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Comparative Analysis of SmartPLS, WarpPLS, and R Studio: Accuracy, Features, Usability, and Licensing

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ABSTRACT

Partial Least Squares Structural Equation Modeling (PLS-SEM) is widely applied to analyze relationships among latent variables using different software tools. This study compared SmartPLS, WarpPLS, and R Studio from quantitative and qualitative perspectives. A synthetic dataset (N=100) with a simple reflective model (X1, X2→Y) was analyzed under equivalent settings, including reflective indicators and bootstrapping with 5,000 resamplings, to ensure structural equivalence and highlight algorithmic differences. Quantitative results showed consistent external loadings above 0.70, with small numerical deviations (overall MAD=0.039) and the largest variation in item Y4 (MaxDiff=0.087). Internal model estimates were stable, with minor differences in path coefficients (MaxDiff≤0.040) and larger variation in R^2 for R Studio (MaxDiff=0.098), reflecting differences in latent score calculations. Bootstrapping confirmed significance (T>1.96; p<0.05), though variability in T statistics was observed across software. Qualitatively, SmartPLS excelled in usability and visualization, WarpPLS in nonlinear analysis, and R Studio in flexibility and cost-effectiveness. Computationally, SmartPLS consumed the most memory, R Studio was moderate, and WarpPLS was most efficient, with all execution times under five seconds. These findings suggest that software choice should consider not only numerical accuracy but also usability, licensing, and computational efficiency to align with research objectives and user competencies.

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1. INTRODUCTION

Partial Least Squares Structural Equation Modeling (PLS-SEM) is a variance-based multivariate analysis method widely used in various fields such as social sciences, marketing, health, economics, and information technology [1],[2],[3]. This method is popular due to its ability to handle complex structural models, relatively small sample sizes, and minimal data distribution assumptions [4],[5],[6]. Furthermore, PLS-SEM is algorithmic, so its estimation results are highly dependent on the computational mechanisms used in the indicator weighting process, latent variable score calculation, and inferential procedures [7],[8].

PLS-SEM implementations are available in various software. SmartPLS and WarpPLS are the most widely used graphical user interface (GUI)-based software due to their ease of use, intuitive visualization models, and structured flow analysis [10],[11],[12]. SmartPLS excels in terms of ease and comprehensiveness of output analysis, while WarpPLS offers additional advantages in modeling nonlinear relationships [13],[14],[15]. However, both software are commercial and subject to relatively expensive licensing policies, which can be prohibitive in academic contexts [16],[17],[18].

On the other hand, R Studio provides PLS-SEM implementations through packages such as seminr and plspm. R is open-source, flexible, and entirely script-based, enabling reproducible, automated, and further extensible analyses, including integration with Shiny-based applications [19],[20]. Despite its significant methodological and computational potential, the use of R Studio for PLS-SEM remains relatively limited due to the requirement for programming skills and the lack of a built-in graphical interface [21],[22].

Comparative research on PLS-SEM software has highlighted different aspects. Rigdon [10], Ringle et al. [23], and Chin [28] emphasized that algorithmic differences may produce small numerical variations without altering substantive conclusions. Fajar et al. [2], Chiarelli et al. [21], and Bleichrodt et al. [22] showed that R-based implementations yield estimates comparable to commercial tools despite their script-based nature. Fornell et al. [26], Gunawan et al. [25], and Monecke & Leisch [29] discussed standards for measurement and structural models, while Ringle et al. [23], Cegarra-Navarro et al. [5], and earlier work [1],[8] highlighted usability, visualization, and nonlinear modeling capabilities of SmartPLS and WarpPLS. However, prior studies rarely combined systematic numerical benchmarking with non-numerical evaluation and computational aspects. This study fills that gap by providing a standardized comparison of SmartPLS, WarpPLS, and R Studio using identical data and configurations, integrating quantitative (numerical consistency, MAD/MaxDiff) and qualitative (features, usability, licensing) perspectives. Based on this description, the research questions are formulated as follows:

a. RQ1: How do SmartPLS, WarpPLS, and R Studio compare in terms of accuracy through numerical assessment in certain models in PLS-SEM analysis?
b. RQ2: How do SmartPLS, WarpPLS, and R Studio compare in terms of non-numerical aspects, including Features, Usability, and Licensing?

2. RESEARCH METHOD

2.1 Research Design

This study employed a mixed methods approach with a comparative design to evaluate the numerical consistency and characteristic differences between three PLS-SEM software tools: SmartPLS, WarpPLS, and R Studio. This approach was chosen because the research objective was not only to assess the equivalence of estimation results quantitatively but also to evaluate non-numerical aspects. The mixed methods strategy employed was parallel convergent, where quantitative and qualitative analyses were conducted in parallel and integrated during the discussion stage to obtain a comprehensive interpretation. The research design focused on numerical comparisons of PLS-SEM estimation results using models, data, and algorithmic configurations that were as closely matched as possible across the three software tools.

2.2 Data Sources and Variables

The data used is a synthetic/simulated dataset with a sample size of N = 100, compiled in CSV and Excel formats without using other data variations such as N = 200, 300, 500 due to SmartPLS licensing limitations. A simple dataset is used to ensure the focus of the numerical comparison. The analyzed model is a simple reflective model with two exogenous variables (X1 and X2) and one endogenous variable (Y). All indicators are coded consistently, using the same scale, without missing values, and verified for equivalence before analysis. The limitations of sample size and model complexity are explicitly acknowledged from the outset as part of the research design.

2.3 Analysis Method

2.3.1 Quantitative

Quantitative analysis was conducted by running PLS-SEM on SmartPLS, WarpPLS, and R Studio with equivalent algorithm configurations, namely the path weighting scheme, Mode A reflective measurements, and a bootstrapping procedure of 5,000 resamplings.

a. Measurement Model Evaluation (Outer Model)

This stage was used to assess the validity and reliability of the indicators for each latent construct. The evaluation was conducted based on the following parameters:

1) Convergent validity, assessed through outer loadings, with ≥ 0.70 considered ideal and ≥ 0.60 acceptable in exploratory research.
2) Construct reliability, tested using Cronbach's Alpha (≥ 0.70), Composite Reliability (≥ 0.70), Average Variance Extracted (≥ 0.50) [24], and rho_A (≥ 0.70) as a more consistent reliability estimator [25].

b. Structural Model Evaluation (Inner Model)

This stage is used to assess the strength of the relationship between latent constructs through:

1) Path Coefficient, considered significant when the T-statistic is ≥ 1.96 at a 5% significance level ($p < 0.05$).
2) The Coefficient of Determination (R^2), a measure of the model's predictive power, is categorized as weak (0.25), moderate (0.50), and strong (0.75) [26].
3) Bootstrapping, used to obtain the Original Sample (O), Sample Mean (M), Standard Deviation (STDEV), T Statistics, P Values, 2.5% CI and 97.5% CI as a basis for evaluating parameter significance [27].

Numerical comparisons between software tools were performed by calculating the absolute difference of each estimated parameter, summarized using the Maximum Difference (MaxDiff) and Mean Absolute Deviation (MAD). This approach was used to assess the level of numerical consistency and identify potential differences that could influence methodological decisions, particularly for indicators or constructs that fall around the threshold values for validity and reliability.

2.3.2 Qualitative

Qualitative analysis was conducted through expert assessments by four authors. The criteria measured were ease of use, graphical interface and application features, licensing, and flexibility of the three software programs in accordance with the research objectives. The assessments used a limited scale of 1–3, were conducted independently, and analyzed based on the total score and percentage of agreement between the raters. The expert assessment scheme can be seen in Table 1.

Table 1. Expert Judgment Questionnaire

No	Assessment Category	Question / Instruction	Scale	Description
1	Ease of Use	How easy is it for you to navigate the interface, build a PLS-SEM model, and export results	1–3	1 = Difficult, 2 = Fair, 3 = Easy
2	Graphics & Application Features	How good is the quality of model visualization and the completeness of analytical features	1–3	1 = Poor/Limited, 2 = Adequate, 3 = Very Good/Comprehensive
3	License	How adequate is the software license price for full access	1–3	1 = Very Expensive, 2 = Sufficient/Standard, 3 = Very Cheap/Free
4	Flexibility	How easy is the software to integrate with other tools or develop in R Shiny	1–3	1 = Limited, 2 = Adequate, 3 = Very Flexible

In addition to the assessments using the table, computational aspects such as memory usage and execution time were also assessed. These approaches allow for the evaluation of practical differences between the three software programs without involving external user studies [32]. While this method is practical and efficient, it can introduce potential bias, which is an acknowledged limitation of this study.

2.4 Analysis Results Comparison Procedure

Quantitative analysis results were compared by calculating the absolute difference between the estimated values generated by the three software tools. The degree of numerical difference was summarized using the Maximum Difference (MaxDiff) and Mean Absolute Deviation (MAD) for each key metric in the outer model, inner model, and bootstrapping. This approach was used to assess numerical consistency and identify potential differences that could impact model validity, reliability, and inference decisions, particularly at values near methodological thresholds. Qualitative analysis results were compared based on score distribution, inter-rater agreement, and the computational aspects measured. The results were then integrated with the quantitative findings in the discussion phase. This integration allowed for a more comprehensive assessment of the strengths and limitations of each software tool.

2.5 Software and Tools

This study used three primary software tools for PLS-SEM analysis: SmartPLS, WarpPLS, and R Studio with a PLS-SEM support package. All analyses were conducted using standard computer systems to ensure that the results can be replicated by researchers with comparable resources.

3. RESULT AND ANALYSIS

3.1 Result

This section presents the main findings from the comparative analysis between SmartPLS, WarpPLS, and R Studio. The results are organized by research objectives and include numerical evaluations of the measurement and structural models, as well as qualitative assessments of usability, features, and licensing. The presentation begins with the consistency of quantitative estimates, continues with numerical variations across software, and concludes with non-numerical differences.

3.1.1 Quantitative (Numeric) Results

A quantitative analysis was conducted to compare PLS-SEM estimates from SmartPLS, WarpPLS, and R Studio on a simple model (X1, X2 → Y; N=100). The primary focus included measurement validity, construct reliability (Outer Model), path coefficients, R^2, and bootstrapping results (Inner Model), with a uniform algorithm configuration to allow for numerical differences to be directly attributed to variations in software implementation. These results are limited to a single, simple reflective model with a small sample size (N=100), and are therefore exploratory in nature. Generalization to more complex models or larger samples should be approached with caution. The results of the numerical analysis are presented in tables 2-5.

Table 2. Outer Model (Loadings Score)

Item	SmartPLS	WarpPLS	R Studio	MaxDiff	MAD
X1A	0.900	0.914	0.920	0.020	0.013
X1B	0.934	0.921	0.954	0.033	0.022
X1C	0.863	0.881	0.847	0.034	0.023
X1D	0.914	0.898	0.954	0.056	0.037
X2A	0.948	0.949	0.995	0.047	0.031
X2B	0.945	0.946	0.954	0.009	0.006
X2C	0.918	0.918	0.995	0.077	0.051
X2D	0.938	0.937	0.995	0.058	0.039
Y1	0.923	0.918	0.934	0.016	0.011
Y2	0.882	0.885	0.876	0.009	0.006
Y3	0.912	0.908	0.925	0.017	0.011
Y4	0.863	0.868	0.950	0.087	0.058

Note: X1A–X1D and X2A–X2D item SmartPLS/WarpPLS; X1_1–X1_4 and X2_1–X2_4 item labels in R Studio, Model (X1, X2 → Y), N=100, MaxDiff represents the maximum absolute difference, while MAD represents the mean absolute difference across software, Overall MAD = 0.039.

Table 3.1 shows that all indicators across the three software packages exhibited Outer Loading values above the 0.70 threshold, confirming convergent validity. From a numerical comparison perspective, differences in outer loadings were generally small, as reflected by the overall MAD of 0.039, indicating high numerical consistency across software implementations. At the item level, most indicators exhibited low MaxDiff values (<0.05), indicating stable loading estimates. The greatest numerical variation was observed in indicator Y4, with a MaxDiff of 0.087 and a MAD of 0.058, primarily due to the higher loading values generated by R Studio. This pattern reflects differences in latent score estimation and internal normalization procedures rather than substantive measurement issues. Importantly, even for indicators with higher numerical variation, all loading values remained well above the minimum criterion, indicating that these differences did not impact the assessment of convergent validity or the interpretation of the measurement model [8].

Table 3. Outer Model (Reliability Score)

Metric	Var	SmartPLS	WarpPLS	R Studio	MaxDiff	MAD
Cronbach's Alpha	X1	0.925	0.925	0.939	0.014	0.009
	X2	0.954	0.954	0.990	0.036	0.024
	Y	0.917	0.917	0.941	0.024	0.016
Composite Reliability	X1	0.946	0.947	0.956	0.010	0.007

	X2	0.967	0.967	0.993	0.026	0.017
	Y	0.942	0.942	0.957	0.015	0.010
Average Variance Extracted (AVE)	X1	0.815	0.817	0.846	0.031	0.021
	X2	0.879	0.879	0.971	0.092	0.061
	Y	0.801	0.801	0.849	0.048	0.032

Note: Model (X1, X2 → Y), N=100, MaxDiff represents the maximum absolute difference, while MAD represents the mean absolute difference across software.

Table 3 shows that all constructs across the three software programs achieved Cronbach's Alpha, Composite Reliability, and AVE values above the recommended threshold, confirming satisfactory internal consistency and convergent validity. From a numerical comparison perspective, Cronbach's Alpha and Composite Reliability showed little difference, as indicated by the low MAD values (≤ 0.024), with SmartPLS and WarpPLS producing nearly identical results. Greater numerical variation was observed for AVE, particularly for construct X2, where MaxDiff reached 0.092 and MAD was 0.061, primarily due to the higher AVE estimation in R Studio. Despite this variation, all AVE values remained well above the 0.50 criterion, indicating that these differences did not alter the interpretation of the measurement model. All observed differences remained within acceptable methodological limits and did not substantially affect the interpretation of the measurement model. These findings are consistent with Monecke and Leisch [29], who noted that variations in algorithm implementation and latent score calculations across PLS-SEM software can produce small numerical differences without altering theoretical conclusions regarding model quality.

Table 4. Inner model (Path Coefficient + R^2)

Metric	Relationship	SmartPLS	WarpPLS	R Studio	MaxDiff	MAD
Path Coefficient	X1 → Y	0.400	0.377	0.409	0.032	0.032
	X2 → Y	0.545	0.569	0.585	0.040	0.040
Coefficient of Determination (R^2)	X1, X2 → Y	0.823	0.830	0.921	0.098	0.065

Note: Model (X1, X2 → Y), N=100, MaxDiff represents the maximum absolute difference across software, while MAD represents the mean absolute difference.

Table 4 shows that all three software programs yield consistent structural relationships, with X2 having a stronger influence on Y than X1 across all platforms. Numerical differences in the path coefficients are relatively small, as indicated by low MAD values (≤ 0.040) and MaxDiff values that do not exceed 0.040, indicating high numerical consistency in the structural path estimates. In contrast, greater numerical variation is observed in the R^2 values, with a MaxDiff of 0.098 and a MAD of 0.065, particularly between R Studio and the GUI-based software. These differences reflect variations in the calculation of latent variable scores and internal scaling. Nevertheless, all R^2 values demonstrate strong explanatory power, and the observed numerical differences do not impact the substantive interpretation of the structural model. [25].

Table 5. Bootstrapping Result with MaxDiff and MAD

Path	Metric	SmartPLS	WarpPLS	R Studio	MaxDiff	MAD
X1 → Y	Original Sample (O)	0.400	0.377	0.409	0.032	0.032
	Sample Mean (M)	0.390	0.324	0.391	0.067	0.045
	Standard Deviation (STDEV)	0.106	0.090	0.101	0.016	0.011
	T Statistics	3.773	4.172	4.060	0.399	0.286
	P Values	0.000	0.001	0.001	0.001	0.001
	2.5% CI	0.166	0.200	0.179	0.034	0.023
	97.5% CI	0.581	0.401	0.566	0.180	0.120
X2 → Y	Original Sample (O)	0.545	0.569	0.585	0.040	0.040
	Sample Mean (M)	0.555	0.506	0.602	0.096	0.064
	Standard Deviation (STDEV)	0.107	0.086	0.096	0.021	0.014
	T Statistics	5.100	6.646	6.105	1.546	1.030
	P Values	0.000	0.001	0.001	0.001	0.001
	2.5% CI	0.353	0.554	0.437	0.201	0.134
	97.5% CI	0.776	0.737	0.804	0.067	0.045

Note : MaxDiff represents the maximum absolute difference between software, while MAD represents the mean absolute difference. All bootstrapping results were obtained using model (X1, X2 → Y), N=100 and 5,000 resamplings.

Table 3.4 shows that the numerical differences in the original path coefficients in SmartPLS, WarpPLS, and R Studio are minimal. For the X1 → Y relationship, the coefficients range from 0.377 to 0.409, resulting in a MAD of 0.032 and a MaxDiff of 0.032. Similarly, for X2 → Y, the coefficients range from 0.545 to 0.585, with a MAD of 0.040 and a MaxDiff of 0.040. These values indicate a high degree of numerical consistency in the primary structural estimates. In contrast, greater numerical variation appears in the derived statistics, particularly the T statistic, where the MaxDiff reaches 0.399 for X1 → Y and 1.546 for X2 → Y. This amplification is driven by differences in bootstrap standard errors rather than differences in the original estimates. Importantly, all T-statistics remained well above the critical value of 1.96, and all p-values were ≤ 0.001, indicating that the observed numerical variations did not alter the inferential decisions. Overall, the comparisons show that the numerical differences between the software are small for the core estimates and larger for the derived statistics, confirming that the algorithmic differences primarily affect the variability measures rather than the substantive path coefficients.

3.1.2 Qualitative (Non-Numeric) results

Qualitative (Non-Numeric) results will show significant differences in interface, features, licensing, and flexibility. This assessment was conducted through expert judgment by the author team, potentially introducing internal bias; however, the authors' direct involvement also provides an advantage because they have in-depth practical experience using all three software packages, so the results remain relevant as an initial exploratory overview.

a. Differences in User Interface Aspects

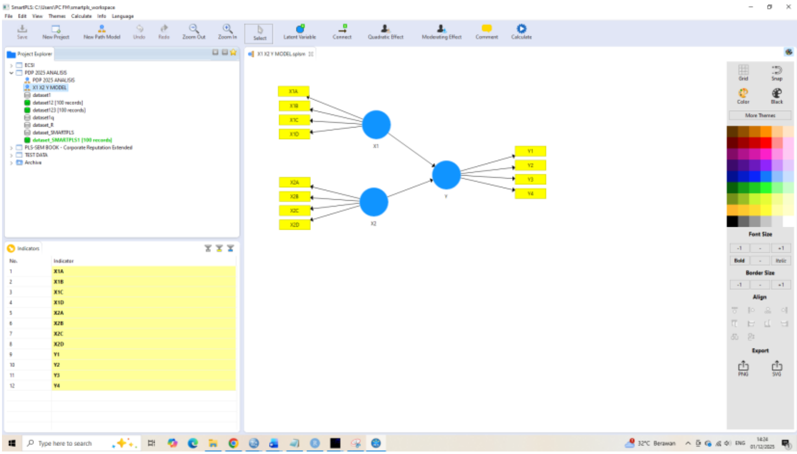

Figure 1. SmartPLS User Interfaces (Main Page)

Figure 1 shows the main page of the SmartPLS application, which is equipped with a modern drag-and-drop interface that allows users to construct models intuitively. The interface provides a workspace where latent variables can be created as nodes and connected with arrows to represent structural relationships. Data files can be imported directly, and indicators are easily assigned to constructs by dragging them into the model canvas. This visual workflow reduces the need for complex coding and enables researchers to focus on the conceptual design of their models. In addition, SmartPLS offers quick access to menus for reliability and validity testing, bootstrapping, and advanced features such as mediation or multi-group analysis, all integrated within the same graphical environment. The combination of visual modeling and automated statistical output makes SmartPLS particularly user-friendly for beginners while still offering comprehensive tools for advanced users.

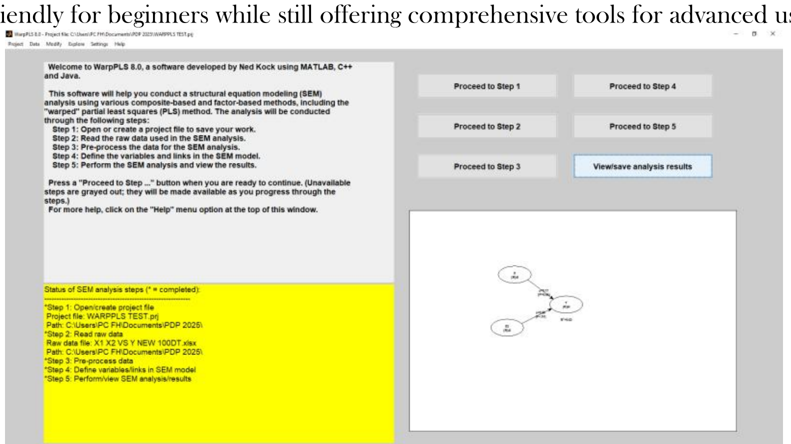

Figure 2. WarpPLS User Interfaces

Figure 2 illustrates the WarpPLS application, which also employs a graphical user interface but with a simpler and more minimalist design compared to SmartPLS. The interface organizes the analysis into a structured sequence of steps, beginning with data input, followed by model specification, estimation, and output interpretation. Each stage must be completed in order, as the software enforces a step-by-step workflow to ensure methodological rigor and prevent errors. This design requires users to have a clear understanding of the analytical process, since skipping or incorrectly executing a step will halt the analysis. While less visually sophisticated, WarpPLS provides built-in guidance and prompts that help users navigate nonlinear modeling options and advanced features. The structured workflow makes the software particularly suitable for users who prefer a guided process, though it may feel restrictive for those accustomed to more flexible or exploratory interfaces.

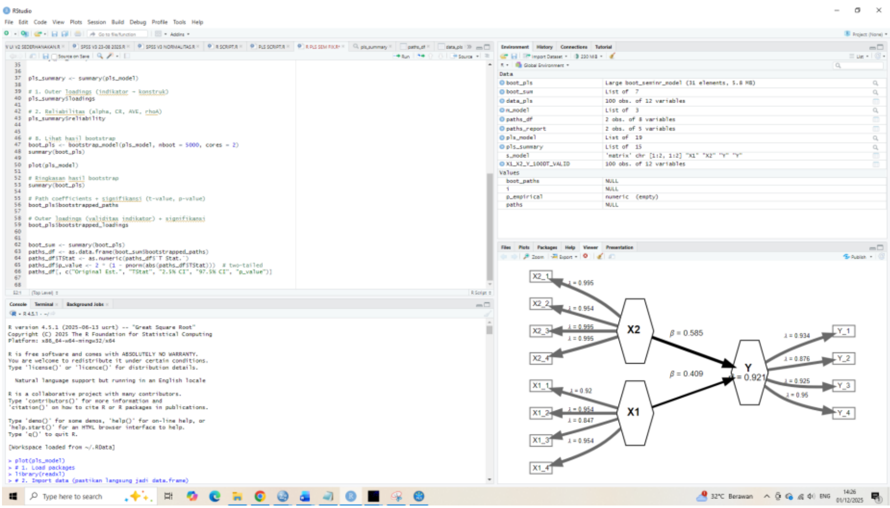

Figure 3. R Studio User Interface

In contrast, in Figure 3 R Studio has syntax-based analysis features and does not provide a built-in visual interface, this makes it difficult for users who are not familiar with syntax, users must have good programming skills to integrate all of its analysis features. Although less user-friendly, R Studio offers high flexibility and access to all features for free, especially when used with packages such as SeminR for PLS-SEM data analysis.

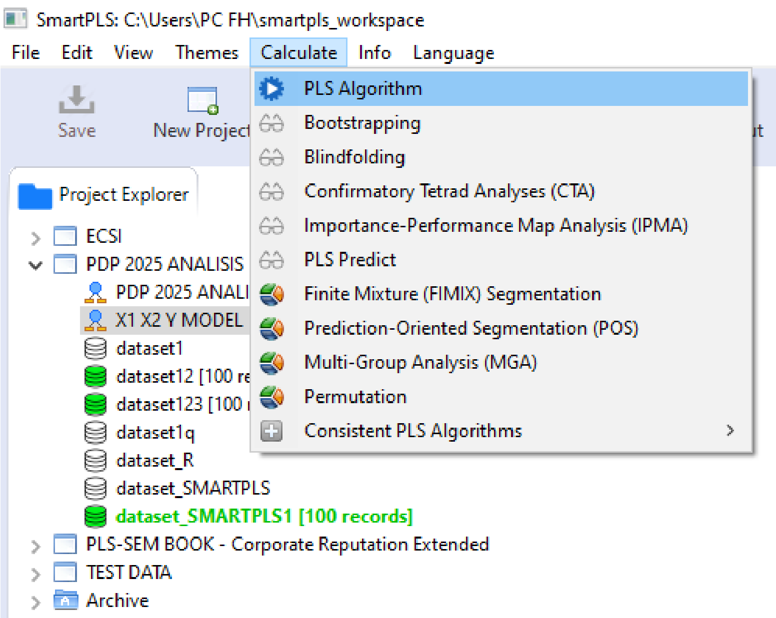

Figure 4. SmartPLS Key Features

Figure 4 shows that SmartPLS provides an intuitive graphical interface for visually building structural and measurement models. Its main features include construct validity and reliability evaluation, path coefficient and R^2 analysis, and significance testing through bootstrapping. SmartPLS also supports multi-group analysis, mediation, and moderation, as well as RSME, while also providing prediction tools (PLS Predict) and Importance-Performance Map Analysis (IPMA). This software makes it easy for users to handle data from various formats, export analysis results, and generate reports automatically, making it suitable for academic research and reference for analytical application development.

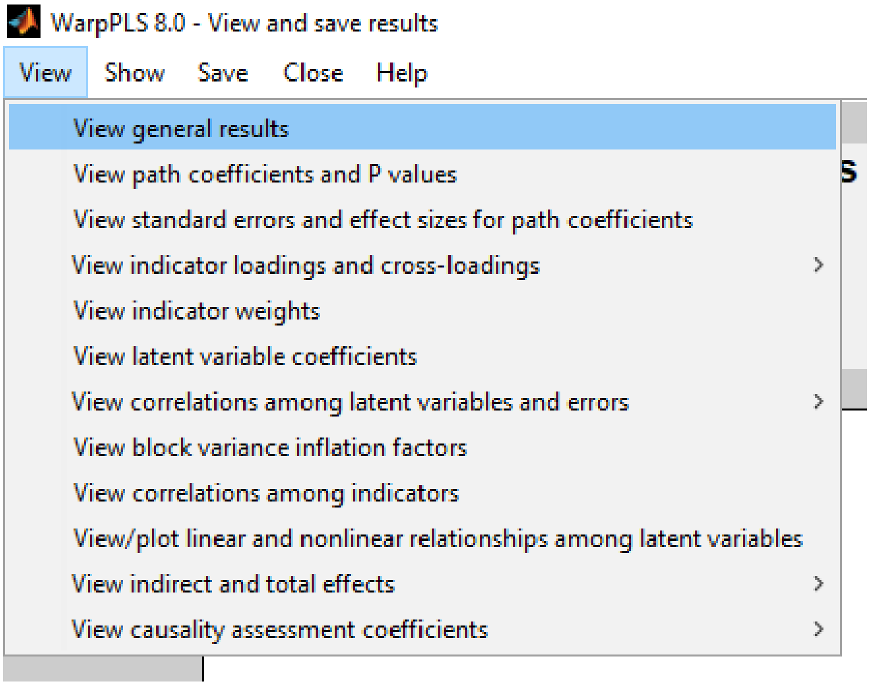

Figure 5. WarpPLS Key Features

In Figure 5 WarpPLS has simpler analysis features compared to SmartPLS. When performing data analysis, WarpPLS has the advantage of built-in features that greatly assist users in the step-by-step process of nonlinear data analysis, starting from data input, modeling, and results. In general, the numerical analysis features available in WarpPLS are quite comprehensive, ranging from result summaries, path coefficients, loading indicators, weights, and more.

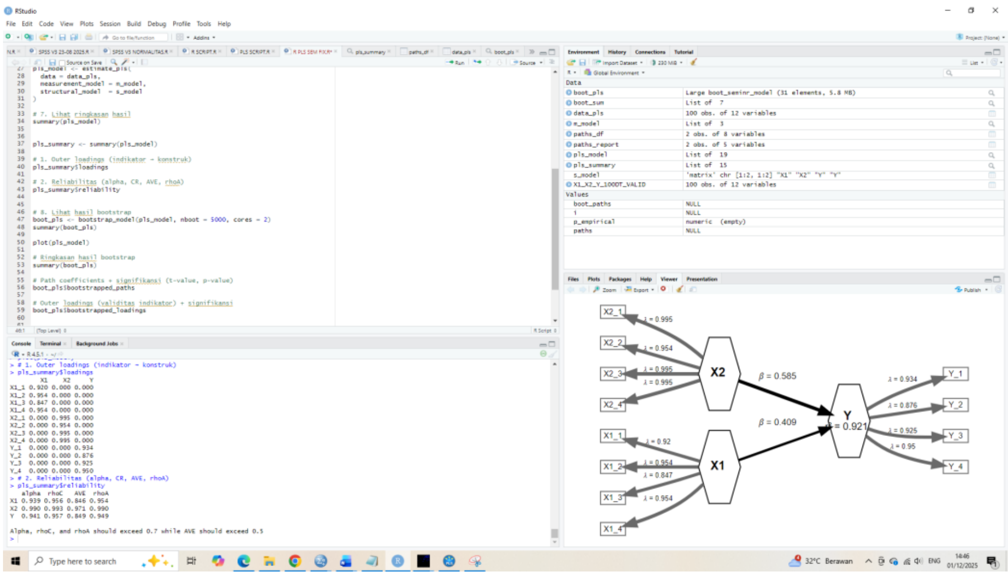

Figure 6. R Studio Key Features

Figure 6 illustrates a syntax-based workflow in R Studio. The left side shows a form for syntax input and numerical output, and the right side shows a form for outputting used features and a diagram plot. R Studio can be customized according to the package used, offering flexibility and powerful potential for integrating analytical applications. Although its built-in model visualization features are still more limited compared to SmartPLS and WarpPLS, R Studio can be integrated with Shiny Dashboard to create GUI-based visualizations [2].

b. Implications of Licensing Differences for Academic Research

SmartPLS is a paid software, and to access all features and functions, a license is required. It offers a free student license, but this is limited to datasets with a maximum of 100 rows (N = 100). The official license costs for SmartPLS are approximately EUR 580 or IDR 11,182,000 (Professional License), EUR 1,160 or IDR 22,254,000 (Professional Floating License), and the most expensive, EUR 4,500 or IDR 86,805,000 (Enterprise Package) for one year. WarpPLS provides a free license for personal use during the first three months and does not restrict the dataset size or application features. Its license fees are lower than SmartPLS, at USD 196 or IDR 3,261,000 for an individual license, while organizational license costs are not specified and depend on the number of users. License information for SmartPLS and WarpPLS is available on their respective official websites. High license costs can be a barrier for students and institutions with limited budgets. In contrast, R Studio is free and open-source, making it more accessible to researchers, lecturers, and universities. These licensing differences directly affect the affordability and sustainability of data analysis practices in academic environments.

c. The Potential of R Studio for PLS-SEM Application Development

R Studio has strong potential as a foundation for developing PLS-SEM analytical applications because it is open-source, flexible, and can be automated. Using packages such as seminr and plspm, the entire analytical process from model estimation and indicator evaluation to structural testing can be executed programmatically and consistently. Its integration with Shiny enables the creation of interactive web-based analytical applications that can be accessed without additional installation, making it highly relevant for academic purposes as well as the development of independent research tools. Although model visualization in R Studio is not as advanced as in SmartPLS, this limitation can be addressed through the addition of specialized visualization packages. With a high level of customization and no licensing restrictions, R Studio offers flexibility that is not available in GUI-based software, making it a highly promising platform for developing Shiny-based PLS-SEM applications.

d. Comparison Result (Interface, Features, Licensing, and Flexibility)

Table 6. Comparison Table Result (SmartPLS, WarpPLS, and R Studio)

Aspect Compared	SmartPLS	WarpPLS	R Studio
Ease of Use	Highly intuitive GUI; easy model building and result export	Simple GUI, less flexible	Code-based; requires programming skills
Graphics & Analytical Features	Excellent visualization, basic features are complete and identical to the other two software.	Quite adequate standard visualizations; rich models and non-linear indicators	Visualization requires additional packages; very extensive features depending on installed packages
License	Paid (limited trial available)	Paid (3 month trial)	Free & open-source
Flexibility	Not customizable	Limited	Very strong; easily integrable with Shiny; highly suitable for tool development

Table 6 concludes that SmartPLS offers a highly imaginative and easy-to-use graphical interface, with superior visualization and comprehensive analytical features, but low integration and development tool transmission, and a paid license. WarpPLS has a simple interface, supports non-linear analysis, adequate visualization and analytical features, but limited transmission and integration, and is also paid. R Studio is free and open-source, code-based so it requires programming, but is very flexible, can be automated, easily integrated with Shiny, and is ideal for developing PLS-SEM applications. Beyond statistical considerations, **computational aspects** further differentiate the software platforms. Empirical observations during the analysis revealed significant differences in memory usage: SmartPLS required approximately 733 MB, WarpPLS 153 MB, and R Studio 351 MB for identical analytical tasks. Despite these differences, bootstrapping execution times for all three software platforms remained below five seconds, indicating comparable computational efficiency for the analyzed models. Execution time from initial data input to model construction and analysis cannot be standardly quantified, as it is highly dependent on the user's technical ability, interface familiarity, and scripting skills, particularly in R Studio.

3.1.3 Comparison of Ease of Use, Interface and Analysis Features, License, Flexibility through Expert Judgment

This section presents the results of a qualitative assessment of SmartPLS, WarpPLS, and R Studio based on the author team's firsthand experience. Aspects compared include ease of use, interface quality and comprehensiveness of analysis features, licensing policies, and integration flexibility. Ratings were conducted using a simple scale (1–3) to provide a practical overview of the strengths and limitations of each software. While this evaluation is potentially biased due to the limited involvement of the author team, the firsthand experience provides an in-depth perspective relevant for this initial exploratory study.

Table 7. Expert Judgment Assessment Results (Ease of Use)

Software	Resp 1	Resp 2	Resp 3	Resp 4	Total Score	Percentage (%)
SmartPLS	3	3	3	3	12	100%
WarpPLS	2	2	2	2	8	67%
R Studio	2	1	1	2	6	50%

Table 7 shows the assessment results with the question "How easy was it for you to navigate the interface, build a PLS-SEM model, and export results" with a score of 1 (Difficult), 2 (Fair), and 3 (Easy). The conclusion is that SmartPLS has the highest score (100%), followed by WarpPLS (67%), and the lowest is R Studio (50%). Respondents assessed that in using the three software, SmartPLS proved to be easier to use than the other two.

Tabel 8. Expert Judgment Assessment Results (Interface, and Analysis Features)

Software	Resp 1	Resp 2	Resp 3	Resp 4	Total Score	Percentage (%)
SmartPLS	3	3	3	3	12	100%
WarpPLS	1	2	2	2	7	58%
R Studio	2	2	1	2	7	58%

Table 8 shows a representation of the question "How good is the quality of the model visualization and the completeness of the analytical features" with a score criteria of 1 (Poor/Limited), 2 (Adequate), 3 (Very Good/Comprehensive). The conclusion is that SmartPLS has the highest score (100%), followed by WarpPLS (58%) and R Studio (58%). Respondents assessed the graphical display and features of the three software, SmartPLS proven to be better than the other two software. Then WarpPLS and R Studio have the same score, which means the display and features are quite adequate.

Table 9. Expert Judgment Assessment Results (License)

Software	Resp 1	Resp 2	Resp 3	Resp 4	Total Score	Percentage (%)
SmartPLS	1	1	1	1	4	33%
WarpPLS	1	2	1	2	6	50%
R Studio	3	3	3	3	12	100%

Table 9 shows the results of the assessment with the question "How adequate is the software license price for full access" with the scoring criteria 1 (Very Expensive), 2 (Sufficient/Standard), 3 (Cheap/Free). The conclusion is that R Studio has the highest score (100%) followed by WarpPLS at (50%) and the lowest SmartPLS (33%). This finding proves that SmartPLS has the highest license price for full version access, WarpPLS is cheaper or considered standard, then R Studio is free without a license fee even though it is lacking in terms of Ease of Use and Appearance.

Table 10. Expert Judgment Assessment Results (Flexibility)

Software	Resp 1	Resp 2	Resp 3	Resp 4	Total Score	Percentage (%)
SmartPLS	1	1	1	1	4	33%
WarpPLS	1	1	1	2	5	42%
R Studio	3	3	3	3	12	100%

Table 10 represents the question "How easy is the software to integrate with other tools or develop in R Shiny" with a score of 1 (Limited), 2 (Adequate), and 3 (Very Flexible). The conclusion is that R Studio has the highest score (100%), followed by WarpPLS (42%) and SmartPLS (33%). Respondents assessed that R Studio has high flexibility and can be further developed through free supporting packages and modules. The other two software cannot be developed independently but can be used as a reference to test the accuracy of results in other software, such as R Studio.

3.2 Discussion

This discussion integrates all research findings to provide a comprehensive understanding of the comparison between SmartPLS, WarpPLS, and R Studio, taking into account both quantitative (numerical) and qualitative (non-numerical) results. Based on quantitative (numerical) analysis results, The Outer Model measurements showed consistent indicator validity across all software, with all loadings >0.70, low maximum absolute differences (MaxDiff) (<0.05), small numerical differences (MAD = 0.039), and the largest variation in item Y4 (MaxDiff = 0.087, MAD = 0.058). Construct reliability through Cronbach's Alpha, Composite Reliability, and AVE were also consistently good; SmartPLS and WarpPLS are nearly identical, with very small numerical differences in Cronbach's Alpha and Composite Reliability (MAD ≤ 0.024). R Studio is more variable, especially in AVE X2 (MaxDiff = 0.092). Although all values remain above the threshold, small deviations can affect marginal indicators or constructs (loading 0.70; AVE 0.50), necessitating cross-checking and reporting of algorithms. This finding aligns with Monecke and Leisch's assertion that algorithm variations can produce small differences without altering model quality [29]. In the Inner Model, all three software produced consistent structural relationships with X2 having a stronger influence on Y than X1. The path coefficients differed slightly (MaxDiff ≤0.040), while the R^2 varied more (MaxDiff = 0.098, R Studio vs GUI), but still indicated strong explanatory power. Bootstrapping results with 5,000 resamplings were also consistently significant ($p<0.05$; $T>1.96$), although the T-statistics varied moderately for X1 → Y (MaxDiff = 0.399) and significantly for X2 → Y (MaxDiff = 1.546) due to differences in resampling algorithms [12]. Overall, the small MAD values confirm high numerical consistency across platforms. Thus, despite variations due to algorithmic and resampling differences, substantive conclusions remain stable, while methodological solutions include transparency in reporting, cross-checking, and the use of theory as the basis for analytical decisions [25], [28].

In the Qualitative (non-numerical) aspect, SmartPLS offers an easy-to-use graphical interface, with better visualization and analytical features, but low integration and transmission of development tools, and a paid license [29], [30]. WarpPLS has a simple interface, supports non-linear analysis, adequate visualization and analytical features, but limited transmission and integration, and is also paid. R Studio is free and open-source, code-based so requires programming, but is very flexible, can be automated, easily integrated with Shiny, and is ideal for developing PLS-SEM applications [31]. Beyond statistical considerations, computational aspects further differentiate the software platforms. Empirical observations during the analysis revealed significant differences in memory usage: SmartPLS requires approximately 733 MB, WarpPLS 153 MB, and R Studio 351 MB for identical analytical tasks. Despite these differences, bootstrapping execution times for all three software platforms remained below five seconds, indicating comparable computational efficiency for the analyzed models. Execution time from initial data input to model construction and analysis cannot be quantified in a standardized manner, as it is highly dependent on the user's technical ability [33],[34], interface familiarity, and scripting skills, particularly in R Studio.

Evaluation results, based on expert jugdement, show that SmartPLS excels in ease of use and interface/analysis features (100%), making it more practical for beginners and users who prioritize visualization. WarpPLS falls in the middle (67% ease of use, 58% interface), being adequate but limited in its visualization. R Studio is lowest in ease of use (50%) and interface (58%) because it is code-based, but still adequate for analysis. Conversely, in licensing and flexibility, R Studio is absolutely superior (100%) because it is free, open-source, and extensible with additional packages. WarpPLS is rated standard (50% license; 42% flexibility), while SmartPLS is lowest (33% license; 33% flexibility) due to its high licensing price and limited integrations. Thus, SmartPLS excels in ease of use and visualization, while R Studio is more strategic in flexibility and cost, although it requires higher technical skills. Therefore, recommendations for using R Studio in developing PLS-SEM data analysis applications must be made with caution, because its advantages are highly dependent on the type of analysis performed and the user's programming skills [30],[31].

Overall, this study demonstrates the high consistency of PLS-SEM analysis results across software (SmartPLS, WarpPLS, R Studio). This confirms that software selection depends not only on numerical accuracy but also on non-numerical factors such as interface, feature completeness, licensing policies, and integration flexibility. SmartPLS excels in ease of use and visualization, WarpPLS falls in the middle, while R Studio is stronger in flexibility and cost. However, this study has certain limitations, such as the use of a simple reflective model (X1, X2 → Y) that does not reflect the complexity of PLS-SEM, a small sample size (N=100) based on simulation, limited measurement criteria to maintain output uniformity, and qualitative assessments, for example, involving only the author team, which can potentially lead to bias. Nevertheless, the authors' direct involvement provides added value in the form of in-depth practical experience. In addition, discriminant validity diagnostics (HTMT) and collinearity checks (VIF) were not included due to software and licensing constraints, which future studies should address to strengthen methodological comprehensiveness. For future research, it is recommended to test more complex models, use larger samples, and involve external users to ensure more representative results and have stronger generalizability.

4. CONCLUSION

This study confirms that SmartPLS, WarpPLS, and R Studio generate consistent PLS-SEM results when identical models and algorithm settings are applied, thereby addressing the research questions on numerical accuracy and non-numerical aspects. While minor numerical differences were observed, they did not change substantive conclusions, highlighting that software choice depends not only on accuracy but also on usability, visualization, licensing, and flexibility. SmartPLS offers ease of use and comprehensive features, WarpPLS provides moderate usability with nonlinear modeling support, and R Studio delivers high flexibility and cost-efficiency through its open-source nature. Limitations include the use of a simple reflective model, a small simulated sample, restricted measurement criteria, and qualitative evaluation based solely on the authors' judgment. Future research should extend this comparison to more complex models, larger datasets, and external user assessments to enhance generalizability and deepen insights into software-specific algorithmic differences.

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