Interdisciplinary Research in Education
Volume 10, Issue 1, 2025: 103-113
DOI: https://doi.org/10.3126/ire.v10i1.86755

Structural Equation Modeling: Effect of VLE in Mathematics Learning

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Keywords
SEM-Structural Equation Modeling, VLE-Virtual Learning Environment, Learning Style, Learning Engagement

Abstract
This research analyzes the relationships amid Virtual Learning Environment (VLE) engagement, student learning engagement, student learning styles, and mathematics achievement. The focus has been given on both the process and result, using a Structural Equation Modeling (SEM). The data were collected from 126 master's level students enrolled in a Differential Geometry course at university campus, Central Department of Education, in the academic year, 2017. The data was elicited by using the tools: mathematics achievement test (MAT), Felder-Silverman developed students learning style index (SLS), questionnaire for students perceive learning engagement (SLE), Moodle based VLE log data, and students final test score. As per the finding of the study, VLE engagement and Test score demonstrated an acceptable to good fit with following statistical value, CFI = 0.96, TLI = 0.93, RMSEA = 0.09, SRMR = 0.08, in which statistically significant factor loadings supported the observed variables' representation of their latent constructs. The study has provided a foundation for further structural analysis, in measuring the constructs as model in educational contexts.

Introduction

In this 21st century education, the goal of mathematics education is to understand learner and improve their performance, get them interested in mathematics and apply student centered pedagogical approaches. However, mathematics is often perceived as a challenging and anxiety-inducing subject for many students (Yunarti et al., 2024). The academic success of learners is significantly impacted by teaching strategies, and consistently by other factors, such as motivation, participation are to be effective for achieving quality learning (Madrilejos, 2024). While various factors—like Virtual Learning Environment (VLE), learing presence (cognitive, social and emotional), learning style have been individually linked to mathematics performance.

In order to understand the relationship among the variables on mathematics performance, Structural Equation Modeling (SEM) emerges as a powerful and appropriate multivariate analysis technique. This "second-generation" statistical method allows researchers to simultaneously test and estimate relationships between latent variables, that cannot be directly observed on indicator (or observed) variables (Khairi et al., 2021).

SEM is a statistical technique to analyze relations among observed and latent variables. It is also called correlation structure analysis or covariance structure analysis (Cheung, 2015; Whittaker & Schumacker, 2022). In SEM, an observed variable is something that can be directly measured or observed in dataset. For example, all variables reported in this research are observed variables. These variables include VLE course hits (CH), VLE days accessed (DA), VLE timestat (timestat), VLE resource accessed (RA), and students perceived emotional engagement (EE). Similarly, other variables are social engagement (SE), cognitive engagement (CE), students perceived learning style active-reflective (AR), sensing-intuitive (SI), visual-verbal (VV), and sequential-global (SG). Students' APOS based learning processes are considered in this research. These include action (A), process (P), object (O) and schema (S). The research also includes students' mathematics test score on the exam of projective geometry (PG), differential geometry (DG), VLE test score (VLE), and mathematics achievement test (MT).

In SEM, a latent variable (also called a construct or factor) is a concept or characteristic that cannot be directly observed or measured. Instead, its value is inferred from the patterns of responses across a set of observed variables that are theoretically related to it. For example, in this study, various latent variables are used, including VLE engagement comprising observed variables: CH, DA, timestat, and RA which is known as SVLE. The test score comprising observed variables are PG, DG, VLE, MT is known as MAT. Likewise, student learning engagement comprising observed variables are EE, SE, CE which is known as SLE, and student's learning style comprising observed variables are SI, VV, SG, AR. In aggregate, it is known as SLS. Similarly, students learning process comprising observed variables are A,P,O,S, which is known as APOS. The latent variables SVLE, MAT, SLE, SLS, and APOS are hypothetical constructs represented by a number of observed variables. Collectively, these are known as data indicators.

The SEM hypothesizes how a sets of observed variables are connected, and/ or how a sets of observed variables define number of constructs, and/ or how different constructs are connected to each other(Flores-Kanter et al., 2025). For example, this research hypothesizes that student's SVLE, SLE, SLS, APOS influences their subsequent mathematics achievement (MAT).

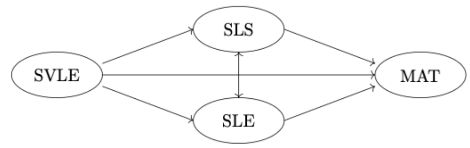

Figure1: *Hypothesized model*

In this study, the researcher has developed a model based on his research experience. The researcher aimed to test whether a set of researchers observed variables are related with the latent constructs that are empirically hypothesized to be related in the model, see Figure 1. So, the purpose of the study is to test whether the theoretical purposed model is supported by research-based sample data. SEM serves as a powerful tool for researchers, enabling them to rigorously test theoretical models (Madrilejos, 2024; Sun & Xiao, 2023).

When sample data align with a proposed model, it means the model demonstrates a "good fit" to the observed data. It indicates a close match between the model's expected covariance matrix and the sample's covariance matrix (Sun & Xiao, 2023). This "good fit" is crucial for SEM analysis and is assessed through various statistical criteria, known as goodness-of-fit indices (Sun & Xiao, 2023). A model with a good fit provides stronger empirical evidence for the hypothesized relationships between the constructs being studied. It supports for the theoretical model's validity.

Conversely, if the research data do not support the proposed theoretical model, it signals a "poor fit" (Madrilejos, 2024). This indicates that the hypothesized relationships or the overall structure of the model does not adequately represent the observed data, and the initial model may be flawed. In such cases, SEM analysis is an iterative process that necessitates a need for refinement, modification, and potentially the development of alternative models.

SEM is applicable in testing a wide range of theoretical models. In fact, many common multivariate statistical methods, such as common correlation analysis, two variate or multivariate regression analysis, ANOVA, MANOVA, factor analysis, and item response theory (Cheung, 2015; Whittaker & Schumacker, 2022).

Moreover, SEM can be based on linear regression and logistic regression, path analysis, and confirmatory factor analysis (CFA). The regression models are used to analyze observed variables, and path models can be used to analyze either observed or latent variables(Cheung, 2015; Whittaker & Schumacker, 2022; Yunarti et al., 2024).

SEM can be described using three equivalent methods: path diagrams, equations, and matrix representations. The most straightforward method involves using equations. For instance, a basic regression model can be written as:

$$y= \beta_0 + \beta_1 x + e_y$$

In addition to traditional equation-based representations, SEMs can also be expressed using path diagrams. These visual models, including path analysis and CFA are particularly useful to illustrate multilevel models, as graphical formats provide an intuitive way to depict complex mathematical relationships (Cheung, 2015).

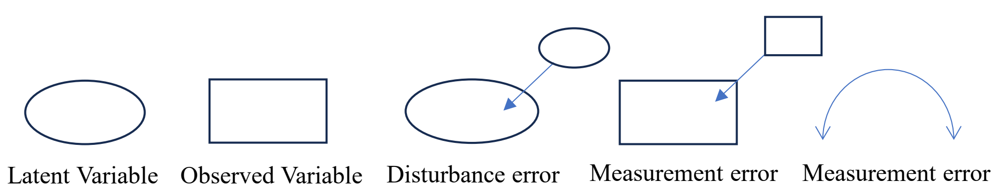

Figure 2: *Path diagram*

In SEM, latent variables are commonly represented by an oval. The observed variable is represented by rectangle. The unidirectional path is represented by a single-headed arrow. This indicates a hypothesized causal relationship or influence from one variable to another. The disturbance or error in latent variable are represented by an arrow pointing from a small circle/oval to a latent variable or similar, often implying an unmeasured cause influencing the latent variable. The measurement error in observed variable is represented by an arrow pointing from a small circle/oval to an observed variable or similar, implying unmeasured error specific to that observed measure. Similarly, correlation between variables are represented by a double-headed curved arrow between two variables or a curved arrow like.

Problem Statement

This research aims to understand and test the relationships among various constructs related to mathematics learning, specifically how VLE engagement, student learning engagement, student learning process, and student learning styles influence mathematics achievement. The core problem is to determine whether a theoretically hypothesized model, which posits causal and correlational links between purposed latent variables and their observed indicators. The next problem is to examine whether it is supported by empirical data or not to enhance mathematical performance.

This research is done because there is a problem of identifying data driven theoretical model to observe some potential variables and define their latent corresponding constructs that enhance mathematics learning. For example, this study examines whether the observed variables SVLE, SLS, APOS, MAT, and SLE contribute to the proposed model. The goal is to help both teachers and learners improve mathematics education by redesigning teaching strategies and learning approaches.

Research Question

The main research question addressed in the study is whether the interplay among the latent variables SVLE, SLE, SLS, SLP address both their correlational relationships and their direct and indirect effects on mathematics achievement (MAT).

This includes investigating how observed variables relate to and define these latent constructs, and how these constructs are interrelated with mathematics performance.

Methods

The study employs a Structural Equation Modeling (SEM) approach, which falls under the" accept-support" paradigm of statistical analysis. The purpose is not to reject the proposed theoretical model. The CFA model measures whether the model-implied covariance, in matrix form differs from the observed covariance, in matrix form. During the test, p-value ($p > 0.05$, in some cases >0.01), which is non-significant, means a good fit, otherwise not. However, chi-square can be sensitive to number of sample size, in large number of samples, even good models often get a significant in Chi-square analysis. That's why we also look at CFI, TLI, RMSEA, SRMR, which are less sensitive to sample size (Cheung, 2015; Whittaker & Schumacker, 2022).

The participants of this study were 126 master's level third semester students enrolled in a course Differential Geometry under the Mathematics Education program at University Campus, Central Department of Education in the academic year 2017.

In this study, a combined tools were used, some of which were created by the researcher himself and the others were adapted from existing instruments. The mathematics achievement test (MT) was a researcher-made tool based on APOS framework. It was designed to specifically assess the content and learning process relevant to the course “differential geometry”, being studied. The students learning style index (SLS) was adopted from the established Felder-Silverman students learning style index. The researcher used this pre-existing, validated index to measure student learning styles. The students perceive learning engagement (SLE) questionnaire was also a researcher-made instrument. It was created to capture students' perceptions of their own engagement in the learning process based on three strata: cognitive engagement, social engagement, and emotional engagement. Moodle based VLE log data were also retrieved for the study.

Theoretical Framework

In statistical analysis, two paradigms often guide hypothesis testing. They are the reject-support framework and the accept-support framework. The majority of conventional statistical techniques—including the t-test, regression models, and analysis of variance (ANOVA)—operate within the reject-support paradigm. In this approach, researchers begin with a null hypothesis, such as

H_0: $\rho = 0$ (indicating no relationship between two variables)

and aim to reject it. The general premises is that, if we reject the null hypothesis, then we accept alternative hypothesis. It is the actual assumption of the researcher.

On the other version, SEM model with CFA utilizes accept-support approach. This means, the researcher(s) proposes a hypothesis and test whether this hypothesis fits observed data without statistical difference. For example, in this case, null hypothesis will be

H_0: $\Sigma = \Sigma(\theta)$,

Here, the purpose or aim of the formation of null hypothesis is to retain on the null hypothesis. This kind of assumption is discussed in a literature, which says that “in the accept-support approach, the aim is to declare as verified for the hypothesis model” (Cheung, 2015; Whittaker & Schumacker, 2022).

In SEM, the hypothesized model fit is analyzed based on the purposed null hypothesis, assuming that all calculated covariances are zero. For example, Cheung (2015) has mentioned that “Non-Normed-Fit-Index -NNFI, is also known as Tucker-Lewis-Index-TLI, in literature. TLI evaluates relative refinement in model fit between a hypothesized model and a purposed null hypothesis” (Cheung, 2015). Chueng (2015) states that TLI is calculated as

$$TLI = \frac{\chi^2_B/df_B - \chi^2_T/df_T}{\chi^2_B/df_B - 1}$$

This TLI index represents the proportionate refinement in the chi-square value over hypothesized model relative to the tested model. The value of TLI, in general, ranges from 0 to 1, but sometimes TLI value can exceed this range. In the literature, it is found that the TLI value of 0.90 or higher, in general, represents acceptable of quite fit of the model.

Similarly, Comparative-Fit-Index-CFI is another fit index of SEM. This CFI is also related with the value of TLI, but CFI ranges in the interval [0, 1]. According to the literature, Cfi is computed as:

$$1 - \frac{\max\left(\chi_T^2 - df_T\right),0)}{\max\left(\chi_T^2 - df_T\right),\left(\chi_B^2 - df_B\right),0)),} =$$

In the literature, it is mentioned that, in general, CFI value more than 0.95 represents a good fitness between the hypothesized model and observed sample data. However, Cheung (2015) has reported that the CFI value which is more than 0.90 is acceptable" (Cheung, 2015).

Another important fit statistic is the RMSEA- Root Mean Square Error of Approximation, which assesses the gap between the hypothesized model and sample data per degree of freedom. It is defined as:

As Cheung (2015) mentioned, standardized root mean square residual (SRMR) is defined as

$$\text{SRMRS} = \sqrt{\frac{\sum_{i=1}^{p}\sum_{j=1}^{i}\left(\frac{s_{ij}-\sigma_{ij}}{s_{ii}s_{jj}}\right)^2}{\frac{p(p+1)}{2}}}$$

Similarly, SRMR for a correlation structure analysis is defined as:

$$\text{SRMRR} = \sqrt{\frac{\sum_{i=2}^{p}\sum_{j=1}^{i-1}\left(\frac{r_{ij}-p_{ij}}{s_{ii}s_{jj}}\right)^2}{\frac{p(p-1)}{2}}}$$

Also, the value of SRMR<0.05 indicates that model is reasonably fit.

Results

In the beginning, Cronbach's alpha test was used to understand how reliably a set of items measures a construct (latent variable). If the items are not internally consistent, then SEM model may show poor fit or give misleading results. The following α coefficient was obtained from the study.

Table 1: *Cronbach's Alpha for Latent constructs*

Latent Variable	Cronbach's α	Remarks
VLE engagement CH, DA, timestat, RA	0.90	Accepted
Student engagement CE, SE, EE	0.62	Dropped
Learning style AR, SI, VV, SG	0.35	Dropped
Learning process Action, Process, Object, Schema	0.56	Dropped
Test score PG, DG, VLE, MAT	0.63	Modified
Test score PG, DG, MAT	0.70	Accepted
Total	0.76	

The analysis shows that the construct measuring VLE engagement (comprising CH, DA, timestat, RA) visualized perfect reliability with a Cronbach's alpha coefficient alpha = 0.9. It indicates a high level of data internal consistency. The constructs representing student learning engagement (cognitive, social, and emotional), learning style (active-reflective, sequential-intuitive, visual-verbal, sensing-global) and learning process (action, process, object, scheme) exhibited to poor data internal consistency, with alpha values of 0.62, 0.35 and 0.56 respectively. The test scores (PG, DG, VLE, and MAT) showed poor reliability, with alpha values of 0.63, when VLE removed, the test scores (PG, DG, and MAT) showed accepted reliability, with alpha values of 0.7. However, the overall alpha for all indicators combined was 0.76, which falls within the acceptable range, supports the general reliability of the measurement model.

Confirmatory Factor Analysis (CFA) models define the relationships between observed variables and underlying latent constructs (Cheung, 2015; Madrilejos, 2024; Whittaker & Schumacker, 2022). A common focus in such models is determining the number of latent factors and understanding how each factor influences its associated observed variables.

When a group of items reflects the same underlying concept, their factor loadings on the corresponding latent factor are expected to be substantial.

For instance, Figure 3 illustrates a CFA involving two latent constructs: VLE engagement (FC1) and test performance (FC2). Since this model captures only the interrelations among latent variables without specifying directional effects, it is classified as a CFA measurement model.

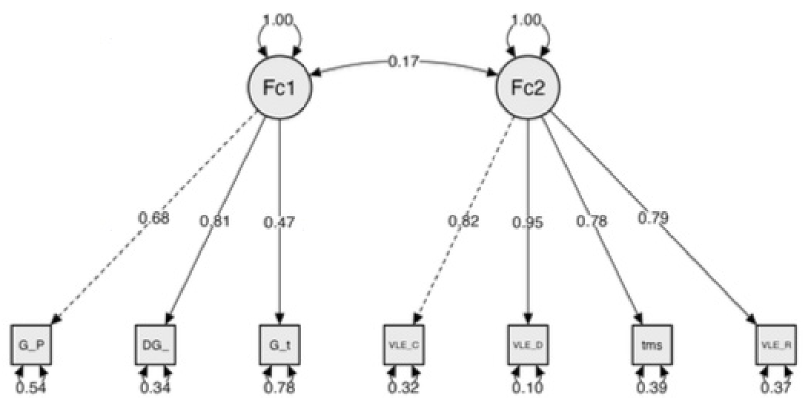

Figure 3: *Confirmatory factor analysis (CFA)*

This CFA was executed using R to evaluate the measurement model for two latent constructs VLE engagement and MAT. The VLE construct was measured using four indicators: RA, timestat (which is the actual time that student spent in VLE), DA, and CH, whereas test score was measured using three indicators (APOS, DG, PG). The CFA model demonstrates $\chi2$ (13) = 27.72, p =0.01. It measures whether the model-implied covariance in matrix form significantly differs from the data based related observed covariance matrix. A p-value ($p > 0.05$, in some cases >0.01), which is non-significant, means a good fit, in this case p = 0.0. This implies that the model somehow fit the data. However, the chi-square test can be sensitive to large sample size, even a good model often can get a significant test result in chi-square test. That's why we look at CFI, TLI, RMSEA, SRMR, which are less sensitive to sample size.

The CFA conducted using R software produced the following values: CFI = 0.96, TLI = 0.93, RMSEA = 0.09, and SRMR = 0.08. This calculated statistical value of CFI = 0.96 and TLI = 0.93indicated a satisfactory fit in the hypothesized model. In addition, calculated statistical value of RMSEA = 0.09 and SRMR = 0.08 lies close to the acceptance range. It further supports that the hypothesized model is quite fit.

In this statistical test, the calculated value of factor loadings represented statistically significant. For example, this value ranged from 0.78 to 0.95 for VLE, this value ranged from 0.53 to 0.79 for Test score. Based on the value, the results evidenced the hypothesized model indicated that "the observed variables sufficiently represent their corresponding latent variables".

Table 2: *Standardized Factor Loadings from CFA*

Latent variable	Observed variable	Factor Loading
VLE Engagement	V LECH	0.82
	V LEDA	0.95
	timestst	0.78
	V LERA	0.79
Test score	GV LE	0.23
	GP G	0.69
	Gtest	0.51
	DGposttest	0.78

Based on the analysis of this theoretical SEM model, the next phase was to estimate the parameters. This parameter estimation is a kind of comparison among sample statistics like mean, variance, covariance, which were observed from the sample data, and the statistics calculated from hypothesized model.

because there are associations as well as structure among the latent variables.

As given in the literature, the essence of this parameter comparison is "to minimize the differences in discrepancy function". This discrepancy function exemplifies divergence value between covariance matrix of observed data and covariance matrix of the model" (Cheung, 2015; Whittaker & Schumacker, 2022). The discrepancy function gives a single scalar value. This value of zero indicates perfect congruence between the observed and implied covariance, which suggest an ideal model fit. Conversely, any positive value denotes discrepancies, with larger values signifying greater divergence between the model's predictions and the empirical data. This quantitative assessment forms the basis for evaluating the extent to which a theoretical model adequately represents the observed relationships among constructs (Cheung, 2015; Whittaker & Schumacker, 2022).

Finally, the structural equation relationships, which are purposed in model, on the latent variables are tested, so they become structural equation model. For example, the SEM of VLE engagement (FC1) and MAT score (FC2) are given in Figure 4. This is SEM

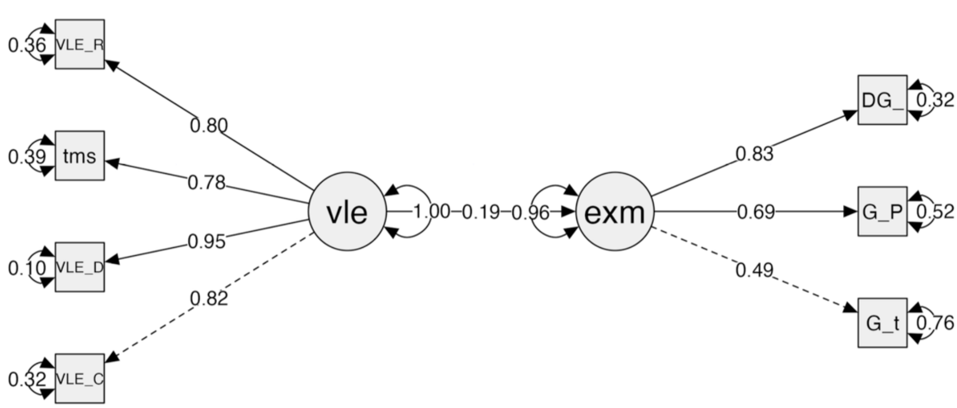

Figure 4: *Structure Equation Modeling (SEM)*

Figure 4 illustrates the results of a SEM analysis that investigates the relationship between two latent constructs: VLE (Virtual Learning Environment) and MAT (Mathematics Examination Performance). The latent variable is measured by multiple number of observed variables, with standardized regression weights indicated along the arrows. The values near double-headed arrows represent error variances.

The latent construct VLE is measured through four observed variables: RA (Resource Use, loading = 0.80), timestat (online time duration in VLE, loading = 0.78), DA (days accessed, loading = 0.95), and CH (VLE course hits, loading = 0.82). Among these, DA shows the highest loading. It indicates that highest the days accessed the virtual learning environment is the most significant contributor to students' engagement in VLE.

The latent variable MAT is defined by three observed variables, which are DG (Differential Geometry test score, factor loading = 0.83), PG (Projective Geometry test score, factor loading = 0.69), and APOS (APOS test score, factor loading = 0.49). Among these values, the highest contribution is made to MAT is DG, and the least contribution is made by APOS, in the figure, this is indicated by a dashed line.

In this study, SEM model is seen as having a perfect relationship in SVLE and MAT. The standardized coefficient of regression between SVLE and MAT was found 0.96. This represented that virtual learning environment has positive and significant contribution in students learning outcomes. Since the sample size is n=126, and regression path coefficient is strong, this study showed that effective virtual learning environments can support students learning performance.

Discussion

The aim of this study was "to investigate the interplay among the latent variables VLE, SLE, SLS, in mathematics achievement (MAT)". During the analysis of the data, initial Cronbach's alpha reliability score resulted with both strong and low level. For example, its score on VLE based learning engagement was $\alpha = 0.90$, where student learning engagement was $\alpha = 0.62$. This score on learning style was $\alpha = 0.35$, and the score for learning process was $\alpha = 0.56$. This showed that reliability score of learning style and learning process was exhibited with poor reliability score.

The finding of this reliability score is particularly on that construct which has low score. This analysis suggested that all items were not consistently correlated, which may not capture underlying latent construct. As mentioned in literature, such kinds of low reliability score may occur due to "ambiguities in the questions, cultural nuances, or the inherent multifaceted nature of these concepts" (Cheung, 2015; Creswell et al., 2018; Denzin & Lincoln, 2018; Madrilejos, 2024).

Then this analysis of CFA score on VLE engagement and MAT showed that further analysis is essential. Then in the next level analysis, the better score on VLE engagement and mathematics test score ensured a sound foundation to accept hypothesized structural relationships model. It resulted with an information that VLE can contribute in learners academic outcomes, the similar findings are also reported in my previous work (Dhakal, 2019, 2023).

Based on the data and discussing with literature, it is found that VLE serves as a valuable learning platform in this 21st era of educational delivery. It is also mentioned in a study that "this kinds of modern learning platform like Moodle, it can significantly support to enhance student learning performance" (Navarro-Ibarra et al., 2017; Phoong et al., 2020). As an author, I have also experienced that Moodle like centralized VLE is suitable for 21st century learners, which can be a "hub of learning resources and learning activities". It is also found from this research that pedagogical thoughtful use of VLE can facilitate self-paced, flexible and autonomy-based anytime anywhere learning opportunities.

It is also found that VLE use is supportive for students because while using Moodle like VLE, it is argued that "students can reuse learning materials, re-attempt learning assignments, and engage with learning content at their own learning convenience (Dhakal, 2023; Onwu Iji & Abah, 2018; Zykova et al., 2018). Furthermore, this study also suggests that VLEs is suitable to integrate diverse types of learning resources like, text, image, media and simulations. It can also offer varied learning activities like games, discussions, quizzes and other interactive exercises. It has been mentioned that "VLEs different learning resources and learning activities is useful to enrich learning process" (Becerra-Romero et al., 2019; Dhakal, 2023).

Thus, from the results and discussion of the presented data, this study found that pedagogically thoughtfully integrated VLE, for example aligning seven pedagogical principles in VLE, which is reported in a paper by Dhakal (2023), VLE can empower 21st century learners with improved learning achievement. In essence, this research has confirmed that hypothesized theoretical model is valid, which reported that student's VLE engagement (SVLE) is instrumental to excel students' mathematics achievement (MAT).

Conclusion

This study is based on SEM to understand the relationships among VLE engagement, student's learning engagement, student's learning styles, student's learning process, and student's mathematics achievement. Based on results and findings, this study confirmed that purposed model of the relationship is valid. Therefore, it is concluded that VLE engagement positively and significantly support for students' academic performance in mathematics learning. However, there is a need for future research on similar relationship to ensure the validity of purposed model so that the researcher can refine measurement tools of latent variables to improve students learning.

Recommendation

This study has found some mixed types of results, on the effect of VLE on student learning achievement. Therefore, it is recommended that future research is necessary to re-validate the effectiveness of latent variables on student achievement.

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