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Applied Structural Equation Modeling in SMARTPLS: A Beginner's Roadmap to SEM, Measurement Models, and Path Testing

Prashanna Neupane[1*], Arju Marasini[2], Govinda Jnawali[3]

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Abstract

Purpose: *This study develops a beginner-oriented roadmap for applying PLS-SEM in SmartPLS, addressing the gaps between theory and practical application.*

Methods: *Using an instructional design-based approach, simulated datasets with six latent constructs were analysed in SmartPLS 4 to demonstrate key steps in measurement validation, structural path testing and model evaluation.*

Results: *The demonstrations shows both acceptable and problematic validity outcomes, highlighting how reliability, discriminant validity and model fit can be refined. The results are pedagogical, not statistically generalizable and shows methodological learning rather than empirical findings.*

Conclusion: *This study provides novice researchers' and educators with a structured, practice-oriented guide that transforms common PLS-SEM pitfalls into learning opportunities, enhancing methodological literacy.*

Keywords: Measurement validation, Methodological guide, Pedagogical simulation, PLS-SEM, SmartPLS

JEL Classification: C30, C38, C87

I. Introduction

Structural Equation Modeling (SEM) is a cornerstone of social science, business and educational research for measuring the complex relationship among the latent constructs. Lately, the variance-based approach to SEM-Partial Least Squares SEM (PLS-SEM) has gained more attention across various disciplines as a feasible, prediction-oriented alternative to traditional covariance-based SEM (Astrachan et al., 2014; Hair & Alamer, 2022). Therefore, PLS-SEM measures both the measurement of outer model and the structural linear model to maximize explained variance, making the analysis more suited for complex models,

[1*]*Mr. Neupane is an MBA-BF scholar from Lumbini Banijya Campus, Tribhuvan University. He can be reached at neupane.prashanna2000@gmail.com, https://orcid.org/0009-0006-9000-0371*

[2]*Ms. Marasini is an MBA-BF scholar from Lumbini Banijya Campus, Tribhuvan University. She can be reached at marasiniarju010@gmail.com, https://orcid.org/0009-0002-5872-4186*

[3]*Mr. Jnawali is an Assistant Professor of Statistics at Butwal Multiple Campus, Tribhuvan University. He can be reached at jnawali.govinda@gmail.com, https://orcid.org/0009-0002-3575-5238*

developing indicators and non-normal data. As compared to CB-SEM, PLS-SEM often yields higher item loadings and composite reliabilities and can deliver solutions with much smaller samples by focusing on partial rather than full data analysis (Dash & Paul, 2021). Due to these features, PLS-SEM have made an increasingly popular: for instance, Cheah et al. (2023) stated that Smart-PLS helped many social science researchers to analyse the complex relationships between latent variables and present as a highly popular multivariate data analysis method. Despite all these explosive adoptions of SmartPLS and PLS-SEM across various multidisciplinary field, beginners still misapply the key steps and under 321 reports essential information which creates "theory-practice" gaps. At the same time SmartPLS 4 introduced features such as HTMT, cIPMA, NCA and others which are powerful: however, not beginner friendly. Thus, this requires urgent need of concise roadmap which shows end-to-end workflow using simulated data, emphasize the correct measurement evaluation and translates the common pitfalls for novices' researchers. Indeed, the release of Smart-PLS contributed to the wide-scale adoption of PLS-SEM and different studies utilizes PLS-SEM in business, social science and education field.

Despite of these numerous implementations of PLS-SEM, recent systematic reviews highlight common pitfalls in PLS-SEM practice. Such as Ghasemy et al. (2020) stated that many higher-education students using PLS-SEM bypass the major key-steps in data screening and model evaluation. Dash and Paul (2021) also stated that even though PLS-SEM and CB-SEM have better reliability and support, PLS-SEM is still missing some accurate model fit statistics. In short, the literature calls for methodological care and clear guidance on PLS-SEM usage. Whereas, given the sophistication of modern PLS-SEM tools such as SmartPLS 4's support for HTMT discriminant validity, multi-group analysis, there is a clear need for up-to-date, step-by-step roadmap that bridge theory and practice to novice learners.

Although, PLS-SEM field is rich with domain-specific application and sophisticated methodological tutorials but there is relatively less beginner-friendly resources which highlights the entire workflow using actual software such as data generation or acquisition, model specification, reliability and validity to interpret the outcomes. Sarstedt et al. (2024) highlights SmartPLS 4 usage using a pre-built sample; however, they do not show users how to get or prepare such data before analysis. Sarstedt et al. explains the use of SmartPLS with a ready-made sample dataset; however, they do not guide users on how to obtain or prepare such data before starting the analysis. In other words, SmartPLS has enabled many researchers to expand their methodological toolbox, beginner often need more relatable examples and roadmap as guidance. While earlier studies have prioritized on connecting theory with empirical findings, there is still gap in providing step-by-step guidelines for beginners, especially on how to measure construct validity, test reliability and carry out model assessment (Hair & Alamer, 2022; Ghasemy et al., 2020; Cheah et al., 2023; Ringle et al., 2023). This gap is most apparent in studies that use simulated data for teaching or interpreting, as of now only few publications shows the complete roadmap from raw data to final PLS-SEM results.

To address these needs, this study provides a beginner's fast-map for applied PLS-SEM analysis in SmartPLS. Using simulated data sets, this study will walk through each stage of PLS-SEM procedure with interpretation and flow chart to access the steps. This paper is organized as follows: Section 2 reviews the theoretical and empirical foundation of PLS-SEM, section 3 deals with methodology and analytical method, whereas Section 4 and 5 presents the SmartPLS result and discussion and conclusion and implication.

II. Reviews

Structural Equation Modeling (SEM) has basically two main routes for beginners to choose from which includes Covariance-based SEM (CB-SEM) and Partial Least Squares SEM (PLS-SEM). CB-SEM is a factor-based and is utilized when objectives of the research is confirming an established theory and report overall model fit and works very well with large datasets, normally distributed samples which reflects constructs purely (Hair et al., 2021).

Similarly, PLS-SEM is composite-based and aims at prediction as well as explanation of the model which tolerate small or non-normal samples and supports formative and reflective measures. It is handy for measuring complex models or early-stage theory building (Dijkstra & Henseler, 2015; Rigdon, 2016). With PLS-SEM, novice researchers can focus on reliability and validity (such as CR, AVE, HTMT) and report SRMR value alongside with R^2, effect size and prediction checks. A simple rule of thumb can be applied here: Choose CB-SEM to confirm mature theories whereas choose PLS-SEM to predict the outcomes and prototype models when data or indicators are non-normal or less ideal (Hair et al., 2021).

Theoretical Foundation

Partial Least Squares Structural Equation Modeling (PLS-SEM) has gained rapid usage across various fields for its flexibility in handling complex causal relationships, small sample sizes and non-normal data distribution (Sarstedt et al., 2024). It is rooted in the concept of composite-based latent variable which spotlight prediction, differentiating it from factor-based CB-SEM (Joreskog, 1982; Hair et al., 2021). Hidayat and Wulandari (2022) states the advantages of SEM which include the ability to build models with different variables, measure latent constructs, measure errors in observed variables and perform confirmatory factor analysis. SEM is classified into two types: Covariance-based SEM (CB-SEM) and Variance-based SEM (VB-SEM), whereas PLS-SEM falls under the VB-SEM. Similarly, CB-SEM is primarily used for confirming established theories, whereas PLS-SEM prediction and estimation with causal explanation in model (Hair et al., 2021). PLS-SEM typically involves a structured methodological approach which can be further divided into three stages: data screening and diagnostic tests, measurement model assessment and structural model assessment (Haji-Othman et al., 2024). PLS-SEM serves both reflective as well as formative measurements models, where reflective model indicators are caused by the constructs, standard reliability and validity are apply with indicator loadings ≥ 0.70, Cronbach’s alpha and composite reliability ≥ 0.70 and AVE ≥ 0.50. Similarly, for formative models, the major shifts are to validate the constructs as a combination of unique indicators which requires test for multicollinearity and external validity (Dash & Paul, 2021).

Once the measurement model is specified, PLS-SEM proceeds to Structural model, where the major goal is to maximize the predictive accuracy of the targeted constructs. The major outputs include path coefficients, R^2 value (variance explained), and effect sizes for each predictor. Significance of variable is measured through non-parametric bootstrapping by resampling data many times, confidence intervals and t-values are obtained without assuming normality (Henseler et al., 2009; Marcoulides, 1998). In PLS-SEM to make constructs different from each other (discriminant validity) has often been difficult; however, older checks like Fornell-lacker test (Fornell & Larcker, 1981) and cross-loadings are still used, but the new HTMT ratio (Henseler et al., 2016) is now preferred with a cut-off value of about 0.85 or 0.90 (Franke & Sarstedt, 2019). Unlike CB-SEM, tests such as CFI or RMSEA do not apply in PLS-SEM. Instead measures like SRMR is suggested (Henseler et al., 2016). Still, researchers inform that PLS-SEM should focus more on good theory, explanatory and prediction power rather than on strict fit measures (Dijkstra & Henseler, 2015; Rigdon, 2016).

Building theory in PLS-SEM needs clear about the assumptions because its not just exploratory. Instead, researcher need to create a conceptual path model based on theories or prior research (Sarstedt et al., 2024; Hair & Alamer, 2022). Furthermore, while teaching or demonstrating studies using simulated data, constructs and hypothesized paths should be priorly define (Rigdon, 2016; Ringle et al., 2023). The Technology Acceptance Model (TAM) explains how perceived usefulness and ease of use influence behavioural intentions and technology adoption (Davis, 1989; Venkatesh & Davis, 2000). Similarly, Social Cognitive Theory (SCT) emphasis on self-efficacy, observational learning and dynamic role of personal factors to explain behaviour (Schunk & DiBenedetto, 2019; Bandura, 1986). Whereas, the Theory of Planned Behaviour (TPB) states that attitudes, subjective norms and perceived behavioural control shape intention and actions (Ajzen, 1991; Fishbein & Ajzen, 2009). Together, these theories highlight how PLS-SEM can be used to test theoretical models through the estimation of structural paths, hypothesised paths and validation of constructs. Beginner researchers' can easily and practically understand different workflows with SmartPLS, from defining to evaluating paths of latent variable and connects those theories to empirical testing.

Empirical Applications and Gaps

Author and Year	Context/ Field	Objectives	Sample and tool	Key Findings	Limitations/ Gap
(Demir & Uşak, 2025)	Educational Technology	Review PLS-SEM use	Systematic review of 57 studies, SmartPLS	Gaps in formative and predictive reporting	Need demonstration with SmartPLS 4
(Nurhidayati et al., 2024)	Educational behaviour	Validate green behaviour instrument	608 students, SmartPLS for reflective measurement model using SEM	Adequate reliability and validity support	Did not demonstrate and interpret structural model testing using SmartPLS 4.
(Costa et al., 2025)	Teacher AI adoption	Examine AI adoption predictors among teachers	372 secondary school teachers, SmartPLS 4 PLS-SEM	Significant path coefficients, R^2 values	Focused on structural model only; minimal measurement model walkthrough; novice may require step-by-step guidance.
(Elareshi et al., 2022)	Education/ Hybrid SEM-ANN modeling	Illustrate SEM followed by neutral network modeling	n= 180 where 93% responded with PLS-SEM + ANN	PLS-SEM effective initial modeling; ANN adds predictive power	Complexity; no simplified stepwise SmartPLS guide
(Subhaktiyasa, 2024)	Educational Research/ Practical guide	Proposved to analyse multivariate in PLS-SEM	Literature based tutorial using SmartPLS	Covers reflective, formative, first/second order models, measurement and structural evaluations	Narrative guide only, lack concrete guidance and interpretations
(Nadella et al., 2024)	Educators and Learning Management System (LMS) use	Compare PLS-SEM and IPMA	237 online respondents; SmartPLS 4; IPMA	Predictors of LMS adoption identified	Need beginner-level roadmap

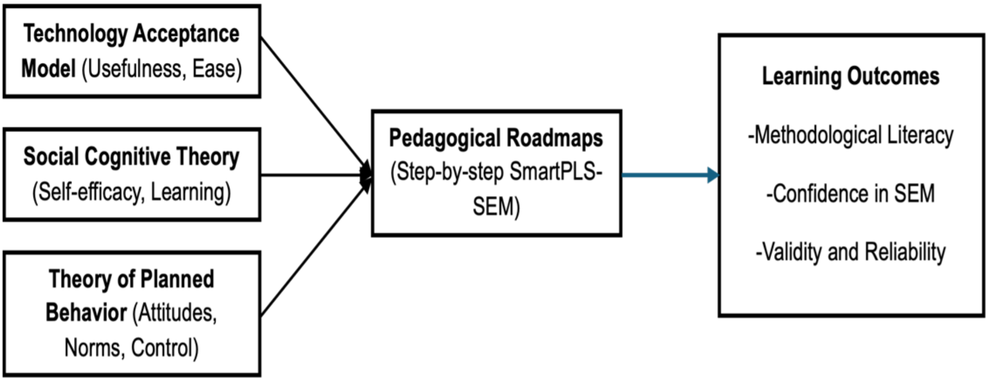
While Demir and Uşak (2025) conducted a systematic literature review of 57 studies and confirmed the widespread use of SmartPLS in PLS-SEM and found underreporting of formative model evaluation and predictive relevance metrics. However, Nurhidayati et al. (2024) did not measured the structural model because bootstrapped path coefficient, R^2 or predictive performance were not shown. Instead, they showed a highly reliable instrument with strong content validity. Moreover, similar patterns are observed in other research too: for instance (Costa et al., 2025; Nadella et al., 2024) which primarily focus on measurement separately, without delivering beginner-friendly, step-by-step workflows that integrate measurement Modeling, hypothesis testing and predictive validity.

Conceptual Review

Using Technology Acceptance Model (TAM), Social Cognitive Theory (SCT) and Theory of Planned Behavior (TPB) together is deliberate and pedagogical, where each theory shows a clear mechanism using simulated model allowing beginners to practice mediation, moderation and discriminant validity. TAM contributes technology-specific, whereas SCT highlights the self-efficacy/confidence as a personal capability belief that mediates and enhance learning usage. Similarly, TPB contributes the perceived control along with subjective norms. Together, TAM (belief about the system), SCT (beliefs about the self) and TPB (social control and intention formation) cover three determinants of system, self and social determinants, justifying the usage of all three theories in single training oriented SmartPLS framework.

Figure 1

Conceptual Framework



The conceptual framework from Figure 1 links TAM, SCT and TPB theories altogether to a pedagogical roadmap of SmartPLS-SEM. By integrating these theories, the framework highlights step-by-step guidance to novice researchers to enhance learners' methodological literacy which ultimately helps to improve research skills and outcomes.

III. Methodology

This study adopts instructional design-based methodological approac h, which is used to demonstrate how SEM can be effectively, taught through simulation, scaffolding. The major goal of this result is not to produce generalizable statistical conclusions instead it aims to improve the pedagogical effectiveness and interpretative skills in SEM Modeling. A simulated dataset was generated, which includes 6 latent constructs including mediating and moderating variables measured by using 4-5 items on a 7-point Likert scale using SmartPLS 4 software. This study entirely simulated datasets for instructional purposes. No human participants were involved and thus no ethical approval was required. The primary objective of this research is to improve statistical literacy and SEM modeling skills among the novice researcher also improve the pedagogical efficacy.

IV. Results and Discussion

The Assessment of measurement model from Table 1 highlights that most indicators load strongly on their respective constructs with values above the recommended 0.70 threshold (Hair et al., 2021). Constructs such as Confidence, Experience, Like and Willingness demonstrate good indicator reliability, but Ease of use also perform well though E_1 value of (0.698) is marginal. Help also has one weak item H_1 which lowers its consistency. Peer constructs include three strong indicators, however P_1 seems to be marginally fit. VIF values are generally below 5, indicating no severe multicollinearity issues (Franke & Sarstedt, 2019).

Step-by-step Guide of SmartPLS 4

a) Create Project and Import data: Open SmartPLS 4 → File → New Project (Name the Project) → Click Import Data →CSV/Excel

b) Build Model: Drag Latent variable from left panel into the Canvas for each LV_s → right click → Assign Indicators (Choose items from the datasets) → Draw arrow between constructs using connect.

c) Run PLS-SEM Algorithm: Top Menu → Calculate → PLS Algorithm: Output gives outer loadings, AVE, CR. R^2, VIF → Mean, median, SD from the descriptive statistics and also cross-check VIF < 5 for collinearity.

Table 1

Assessment of Measurement Title

Variables	Indicators	Outer loading	Mean	Median	SD	VIF
C <- Confidence	C1	0.692	5.094	6	1.762	1.448
	C2	0.785	5.461	6	1.739	1.777
	C3	0.848	5.104	6	1.702	2.315
	C4	0.818	5.133	6	1.797	2.203
	C5	0.838	5.445	6	1.544	2.294
E <- Ease of use	E1	0.698	3.659	4	2.055	1.41
	E2	0.732	2.841	2	1.719	1.572
	E3	0.894	2.878	2	1.571	3.423
	E4	0.803	3.289	3	1.799	2.286
	E5	0.857	2.919	3	1.531	2.581
EXP <- Experience	EXP1	0.86	5.104	6	1.702	2.419
	EXP2	0.838	5.133	6	1.797	2.242
	EXP3	0.861	5.445	6	1.544	2.439
	EXP4	0.791	5.768	6	1.586	1.96
	EXP5	0.773	5.122	5	1.629	1.799
H <- Help	H1	0.561	3.232	3	1.778	1.035
	H2	0.848	3.339	3	1.946	2.787
	H3	0.831	3.734	4	1.965	2.554
	H4	0.767	3.625	4	2.051	2.172
L <- Like	L1	0.839	4.086	4	1.941	2.509
	L2	0.837	3.799	4	1.981	2.505
	L3	0.834	4.372	5	1.926	2.537
	L4	0.82	4.828	5	1.847	2.502
	L5	0.881	4.276	5	1.892	2.789

P <- Peer	P1	0.629	3.339	3	1.946	1.264
	P2	0.897	5.951	6	1.384	3.034
	P3	0.92	5.844	6	1.462	3.777
	P4	0.895	5.719	6	1.609	3.169
W <- Willingness	W1	0.718	5.768	6	1.586	1.482
	W2	0.834	5.122	5	1.629	2.735
	W3	0.813	5.719	6	1.609	2.373
	W4	0.75	5.094	6	1.762	1.996
	W5	0.856	5.461	6	1.739	3.063

Assessment of Measurement Title Refinement Guidelines

When using real datasets, researchers should carefully review the items with low or negative loadings and consider rewording or removing them to improve construct validity (Franke & Sarstedt, 2019). Indicators which are slightly below 0.70 can sometimes be used if AVE and composite reliability remain acceptable but required clear justification. Novice researchers should look after the values of VIF to detect redundancy and learn to balance theoretical reliability with statistical thresholds. These refinements will not only improve measurement quality but also helps to understand how to evaluate and refine the constructs in SEM practice.

In Table 2, most constructs show strong reliability: Confidence (α=0.856, ρc=0.897, AVE=0.637), Ease of use (α=0.857, ρc=0.898, AVE=0.640), similar for Experience, Like and Willingness, all exceed recommended thresholds, ensuring good reliability and convergent validity. However, Help (α=0.750, ρc=0.878, AVE=0.578) is acceptable but weaker. Peer is inconsistent (α=0.473) but acceptable in (ρa=0.878, ρc=0.791 and AVE= 0.712) which indicates item inconsistency yet overall construct validity (Fornell & Larcker, 1981; Hair & Alamer, 2022).

Reliability and Validity Checks: Results → Quality Criteria Export: Outer loadings, Alpha, rho_A, CR, AVE.

Table 2

Construct, Reliability and Validity

Variables	Alpha	rho_c	rho_a	AVE
Confidence	0.856	0.897	0.86	0.637
Ease of use	0.857	0.898	0.862	0.640
Experience	0.882	0.914	0.887	0.681
Help	0.75	0.843	0.734	0.578
Like	0.898	0.924	0.904	0.71
Peer	0.473	0.791	0.878	0.712
Willingness	0.854	0.896	0.858	0.633

Construct Refinements Guidelines

Beginners should review all reliability indices: Cronbach's Alpha, CR values for rho_A and rho_C from Table 2 should surpass the threshold values of 0.70 and AVE value should exceed 0.50 which indicates the robust measure for consistency. The peer construct should be carefully reviewed since its low alpha may reflect some inconsistent items and can be improved by either dropping weakly loading indicators, checking discriminant validity through HTMT or rephrasing survey items which may align better. Highlighting composite reliability and AVE alongside ensures methodological robustness and SEM best practices (Henseler et al., 2016; Dijkstra & Henseler, 2015).

The majority of HTMT ratios fall within acceptable limits, reflecting good discriminant validity. However, there are few values exceed the recommended threshold: Confidence-Ease of use (0.978), Experience-Confidence (1.100), Help-Like (0.936), Peer-Willingness (1.006) and Confidence-Willingness (1.058) which shows potential constructs overlap, meaning some variables may not be sufficiently distinct.

Discriminant Validity: HTMT → Results → Discriminant Validity → HTMT

Table 3

Heterotrait-Monotrait (HTMT Ratio Matrix)

	Confidence	Ease of use	Experience	Help	Like	Peer	Willingness
Confidence							
Ease of use	0.978						
Experience	1.1	0.971					
Help	0.762	0.705	0.786				
Like	0.576	0.526	0.579	0.936			
Peer	0.861	0.713	0.796	0.889	0.599		
Willingness	1.058	0.89	0.99	0.802	0.554	1.006	

HTMT Refinements Guidelines

Novice researchers should treat high HTMT values not as Failure instead as learning opportunity. When value exceeds 0.90, researcher should check for item redundancy or conceptual overlap between constructs. Bootstrapping HTMT ratios helps to make model more robust validity checks. Importantly, these simulated datasets like this are very useful learning tools as they show both acceptable and problematic validity cases, allowing beginner to get refine on their real dataset's issues (Dijkstra & Henseler, 2015).

The diagonal values in Table 4 shows square roots of AVE for each construct such as Confidence = 0.798, Ease of use = 0.8, Willingness = 0.796). According to this, these diagonal values should be greater than the correlation between the constructs. Whereas, in this data sets some correlations are larger than the diagonal values such as Confidence-Experience = 0.962 > 0.798 and Willingness-Confidence = 0.905 > 0.796, which shows that there are issues with discriminant validity, meaning that certain constructs may be overlapping instead of being distinct.

Fornell-Larcker Criterion: Results → Discriminant Validity → Fornell-Larcker

Table 4

Fornell Larcker Criterion

	Confidence	Ease of use	Experience	Help	Like	Peer	Willingness
Confidence	0.798						
Ease of use	-0.84	0.8					
Experience	0.962	-0.846	0.825				
Help	-0.649	0.6	-0.667	0.76			
Like	-0.513	0.466	-0.519	0.754	0.842		
Peer	0.736	-0.609	0.683	-0.696	-0.502	0.844	
Willingness	0.905	-0.763	0.857	-0.67	-0.496	0.857	0.796

Fornell-Larcker Criterion Refinements Guidelines

When overlaps appear just like in Table 4, it is important not to rely on this Fornell-Larcker Criterion test. Instead, a better test is use it together with other measures such as HTMT ratio which is more reliable. If correlations remain, novice researchers should carefully examine the wording of the items, whether two constructs are similar and decide to remove or merge of construct. For the study purpose, these results are meaningful, as it helps new researcher to understand the limitations of Fornell- Larcker Criterion test and need for use of other various methods to establish discriminant validity (Henseler et al., 2014; Roemer et al., 2021; Cheung et al., 2023).

In Table 5, most indicators value load highest on their intended constructs supporting convergent validity such as Confidence items range from 0.692 (C1) to 0.0843 (C3), Ease of Use from 0.698 (E1) to 0.894 (E3), Experience from 0.773 (EXP5) to 0.861 (EXP3), Like From 0.820 (L4) to 0.881 (L5) and Willingness from 0.718 (W1) to 0.856 (W5). However, help item H1 loads only 0.561 and cross loads with Ease of use only 0.612 while Peer item P1 shows a negative loading (-0.629) both of which indicate measurement issues. It is required to determine that indices of an indicator should exhibit a loading of at least 0.70 towards its own constructs and should not contain any cross loading on any other construct while model measurement (Kline, 2015; Gefen et al., 2000).

Cross-loadings: Results → Cross loadings (Each indicator should load highest on its own construct).

Table 5

Cross-loadings,

Indicators	Confidence	Ease of use	Experience	Help	Like	Peer	Willingness
C1	0.692	-0.526	0.546	-0.347	-0.277	0.62	0.75
C2	0.785	-0.646	0.712	-0.624	-0.481	0.695	0.856
C3	0.848	-0.804	0.86	-0.537	-0.448	0.543	0.685
C4	0.818	-0.674	0.838	-0.486	-0.42	0.486	0.622
C5	0.838	-0.686	0.861	-0.569	-0.403	0.589	0.693
E1	-0.654	0.698	-0.649	0.489	0.536	-0.466	-0.621

E2	-0.644	0.732	-0.646	0.408	0.3	-0.491	-0.616
E3	-0.725	0.894	-0.739	0.528	0.403	-0.524	-0.652
E4	-0.604	0.803	-0.605	0.459	0.268	-0.483	-0.531
E5	-0.718	0.857	-0.729	0.505	0.347	-0.471	-0.622
EXP1	0.848	-0.804	0.86	-0.537	-0.448	0.543	0.685
EXP2	0.818	-0.674	0.838	-0.486	-0.42	0.486	0.622
EXP3	0.838	-0.686	0.861	-0.569	-0.403	0.589	0.693
EXP4	0.695	-0.646	0.791	-0.591	-0.405	0.601	0.718
EXP5	0.755	-0.675	0.773	-0.584	-0.467	0.615	0.834
H1	-0.578	0.612	-0.579	0.561	0.202	-0.427	-0.521
H2	-0.494	0.395	-0.514	0.848	0.742	-0.629	-0.542
H3	-0.437	0.357	-0.45	0.831	0.711	-0.542	-0.482
H4	-0.354	0.345	-0.38	0.767	0.692	-0.465	-0.407
L1	-0.457	0.39	-0.455	0.679	0.839	-0.461	-0.453
L2	-0.442	0.388	-0.454	0.796	0.837	-0.512	-0.487
L3	-0.389	0.354	-0.408	0.533	0.834	-0.338	-0.33
L4	-0.368	0.345	-0.366	0.494	0.82	-0.323	-0.33
L5	-0.487	0.467	-0.486	0.643	0.881	-0.452	-0.461
P1	-0.494	0.395	-0.514	0.848	0.742	-0.629	-0.542
P2	0.65	-0.554	0.617	-0.516	-0.346	0.897	0.748
P3	0.663	-0.558	0.603	-0.559	-0.374	0.92	0.761
P4	0.66	-0.532	0.571	-0.503	-0.321	0.895	0.813
W1	0.695	-0.646	0.791	-0.591	-0.405	0.601	0.718
W2	0.755	-0.675	0.773	-0.584	-0.467	0.615	0.834
W3	0.66	-0.532	0.571	-0.503	-0.321	0.895	0.813
W4	0.692	-0.526	0.546	-0.347	-0.277	0.62	0.75
W5	0.785	-0.646	0.712	-0.624	-0.481	0.695	0.856

Cross-Loadings Refinements Guidelines

New researcher should give attention to the indicators like H1 (0.561) and P1(-0.629) item with weak and negative loadings that should be carefully reviewed, reword or even removed from the construct's clarity. The general rule is that an indicator should cross the load above 0.70 on its own constructs and sustainably lower on others. Cross-loadings should be interpreted along with other validity checks such as HTMT and Fornell-Larcker, since relying on single criterion may be misleading. Thus, using simulated datasets helps to access the problematic items for demonstrating how to detect and correct the issues before applying to real-world research.

Model Fit Assessment

The model fit values highlight SRMR value = 0.104 (saturated) and 0.109 (estimated) which are slightly above the commonly accepted threshold values of (0.8-0.10) (Henseler et al., 2016). This result indicates that model doesn't achieve ideal fit but remains as interpretable given the simulated datasets context so that novice researcher doesn't repeat these mistakes. The d_ULS values (7.933 and 8.331) provide absolute measure difference between empirical and model-implied covariances matrices; however, benchmark for d_ULS are less standardized, interpretation mainly relies on values of SRMR. Overall, fit values indicate moderate model adequacy, acceptable for instructional demonstration but not optimal for statistical empirical generalization.

Model Fit Assessment: Results → Model Fit → Check SRMR

Model Fit Assessment Refinements Guidelines

Novice researchers should use model fit values as the diagnostic tools rather than rigid pass or fail test. High SRMR values can generate signal issues such as model complexity, item redundancy or misspecification. Beginners should practice comparing saturated vs estimated models, test simplified models, and report SRMR value alongside with other criteria such as reliability, validity to provide a balanced evaluation. In this simulated datasets, slightly poor fit can be teaching opportunity which ultimately helps novice to understand the important of refining measurements before applying SEM in real-world research datasets.

In Figure 2, model shows that confidence is strong mediator with the value of R^2 = 0.9420 which explains most of the variation in Willingness R^2 = 0.8140. Confidence has a very strong direct effect on Willingness (β = 0.878, $p < 0.001$), confirming its major central role. Among independent variable, Help and Peer contribute positively and Ease of use and Like shows negative influences. The moderating effect of experience on other paths are minimal and insignificant in statistical terms, demonstrating very little interaction strength, although experience explains an enormous amount of variance (R2 = 0.814).

Bootstrapping (Significance testing): Calculate → Bootstrapping → Settings: 5000 or 10000 subsamples, Two-tailed test → Output: Path coefficients, t-values, p-values, CI.

Structural Equation Model

Novie researcher should not only report significant paths but also learn from non-significant paths too, as they highlight model complexity. Visualizing the model with clear value of R^2 and β coefficient helps to gain insights about mediation and moderation. Researcher should also state both positive and negative effects, instead of emphasizing theoretical justifications over significance chasing. Although the model shows strong explanatory power, refinement is needed for model robustness. Non-significant moderators indicate measuring the larger sample size or alternative moderation approaches (Henseler & Chin, 2010). Negative paths such as Ease of use should be revisited for possible measurements or theoretical misalignments. Reporting indirect effects along with HTMT would strengthen methodological rigor. Thus, improving all these by researcher can enhance the pedagogical as well as technical value in SmartPLS modeling (Franke & Sarstedt, 2019).

The structural model was assessed with the help of bootstrapping in SmartPLS, which provides non-parametric estimates of path significance performed with 10000 subsamples which examined the hypothesis. Results from Table 6 highlights that confidence strongly predicts willingness, confirming its central mediating role. Similarly, experience, peer, help significantly enhance confidence. In contrast, Ease of use showed a small negative effect (β = –0.082, p = 0.002), while Like (β = –0.039, p = 0.133) and all interaction terms with Experience were statistically insignificant. These findings suggest how bootstrapping captures both significant and non-significant relationships which helps to provide novice researcher a practical guide to interpret such results (Henseler & Chin, 2010; Nitzl et al., 2016).

Figure 2

Structural Equation Model Refinements Guidelines

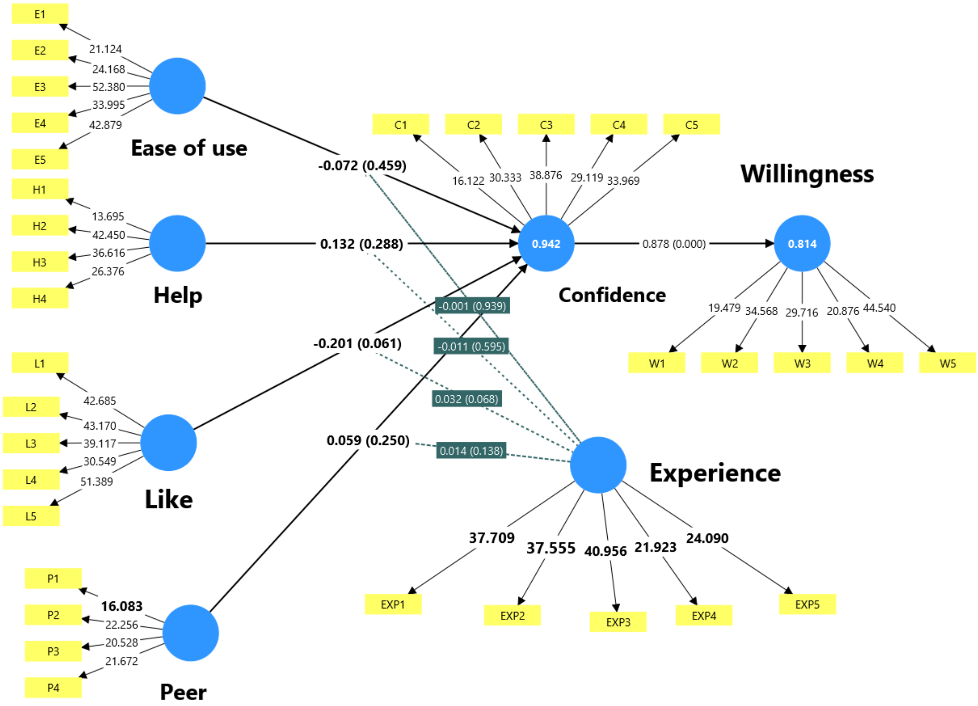


Table 6

Hypotheses Testing Using Bootstrapping

Hypotheses	Beta(β)	Sample mean (M)	Standard deviation (STDEV)	Confidence Interval 2.50%	97.50%	T-stat	P values	Decision
H1 Confidence -> Willingness *(Mediator-DV)*	0.905	0.905	0.012	0.879	0.926	76.13	0	Accepted
H2 Ease of use -> Confidence *(IV-Mediator)*	-0.082	-0.08	0.026	0.759	0.875	3.152	0.002	Accepted
H3 Experience -> Confidence *(Moderator main effect-mediator)*	0.816	0.817	0.03	0.154	0.253	27.412	0	Accepted

H4 Experience x Ease of use -> Confidence *(Interaction)*	0.008	0.007	0.024	0.042	0.15	0.325	0.745	Rejected
H5 Experience x Help -> Confidence *(Interaction)*	-0.041	-0.044	0.032	0.004	0.114	1.29	0.197	Rejected
H6 Experience x Like -> Confidence *(Interaction)*	0.054	0.057	0.028	-0.042	0.053	1.958	0.05	Rejected
H7 Experience x Peer -> Confidence *(Interaction)*	0.016	0.014	0.019	-0.024	0.05	0.853	0.394	Rejected
H8 Help -> Confidence *(IV-Mediator)*	0.091	0.094	0.028	-0.108	0.016	3.272	0.001	Accepted
H9 Like -> Confidence *(IV-Mediator)*	-0.039	-0.041	0.026	-0.092	0.01	1.502	0.133	Rejected
H10 Peer -> Confidence *(IV-Mediator)*	0.197	0.2	0.025	-0.131	-0.029	7.757	0	Accepted

Note. Dependent variable (DV)= Willingness; Independent Variables (IV_s)= Ease of Use, Help, Like, Peer; Mediator= Confidence; Moderator= Experience.

Hypothesis Refinements Suggestions

Bootstrapping values always include t-values, p-values and Confidence Interval (C.I.). Researcher should practice why some hypotheses are rejected, since these non-significant paths are valuable source of teaching. For robust methodological accuracy, as this is simulated datasets used for pedagogy efficiency, researcher should report indirect mediation effects with bias-corrected bootstrap confidence intervals, refine moderation tests either by increasing sample size or visualizing slopes and aligning the results by revisiting items wording or multicollinearity checks. Thus, this will increase pedagogical efficiency by strengthening technical accuracy.

Table 7 shows that Confidence (71.091, 0.878) is the major driver of Willingness, followed by Experience (72.012, 0.555). However, Help (40.59, 0.116) has low performance but some positive potential, while peer support (87.87, 0.052) is strong but low in importance. In contrast, Ease of use and Like shows negative or weak importance, meaning they do not increase Willingness.

Calculation of IPMA: Calculate → IPMA → Select target Constructs → Results: Performance, Importance → Compute mean values to draw crosshairs.

Table 7

Importance Performance MAP Analysis

Variables	LV Performance	Importance
Confidence	71.091	0.878
Ease of use	34.204	-0.063
Experience	72.012	0.555
Help	40.588	0.116
Like	54.398	-0.176
Peer	87.866	0.052
Mean	60.0265	0.227

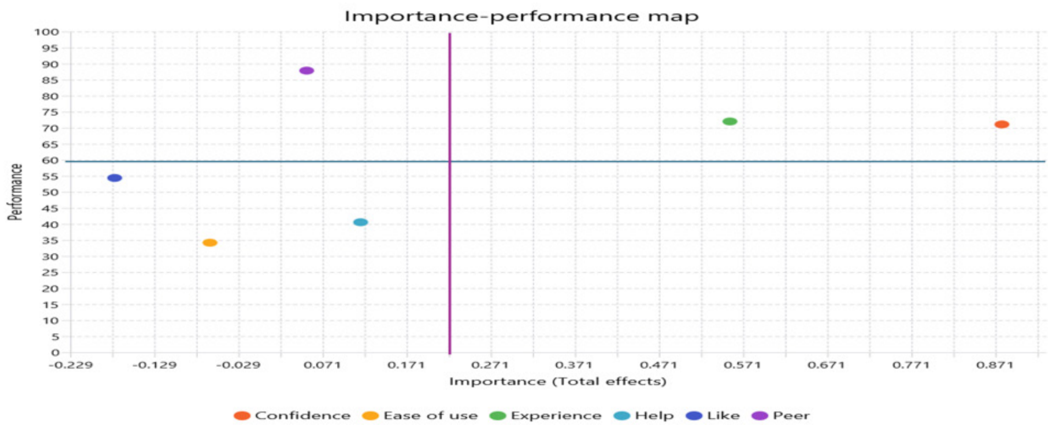
Importance Performance MAP Analysis Refinements Suggestions

Novice researcher should focus on building confidence through guided practice and build their experience through step-by-step simulations. Improve variable Help with better scaffolding and support, while Peer support as secondary. Avoid overemphasizing Ease of use and Like, since they do not positively drive learning outcomes.

The analysis in Figure 3 using performance (60.03) and importance (0.23) as divider lines between graph, shows Confidence and Experience as high-priority strengths, while Help requires refinement. However, Peer is effective, but it doesn't show as a key driver. Ease of use and Like are the lowest priority.

Figure 3

Importance-Performance MAP



Importance Performance MAP Refinements Suggestions

The MAP from Figure 3 shows that Confidence and Experience are the key drivers giving learners a clear image of how strong constructs should appear. Similarly, Help has weak performance but some importance, which is useful for showing need to improve support and scaffolding. Peer indicates even though there are strong scores which are not always central, while Ease and Like highlights how constructs can be misleading. This result helps beginner learn to identify the strength, weakness and mistakes in SEM before applying it to the real-world research datasets.

V. Conclusion and Implications

This study was undertaken to respond a methodological gap identified in the literature although the widespread utilization of PLS-SEM, novice researchers continue to lack a complete and accessible roadmap which connects theory, data and interpretations through SmartPLS. Prior studies often concentrated on either measurement or structural modes or overlooked the fundamental checks of reliability and discriminant validity. Such gaps left a practical divide between the theoretical foundations of SEM and its applied use in research and pedagogy efficiency. Thus, this research provides roadmap for beginner to apply PLS-SEM using SmartPLS. Unlike empirical research aimed at generalization, the analysis was based on simulation datasets designed to demonstrate methodological workflows and highlights common mistakes that researchers' make.

Outlining on Technology Acceptance Model (TAM), Social Cognitive Theory (SCT), and Theory of Planned Behaviour (TPB), theoretical foundation strengthens the research's objective. TAM shows how transparent and structured processes creates low barriers to adapt the new tools, indicating even error-prone practice can increase learners' openness to technology. SCT also indicates the role of practice and feedback in building self-efficacy, working through the mistakes and provides students with confidence to manage complex models. Likewise, TPB also highlights that positive attitudes and supportive guidelines helps to lead learning intentions through the help of errors and the fast map fosters positive attitudes and reduces resistances.

The implication of this study is twofold: theoretically, this roadmap helps to strengthen the bridge between SEM's conceptual underpinnings and applied practice. For practice, it provides educators and early-career researchers with a step-by-step guide which transforms methodological pitfalls into opportunities for learning. SmartPLS is not just a statistical tool, but also a pedagogical framework which strengthens both methodological robustness and teaching of applied research methods. Overall, this research findings are not statistically generalizable; however, pedagogically significant.

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