 0.915, 0.880, 0.909, 0.936, 0.926, 0.888, and 0.869, respectively. All reliability values greater than 0.700 indicate the consistency of the result of a questionnaire, test, observation, or measurement method. It refers to the consistency of ratings across time or raters.

Table 2 Questionnaire

Concept	Variable Name	Item wording
Instructor	INST1	There was clear communication of class assignments.
	INST2	Evaluations, tests, and feedback were given on time.
	INST3	I felt a part of the class and belonged to the online session.
	INST4	I am satisfied with the faculty's accessibility and availability.
	INST5	I am satisfied with online discussion forums.
Technology	TECH1	I am satisfied with the features of Google Class Room for online education.
	TECH2	I am satisfied with the online education tools offered by Google Meet.
	TECH3	I am satisfied with the online education platform offered by Line.
	TECH4	I am satisfied with Facebook's online education features.
Setup	SET1	I am satisfied with the number of online sessions.
	SET2	Online courses offered flexible timing.
	SET3	I am satisfied with the self-directed responsibilities assigned to me. (Recorded)
	SET4	I enjoyed working on projects during online learning.
Interaction	INTER1	I am satisfied with the quality of the interactions between me, the faculty and, my peers.
	INTER2	I am satisfied with the collaborative activities during online learning.
	INTER3	I can relate my level of understanding to that of other students.
	INTER4	I am comfortable with participating in online sessions.
Outcomes	OUTP1	I am satisfied with the level of required effort in online courses.
	OUTP2	I am satisfied with my performance in online courses.
	OUTP3	I am satisfied with my final grade.
	OUTP4	I can apply what I learned in this online course.
Total Satisfaction	SATIS1	I will recommend this online learning experience to others.
	SATIS2	I am more satisfied with online learning than with face-to-face sessions. (Recorded)
	SATIS3	My satisfaction level encourages me to register for other available online courses.
Quality of life	QOL1	How would you rate the impact of the COVID-19 pandemic on your quality of life?
	QOL2	How would you rate the impact of the COVID-19 pandemic on your general health?
	QOL3	How would you rate the impact of the COVID-19 pandemic on your feelings of being safe in your daily life?
	QOL4	How would you rate the impact of the COVID-19 pandemic on your physical environment?
	QOL5	Keeping in mind the impact of the COVID-19 pandemic, was the information needed in your daily life now available to you?
	QOL6	How would you rate the impact of the COVID-19 pandemic on your income?
	QOL7	How would you rate the impact of the COVID-19 pandemic on your access to health services?
	QOL8	How would you rate the impact of the COVID-19 pandemic on maintaining a relationship with your friends?
	QOL9	How would you rate the impact of the COVID-19 pandemic on maintaining a relationship with your family?
	QOL10	Considering the impact of the COVID-19 pandemic, how satisfied were you with the support you got from your friends?
	QOL11	To what extent does faith give you comfortable with the hard times of the COVID-19 pandemic?
	QOL12	How would you rate the impact of the COVID-19 pandemic on your spiritual connections/practices?

Results

Sample information

The data of this study were collected from students enrolled in the faculty of management science of an anonymous Rajabhat university. The sample consisted of 257 individuals, of which approximately 77% were male. Approximately 24%, 28%, and 33% are registered in years 1, 2, and 3, respectively. They studied the majors of general management, business administration, and accounting, respectively, about 36%, 21%, and 23% of the total. Almost 55 % earned less than 7,000 baht monthly, and 62% were regular semester students. Table 3 shows the data.

Table 3 Sample information

Variables	Details	Amount	Percentage
Gender	1.Female	60	23.30
	2.Male	197	76.70
Education	1.Year 1	61	23.70
	2.Year 2	71	27.60
	3.Year 3	85	33.10
	4.Year 4	40	15.60
Major	1. Tourism Management	-	-
	2. General Management	92	35.80
	3. Modern Retail Business Management	14	5.40
	4. Logistic and Supply Chain Management	25	9.70
	5. Business administration	55	21.40
	6. Accounting	58	22.60
	7. Digital Business	8	3.10
	8. Communication Art	5	1.90
Income per month	1. Lower or equal to 7,000 baht	140	54.50
	2. 7,001-10,000 baht	31	12.10
	3. 10,001-13,000 baht	32	12.50
	4. 13,001-16,000 baht	25	9.70
	5. More than 16,000 baht	29	11.30
Type	1. Regular semester students	158	61.50
	2. Supplementary class students	99	38.50

Total model fit

Model fit tests employ bootstrapping to ascertain the likelihood of generating a correlation matrix discrepancy as large as the one seen between the empirical and model-implied correlation matrix for the sample in question. The results revealed that the saturated model’s SRMR, d_{ULS}, and d_G values are less than the 99^{th} percentile bootstrap value (HI99), suggesting that the hypothesized model is accurate or that the data fit the model.

Table 4 Total model fit

	Saturated Model		
Parameters	**Values**	**HI95**	**HI99**
SRMR	0.041	0.038	0.042
d_{ULS}	0.558	0.472	0.584
d_G	0.405	0.363	0.404

Measurement model

The quality of a measurement model is determined by its nomological validity, reliability, weight relevance, and lack of multicollinearity (mode B). The model fit index suggests that the nomological net is valid, whereas the reliability is one. When analyzing VIFs, one must ensure that all indicators are less than 3.3 and that the study recognizes of common methods variance. Most of weight indicators were statistically significant exceptQOL7, QOL8, QOL10, QOL11, QOL12, INST1, and SET1. A loading value of more than 0.5 indicates that each item in the model can be retained. By removing indicators with a VIF more significant than 3.3, the remaining indicators within the same construct get greater relevance. The results indicate that the remaining indicators can appropriately define their emergent variables.

Table 5 Measurement model of CCA

Indicator	Loading	Weight	t statistic of weight	VIF
Student quality of life				
QOL5	0.765	0.421	2.044	1.315
QOL7	0.786	0.349	1.385	1.695
QOL8	0.725	0.213	0.710	2.359
QOL10	0.688	0.044	0.153	2.530
QOL11	0.667	0.195	0.831	1.976
QOL12	0.754	0.118	0.469	2.402
Instructors				
INST1	0.831	0.213	1.762	2.316
INST3	0.883	0.317	2.850	2.537
INST4	0.869	0.266	2.144	2.503
INST5	0.883	0.353	3.274	2.313
Technology				
TECH1	0.857	0.372	3.580	2.012
TECH3	0.930	0.466	3.984	2.590
TECH4	0.799	0.311	3.285	1.732
Setup				
SET1	0.850	0.157	1.685	3.010
SET2	0.854	0.220	2.431	2.845

Indicator	Loading	Weight	t statistic of weight	VIF
SET3	0.857	0.233	2.249	2.504
SET4	0.949	0.504	4.880	3.026
Interaction				
INTER2	0.945	0.568	6.519	2.330
INTER4	0.928	0.499	5.448	2.330
Output				
OUTP1	0.871	0.210	2.450	2.827
OUTP3	0.885	0.360	3.702	2.302
OUTP4	0.948	0.526	5.477	2.987
Student satisfaction with online education				
SATIS1	0.945	0.523	6.162	2.676
SATIS2	0.888	0.324	3.750	2.536
SATIS3	0.866	0.252	3.414	2.517

Structural model

The values of the t-statistic, Cohen's f^2, and *p*-value were all substantial enough to show a significant path coefficient. There is a relationship between interaction, output, set up, and satisfaction with online education and student quality of life and satisfaction with online education. As a result, hypotheses H3, H5, and H6 are supported, as shown in table 6 and figure 3.

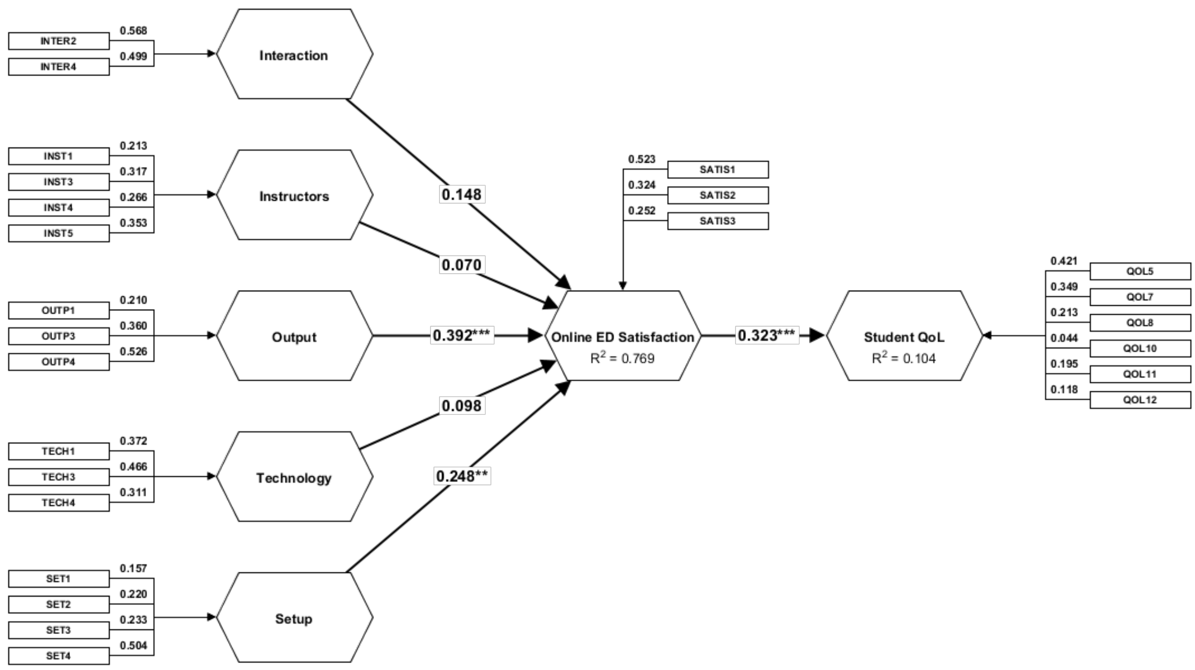


Figure 3 Results of structural model

Table 6 Hypothesis

The effect	Beta	Standard error	t-value	p-value	Cohen's f^2	Hypothesis
H1: Interaction -> Online ED Satisfaction	0.148	0.092	1.611	0.107	0.024	Not supported
H2: Instructors -> Online ED Satisfaction	0.070	0.055	1.266	0.205	0.008	Not supported
H3: Output -> Online ED Satisfaction	0.392	0.084	4.648	0.000	0.168	Supported
H4: Technology -> Online ED Satisfaction	0.098	0.060	1.634	0.102	0.015	Not supported
H5: Setup -> Online ED Satisfaction	0.248	0.079	3.133	0.002	0.056	Supported
H6: Online ED Satisfaction -> Student QoL	0.323	0.066	4.872	0.000	0.116	Supported

Discussion

This study's primary objective was to review ADANCO, which the creators developed based on the advancement of PLS-SEM, making it capable of working with CFA and CCA. However, this study only focused on CCA. The study investigated the factors affecting student satisfaction with online education and the relationship between student satisfaction and student quality of life during the COVID-19 pandemic through emergent variables. According to the data, there is a strong correlation between output and setup with online education. Student satisfaction with online education was crucial for maintaining a quality lifestyle throughout the COVID-19 pandemic.

ADANCO and Composite model: ADANCO is one of the few simple programs for common factors (PLSc) and emergent variables, which are analyzed as CFA and CCA, respectively. Compared to GSCA, and cSEM, which use an R environment, ADANCO is easier. Constructing emergent variables from latent variables is not only achievable but also better, according to Yu et al. (2021), Hubona et al. (2021), and Jhantasana (2022). This investigation has generated emergent variables from attitude, as shown in Figure 3 (c). When PLSc fails, a composite model can be utilized; however, its validity is conditional on the population size and composition. Power analyses should consider the model structure, expected effect sizes, and degree of significance when calculating the sample size (e.g., Marcoulides & Chin 2013). This study calculates the adequate sample size, including statistical power, using Soper (2022), a five-parameter calculation. The creators of ADANCO (Henseler & Dijkstra, 2017) are not only PLS expert who presents PLSc and CCA.

For online education to be effective, its five dimensions must be positively related to student satisfaction with online education at a statistically significant level; otherwise, it is ERT. No significant associations between interaction, instructor, and technology and online education satisfaction were discovered in the study, demonstrating that the university was offering ERT rather than effective online education. ERT is unusual in that it is an unplanned practice that requires the utilization of any available offline and online resources (Bond et al, 2021) and a quick response to an emergent situation (Misirli & Ergulec, 2021), such as the COVID-19 pandemic. The pandemic made it necessary to have ERT, in contrast to an effective online education environment established for instructors, students, and parents (Misirli & Ergulec, 2021). This Rajabhat university more in terms of effective online education prior to the COVID-19 pandemic, which resulted in several determinants, such as technology and instructors, having little effect on overall satisfaction with online education. Although~~,~~ the Rajabhat did not have an online education platform, the instructors could use any of the freely available technologies on the internet, such as Google Classroom, Google Meet, the Line application, or Facebook. Unfortunately, the instructors needed more preparation for online material and knowledge acquisition training. The results contrast with Eom & Ashill's (2018) findings of a study done at a university in the Midwestern United States which was well prepared. Jiménez-Bucarey et al. (2021) conducted a study on online education satisfaction in Latin America involving 1,430 students at a school of medicine. They discovered that all of the indicators, including instructor quality, technical service quality, and service quality, had an influence. There is a substantial correlation between these determinants and student satisfaction. Three important criteria for online education success have been identified: technology, instructors, and the students' prior knowledge of technology. Additionally, the instructors will continue to play a critical role in online education, mainly as catalysts for learning and knowledge navigation (Volery & Lord, 2000). Thus, assuming the current findings can be applied to most or all Rajabhat universities, it can be assumed that their online delivery strategies must be redesigned in consultation with the faculties, the students, and the administrators.

Concerning student quality of life: researchers (Aslan et al., 2020; Bodys-Cupak et al., 2022) discovered increased perceived stress and mental health concerns among university students during the COVID-19 pandemic, which negatively impacted student life quality. Sirgy et al. (2007) examined the quality of student life as determined by their satisfaction with college facilities and essential services, with academic and social satisfaction as mediators. Their results confirm our study, with all four hypotheses shown to be true.

Limitations of the study: There are several drawbacks to this study. One is that the study was conducted using a single university faculty. It is a fact that ERT is commonly used in practically every university around the world, and so this Rajabhat is likely the same as other universities. The results could effectively be generalized to all Rajabhat universities, provided data were drawn from a sample representing all 38 Rajabhat universities.

Further research: Future studies are recommended as a result of this study. First, future studies should quantify the characteristics of effective online education and ERT to differentiate them and determine how to improve the efficiency of online education. Second, future studies could compare CFA and CCA and could be applied to other Rajabhat universities using the same scenario as this research. Third, although the t-statistics, path coefficients, p-values, and effect size (f^2) showed a strong correlation between student satisfaction and student life quality, the R-squared (R^2) value was only about 10.40 percent. The R-squared (R^2) statistic indicates how much of a regression model's variance is explained by independent variables; a future study should ensure a higher R^2 value. As a result, the research should gain more insight into the factors influencing university students' quality of life. This study made significant efforts to control common method variance by removing any indicators with a VIF of more than 3.3. This resulted in a very positive conclusion, indicating that future research on composite models should be cognizant of such issues.

Conclusion

This study supports Dijkstra and Henseler (2015a, b); Henseler's et al. (2014) responses to Rönkkö and Evermann's (2013) criticism. Modern PLS-SEM that can operate both CCA and CFA exist, and ADANCO is one of the few packaged software capable of doing so. This study briefly reviewed it. Also relevant to this study is the ability to transform latent, variables into emergent variables, such as student satisfaction, dimensions and quality of life. That process has not been the focus of many previous studies. The results indicate that Rajabhat university's online education was ineffective emergency remote teaching. Moreover, its significance was positively related to the student's quality of life during the COVID-19 pandemic. Finally, ADANCO is a great PLS-SEM software because it can perform both CCA and CFA and effectively transform latent and observable variables into emergent variables. Its creator is a PLS group leader who actively responds to new developments.

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