INJCEI
International Journal of Community Engagement and Impact

INJCEI: International Journal of Community Engagement and Impact
Available at ojs.gramatikal.academy/INJCEI
Vol. 1, No. 1, 30 April 2026, pp. 41–45

Simple Technology Is Not Enough: A SEM-PLS Analysis of Data Literacy and Spectral Signal Analysis Quality in Beginner Researcher Communities

Ibrahim Fanji Dipura[1], Fitri Aditri[1], Taufik Hudha Nursyafaah[1], Hulwatul Adzro[1], Neni Alyani[1,2], M Miftahul Madya[1]

[1]Lembaga Riset AI Creation (LRAC), Depok, Indonesia
[2]Institut Pemerintahan Dalam Negeri, Sumedang, Indonesia

*Email corresponding author: mmiftahulm29@gmail.com

Received 7 March 2026 **Accepted 1 April 2026** **Available Online 30 April 2026**

ABSTRACT: The development of simple technology such as Orange Data Mining has improved accessibility in chemometric data analysis, particularly for beginner researchers. However, the quality of spectral signal analysis remains dependent on users' analytical capabilities. This study aims to examine the effect of *Simple Technology Implementation* on the effectiveness of spectral analysis, with community data literacy as a moderating variable. A quantitative approach was employed using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with data collected from 113 respondents through a 5-point Likert scale questionnaire. The results indicate that several indicators do not meet validity criteria (outer loading < 0.70; AVE < 0.50), although some constructs demonstrate acceptable reliability. The data literacy variable also shows weak measurement performance. These findings suggest that simple technology alone is insufficient to improve analytical quality without adequate user understanding. Therefore, strengthening data literacy is essential to optimize the use of analytical tools in spectral data analysis.

ABSTRAK: Perkembangan teknologi sederhana seperti Orange Data Mining telah meningkatkan aksesibilitas dalam analisis data kemometrik, khususnya bagi peneliti pemula. Namun, kualitas analisis sinyal spektra tetap bergantung pada kemampuan analitis pengguna. Penelitian ini bertujuan untuk menganalisis pengaruh *Simple Technology Implementation* terhadap efektivitas analisis spektra dengan literasi data komunitas sebagai variabel moderasi. Pendekatan kuantitatif digunakan dengan metode Structural Equation Modeling–Partial Least Squares (SEM-PLS) terhadap 113 responden melalui kuesioner skala Likert 1–5. Hasil penelitian menunjukkan bahwa beberapa indikator belum memenuhi kriteria validitas (outer loading < 0,70; AVE < 0,50), meskipun beberapa konstruk memiliki reliabilitas yang cukup. Variabel literasi data juga menunjukkan kinerja pengukuran yang lemah. Temuan ini menunjukkan bahwa teknologi sederhana saja belum cukup untuk meningkatkan kualitas analisis tanpa didukung pemahaman pengguna yang memadai. Oleh karena itu, peningkatan literasi data menjadi penting untuk mengoptimalkan penggunaan tools analisis dalam analisis data spektra.

Keywords: Analytical tools; Chemometrics; Data literacy; Orange Data Mining; Spectral analysis

1. INTRODUCTION

The development of simple technology based on visual analytics has increased accessibility in data analysis, particularly in chemometrics, which involves processing complex data such as spectral signals. One of the widely used tools is Orange Data Mining, which offers ease of use through a drag-and-drop interface without requiring programming skills (Demšar et al., 2013). The implementation of such simple technology is especially important for beginner researcher communities who have limited proficiency in complex data analysis software. With this convenience, the process of spectral data analysis is expected to be carried out more effectively and efficiently.

In chemometric analysis, the quality of spectral signals is a crucial aspect as it is directly related to the accuracy of data interpretation and decision-making. Processes such as noise reduction, spectrum pattern visualization, and interpretation of analysis results play a significant role in determining the quality of the output (Brereton, 2009). However, although tools like Orange simplify the analytical process, users' understanding of data and their interpretative abilities remain key factors influencing the final results. Therefore, the success of technology implementation depends not only on system usability but also on the users' data comprehension.

Several previous studies have employed a quantitative approach using Structural Equation Modeling based on Partial Least Squares (SEM-PLS) to analyze relationships between variables in technology adoption and data analysis quality. This method is considered effective for testing research models involving latent variables and reflective indicators, particularly in exploratory research contexts and model development (Hair et al., 2017). Prior studies have applied SEM-PLS across various domains, including digital technology adoption in education (Pratama et al., 2025), chemometric competence analysis (Alyani et al., 2025a), community-based social behavior modeling (Alyani et al., 2025b), workforce readiness in internship programs (Adzro et al., 2026; Nursyafaah et al., 2026a), as well as the analysis of cognitive variables in method validation within the field of chemistry, which highlights the importance of conceptual understanding in ensuring systematic and reliable analytical practices (Nursyafaah et al., 2026c). Furthermore, SEM-PLS has also been utilized to examine behavioral and decision-making factors such as online purchasing behavior (Dipura et al., 2026), library service utilization (Nursyafaah et al., 2026b; Alyani et al., 2026a; Alyani et al., 2026b), and work readiness through competence development. In the context of emerging technologies, studies have explored the role of technology readiness, digital capability, and perceived ease of use in influencing AI adoption and organizational performance using SEM-PLS. These studies indicate that factors such as ease of use, perceived usefulness, and technological readiness influence the effectiveness of technology utilization, although the results vary depending on user characteristics and research context.

However, despite the extensive application of Structural Equation Modeling–Partial Least Squares (SEM-PLS) across various domains, several research gaps remain. Most prior studies have focused on technology adoption, behavioral intention, and organizational performance, with limited attention to the specific context of chemometric analysis, particularly in evaluating the quality of spectral signal analysis. Additionally, existing research predominantly emphasizes general outcomes such as effectiveness, readiness, or decision-making, rather than the technical quality of analytical outputs such as noise reduction, pattern clarity, and spectral accuracy. Furthermore, the role of simple technology implementation, especially using user-friendly tools like Orange Data Mining has not been thoroughly examined in relation to analytical quality in beginner researcher communities. Another important gap lies in the limited exploration of data literacy as a moderating variable, which may significantly influence how users interpret and utilize analytical results. Therefore, this study addresses these gaps by investigating the effect of simple technology implementation on the quality of spectral signal analysis, while incorporating community data literacy as a moderating factor using the SEM-PLS approach.

2. METHODOLOGY

This study employed a quantitative approach using Structural Equation Modeling based on Partial Least Squares (SEM-PLS) to analyze the relationships among variables in the research model. The SEM-PLS method was selected due to its ability to examine models with latent constructs and reflective indicators, particularly in predictive and exploratory research contexts (Hair et al., 2017). The research model consists of an independent variable, namely *Simple*

Technology Implementation, a dependent variable, namely the effectiveness of outlier detection in spectral analysis, and a moderating variable, namely community data literacy. The indicators of each variable are not described narratively in this section, as they are presented in a separate table of variables and indicators.

Data were collected through a survey using a questionnaire with a 5-point Likert scale, representing respondents' level of agreement with each statement. The respondents in this study consisted of 113 individuals who are part of beginner user communities in data analysis, particularly those using Orange Data Mining. The sampling technique employed was purposive sampling, considering respondents' experience in using simple data analysis tools. The use of the Likert scale in quantitative research is widely recognized as effective in measuring perceptions, attitudes, and understanding of respondents toward the studied variables (Likert, 1932).

Table 1 Variable, Definition, and Indicator

Variable	Type	Code	Indicator
X	Independent	X1	I can install Orange Data Mining easily
		X2	The visual interface of Orange is easy for new users to understand
		X3	The process of inputting analytical data into Orange is easy to perform.
		X4	I can create an analysis workflow using the drag-and-drop system easily.
		X5	The chemometric analysis features in Orange are easy to use.
		X6	The analysis results displayed by Orange are easy to understand.
Y	Dependent	Y1	Orange helps display spectral patterns clearly.
		Y2	I can interpret spectral data more easily.
		Y3	The signal processing process helps reduce spectral noise.
		Y4	The resulting spectral analysis is sufficiently accurate.
Z	Moderator	Z1	I Understand the basic concepts of data analysis.
		Z2	I am able to read graphs and data visualizations effectively.
		Z3	I am capable of interpreting data analysis results.
		Z4	I have experience using data analysis software.

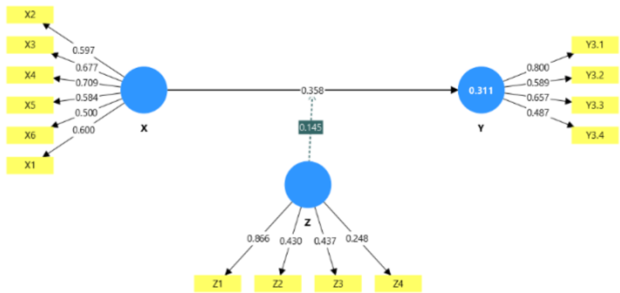

Fig. 1 Model Diagram and Intervariable Relationship

Data analysis was conducted using the SEM-PLS method with two main stages: evaluation of the measurement model (outer model) and the structural model (inner model). The outer model evaluation aims to assess the validity and reliability of constructs using several criteria, including outer loading for indicator validity, Average Variance Extracted (AVE) for convergent validity, and Variance Inflation Factor (VIF) for multicollinearity assessment. In addition, construct reliability was measured using Cronbach's Alpha and composite reliability (rho_c) to ensure the internal consistency of the indicators (Hair et al., 2017; Ringle et al., 2015).

Furthermore, the results of the model evaluation were used to ensure that the constructs met the required criteria before testing the relationships among variables in the structural model. The moderating variable in this study was analyzed to examine the role of community data literacy in strengthening or weakening the relationship between simple technology implementation and the effectiveness of outlier detection. Thus, the SEM-PLS method not only enables the testing of direct relationships among variables but also provides a more comprehensive understanding of variable interactions within the research model (Hair et al., 2017).

3. RESULT

The evaluation of the measurement model (outer model) was conducted using outer loading, Average Variance Extracted (AVE), Cronbach's Alpha, composite reliability (rho_c), and Variance Inflation Factor (VIF). The results indicate that the AVE values for all constructs are below the recommended threshold of 0.50, with values of 0.378 for *Simple Technology Implementation* (X), 0.414 for the effectiveness of outlier detection in spectral analysis (Y), and 0.297 for community data literacy (Z). These findings indicate that none of the constructs meet the criteria for convergent validity. At the indicator level, only a limited number of indicators meet the required outer loading threshold of ≥ 0.70. Specifically, X4 (0.709), Y1 (0.800), and Z1 (0.866) are considered valid, while the remaining indicators do not meet the validity criteria. This suggests that most indicators have weak contributions to their respective constructs.

In terms of reliability, the results show that the composite reliability (rho_c) values for constructs X (0.783) and Y (0.732) exceed the acceptable threshold of 0.70, indicating acceptable reliability. However, Cronbach's Alpha values for both constructs are below 0.70, with values of 0.678 (X) and 0.525 (Y). Meanwhile, construct Z shows low reliability, with Cronbach's Alpha of 0.340 and rho_c of 0.582, both below the acceptable threshold. Furthermore, the VIF values for all indicators range from 1.090 to 1.611, which are below the threshold of 5. This indicates that there are no multicollinearity issues in the measurement model.

Construct & Indicator	Loading Factor	AVE	Cronbach's Alpha	rho_c	VIF
X		0.378	0.678	0.783	
X1	0.600				
X2	0.597				1.135
X3	0.677				1.321
X4	0.709				1.611
X5	0.584				1.512
X6	0.500				1.207
Y		0.414	0.525	0.732	
Y1	0.800				1.278
Y2	0.589				1.251
Y3	0.657				1.161
Y4	0.487				1.090
Z		0.297	0.340	0.582	
Z1	0.866				1.278
Z2	0.430				1.251
Z3	0.437				1.161
Z4	0.248				1.090
Z x X	1.000				1.000

Construct & Indicator	Description
X	**Not valid, Acceptable reliability**
X1	Not valid
X2	Not valid
X3	Not valid
X4	Valid
X5	Not valid
X6	Not valid
Y	**Not valid, but reliable**
Y1	Valid
Y2	Not valid
Y3	Not valid
Y4	Not valid
Z	**Not valid, Not reliable**
Z1	Valid
Z2	Not valid
Z3	Not valid
Z4	Not valid
Z x X	Valid

4. DISCUSSION

The findings of this study indicate that the measurement model does not fully meet the validity and reliability criteria, particularly in terms of convergent validity and the consistency of several constructs. The low AVE values across all variables suggest that the indicators are not sufficiently capable of explaining the variance of their respective constructs. This condition implies that the measurement model still requires refinement, especially in improving the quality and relevance of the indicators used.

The limited number of valid indicators further reflects that users' perceptions of simple technology implementation and spectral analysis effectiveness are not consistently captured. This may be influenced by the respondents' varying levels of experience and understanding, particularly as they belong to beginner researcher communities. In this context, although Orange Data Mining offers ease of use, its effectiveness in improving analytical outcomes is not automatically achieved without adequate user competence.

The reliability results also highlight an important issue, particularly in the moderating variable of community data literacy, which shows low internal consistency. This indicates that respondents' data literacy levels are not well-structured or consistently measured, which may weaken its role as a moderating variable. This finding supports the argument that data literacy is a critical factor that must be strengthened to enhance the effectiveness of technology utilization in data analysis.

Overall, these results emphasize that the implementation of simple technology alone is insufficient to improve the quality of spectral signal analysis. Instead, it must be supported by adequate data literacy and well-designed measurement constructs. Future research is recommended to refine the indicators, improve construct validity, and further explore the moderating role of data literacy to obtain more robust and reliable findings.

5. CONCLUSION

This study shows that *Simple Technology Implementation* using Orange Data Mining alone is not sufficient to ensure effective spectral analysis, as the measurement model does not fully meet validity and reliability criteria. The weak performance of several indicators, particularly in the data literacy construct, indicates that users' ability to understand and interpret data plays a crucial role. Therefore, strengthening community data literacy is essential to optimize the effectiveness of analytical tools, and future research should focus on improving measurement indicators and model quality.

REFERENCES

Adzro, H., et al. (2026). Analysis of interns' work readiness: The roles of program quality, mentor support, and project management tools using SEM–PLS. *J-GADS: Journal of Governance and Applied Data Science, 1*(1).

Alyani, N., et al. (2025a). Analysis of perception and knowledge on chemometric competence among students and practitioners using SEM–PLS. *Jurnal Manajemen Sumber Daya Aparatur, 13*(2).

Alyani, N., et al. (2025b). Building a culture of tolerance through sustainable leadership, cultural intelligence, and social adaptation: Evidence from a multicultural community in Indonesia. *Khazanah Sosial, 7*(4).

Alyani, N., et al. (2026a). Pengaruh digital capability terhadap innovation capability dan operational efficiency startup melalui pemanfaatan AI generatif. *J-KBDI: Jurnal Kecerdasan Buatan dan Data Science Industri, 1*(1).

Alyani, N., et al. (2026b). Pengaruh perceived ease of use terhadap AI generative adoption dalam meningkatkan competitive advantage startup digital. *J-KBDI: Jurnal Kecerdasan Buatan dan Data Science Industri, 1*(1).

Alyani, N., et al. (2026c). Service awareness and management effects on library visit frequency mediated by user interest using SEM-PLS. *J-GADS: Journal of Governance and Applied Data Science, 1*(1).

Brereton, R. G. (2009). *Chemometrics for pattern recognition*. Wiley.

Demšar, J., et al. (2013). Orange: Data mining toolbox in Python. *Journal of Machine Learning Research, 14*, 2349–2353.

Dipura, I. F., et al. (2026). The influence of promotion and social influence on online purchase decisions mediated by convenience. *J-GADS: Journal of Governance and Applied Data Science, 1*(1).

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage.

Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology, 22*(140), 1–55.

Nursyafaah, T. H., et al. (2026a). The effect of work environment and motivation on work readiness through competence using a SEM-PLS approach. *J-GADS: Journal of Governance and Applied Data Science, 1*(1).

Nursyafaah, T. H., et al. (2026b). Pengaruh technology readiness terhadap adopsi AI generatif dan dampaknya terhadap kinerja startup menggunakan SEM-PLS. *J-KBDI: Jurnal Kecerdasan Buatan dan Data Science Industri, 1*(1).

Nursyafaah, T. H., et al. (2026). Pemanfaatan SEM-PLS dalam menganalisis variabel kognitif terhadap validasi metode pada bidang kimia. *J-TP MIPA: Jurnal Transformasi Pendidikan MIPA*, 1(1)

Pratama, M. O., et al. (2025). Analisis kebutuhan dan minat dalam pemanfaatan teknologi digital di SMK Depok menggunakan SEM-PLS. *Jurnal Terapan Informatika Nusantara, 6*(6), 635–643.

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). *SmartPLS 3*. SmartPLS GmbH.