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The Role of Attitude Toward Learning, Interest in Learning and Digital Literacy in Inventive Thinking Skill: SEM Approach

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ABSTRACT

The urgency of this research stems from a follow-up to previous research that mapped the level of inventive thinking among chemistry education students at Sriwijaya University, which was found to be at a moderate level. Therefore, it is necessary to conduct further analysis of the factors that influence inventive thinking. This study aims to determine the relationships among Attitude toward Learning, Interest in Learning, and Digital Literacy and Inventive Thinking among Chemistry Education Students at Sriwijaya University. This research is a quantitative, cross-sectional study. Data were collected through a survey. The instrument used was a 59-item Likert-type questionnaire with 4 points on the scale. The questionnaire included 23 items on inventive thinking, 18 on attitude toward learning, 8 on interest in learning, and 10 on digital literacy. The sample for this study consisted of students in the Chemistry Education study program at Sriwijaya University. The research data were analyzed using Structural Equation Modeling (SEM). The results of the measurement model test indicated 26 indicators that were valid and reliable. The results of the structural model evaluation showed no multicollinearity problems, and the model explained 61.1% of the variance in the inventive thinking variable, which was classified as high. The results of the path coefficient significance test showed that only Hypothesis 3 had a t-statistic greater than 1.96 and a p-value less than 0.05, indicating that only digital literacy had a positive and significant effect on inventive thinking. Then the results of this research will have implications for the development of learning designs/learning environments that can support the inventive thinking of chemistry education students by integrating learning with digital literacy.

Keywords: Attitude toward Learning; Interest in Learning; Digital Literacy; Inventive Thinking; SEM.

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1. INTRODUCTION

Students with 21st-century capabilities are better equipped to handle global concerns. Digital literacy, creative thinking, excellent communication, high productivity, and strong values are among these abilities. Inventive thinking is one of the 21st-century skill constructs needed by the workforce of the future (Turiman et al., 2020a). The capacity to solve non-typical (creative) problems successfully across a variety of fields without a lot of trial and error is known as inventive thinking skills (Sokol et al., 2008). Students should develop inventive thinking as a 21st-century ability because it gives them the cognitive abilities that promote critical and creative thinking in creative problem-solving. Every student needs to be able to think creatively in order

Vol. 8, No. 3, December 2025, pp. 331-343

to tackle real-world problems in accordance with the vision and paradigm of 21st-century learning (Samad et al., 2023).

Students must be in a learning environment that offers an understanding of these essential 21st-century skills and opportunities to apply them in practice. However, it's not just students who must develop these skills (Feyza & Seyda, 2023). Organized support, instruction, and well-designed learning opportunities are necessary to move from awareness to active practice. At this point, the teacher's role becomes crucial in helping students navigate these challenges (Shopia & Fadhil, 2025). To realize inventive students, the education system must be empowered by using an approach that covers various aspects to ensure that students can maintain independence, creativity, critical thinking, self-efficacy, and a culture that supports the new paradigm (Turiman et al., 2020a).

The study's findings indicate that most Sriwijaya University chemical education students have a modest degree of creative thinking. Furthermore, the study's findings indicate that pupils in the classes of 2022, 2023, and 2024 do not significantly differ from one another (Ad'hiya et al., 2024, 2025). Therefore, efforts are needed to increase students' level of inventive thinking. Existing research indicates that several abilities can influence thinking skills, including attitude toward learning (Lestari Pasaribu et al., 2023; Nursiwan & Hanri, 2023; Saifulkhair Omar & Isha Awang, 2021), literacy (Ad'Hiya & Laksono, 2018; Listiani et al., 2022), and interest in learning (Marwati et al., 2024).

Attitude is the tendency to consider something, expressed as acceptance, rejection, or disregard. An individual's assessment of something can also be called perspective. Attitudes reflect a person's personality and can be concrete or abstract. Everyone has strong, persistent beliefs and feelings known as perspectives. Measuring attitudes is crucial for teachers to determine whether students are receptive to science lessons. In the final assessment, student attitude measurements are correlated with student learning outcomes, which are closely related to students' understanding of what they have learned (Anggraini et al., 2022). One indicator in education and culture that is considered to improve students' critical and creative thinking is digital literacy, which refers to a person's ability to find content, think critically, choose what is good and accurate, and then share it with others. Digital literacy also refers to a person's ability, awareness, and attitude to appropriately use digital devices and share information (Ardhiani et al., 2023). Research results have shown a strong positive correlation, indicating that higher learning interest is correlated with better academic achievement. This finding demonstrates the importance of cultivating learning interest to improve academic achievement. Both internal factors, such as motivation, and external factors, such as learning methods, are crucial for increasing student engagement (Primastami & Insani, 2024).

These existing research findings need to be corroborated with analysis using more accurate and comprehensive statistical tests. Therefore, an analysis is necessary to identify the influencing factors. Factor analysis is a set of data analysis techniques that encompasses hypothesis testing and data reduction. It encompasses research methods for a set of correlated variables, aiming to explain the structure of the relationships between the observed variables (Sappaile et al., 2023). In addition, over the years, interest in learning has been recognized as an important component of academic success, as students with high interest tend to participate more actively in the learning process, which positively impacts their understanding of the material (Mulyamti & Tarumingkeng, 2025). One test that can be used is Structural Equation Modeling (SEM). Using structural equation modeling, researchers can simultaneously test and estimate latent variables that include indicator variables, both exogenous and endogenous. Factor analysis and path analysis are combined in this second-generation multivariate analysis method (Khairi & Susanti, 2021).

In statistics, structural equation modeling (SEM) is widely used because of its adaptability and accessibility (Lim et al., 2023). Structural equation modeling (SEM), a combination of factor analysis and path analysis, can determine the relationship between a number of exogenous and endogenous variables and a number of latent variables or indicators. SEM is also used to test models and ensure their validity (Salma et al., 2020). PLS-SEM iterates back and forth repeatedly: optimizing the measurement model, then the structural model, then back to the measurement model, then back to the structural model, and so on until the final goal is to optimize prediction rather than model fit. In fact, this "partial" approach to data analysis is the source of the term "partial least squares" (Hair & Alamer, 2022a). Based on the research background, the problem formulation in this research is: What is the model of the factors that influence the inventive thinking of chemistry education students at Sriwijaya University?. Based on the formulation of the problem, the research hypothesis is as follows:

H1: Attitude towards learning has a significant influence on inventive thinking.
H2: Interest in learning has a significant influence on inventive thinking.
H3: Digital literacy is significant influence on inventive thinking.

The urgency of this research is as a follow-up step from previous research which has mapped the level of inventive thinking of chemistry education students at Sriwijaya University at a moderate level, so it is necessary to conduct further analysis of the factors that influence inventive thinking, which in turn the results of this research will have implications for the development of learning designs/learning environments that can support the inventive thinking of chemistry education students.

2. METHODS

2.1 Types of Research

This research is a quantitative study with a cross-sectional design. A cross-sectional study, also known as prevalence or transversal research, captures a snapshot of the attitudes, actions, or other characteristics of study participants at a particular moment in time (Maier et al., 2023).

2.2 Research Subjects

This research was conducted in the Chemistry Education Study Program at Sriwijaya University. The sampling technique used was purposive sampling, namely, chemistry education students at Sriwijaya University. The sample of this study was 213 students of the chemistry education study program, consisting of 23 students from the class of 2022, 64 students from the class of 2023, 81 students from the class of 2024, and 45 students from the class of 2025.

2.3 Research Instruments

The instrument used was a 59-item Likert-type questionnaire with 4 points on the scale:

a. 23 items on Inventive Thinking (IT) Measurement Instrument (Turiman et al., 2020b).
b. 18 items on attitude towards learning (ATL) instrument adopted from Hassan (2018). This instrument consists of (a) Learning environment; (b) Student engagement; (c) Well-being; (d) Cognitive; and (e) Behavior.
c. 10 items on digital literacy (DL) instrument adopted from Afandi et al. (2024). This instrument consists of the aspects of (a) Information and Data Literacy; (b) Communication and Collaboration; (c) Digital Content Creation; and (d) Security.

Vol. 8, No. 3, December 2025, pp. 331-343

d. 8 items on interest in learning (IL) instrument adopted from Hasanati & Purwaningsih (2021).

2.4 Data analysis

The research data were analyzed using Structural Equation Modeling (SEM) in SmartPLS4. SEM analysis involves two stages, namely measurement model testing and structural model evaluation (Firdaus et al., 2025). Measurement model testing is used to gather reflective construct values, and a set of regression equations is estimated to produce structural model coefficients for links between constructs (Hair et al., 2021).

3. RESULT AND DISCUSSION

3.1 Testing Measurement Model

The measurement model's validity and reliability are evaluated for each variable's indications. Convergent validity, discriminant validity, and construct reliability are also tested. The concept of discriminant validity states that the variance of each latent variable within its indicator group is greater than the variance of other latent variables within their indicator groups.

a. Convergent *validity*

Convergent validity is a metric used to assess the quality of a measurement tool, typically a set of statements or questions. If respondents understand the questions and statements (or other measures) connected to each variable as intended by the question and statement designers, then the measurement tool has strong convergent validity (Amora, 2021).

Two criteria are used to determine convergent validity, which highlights the internal consistency of indicators measuring the same construct: Average variance extraction (AVE) and factor loading (Cheung et al., 2024a). Specific constructs show high similarity when their external loadings are high. This situation is referred to as indicator reliability. All external loadings of an item must be statistically significant and have a minimum of 0.708. This study examines the effect of item deletion on composite reliability if the external loading is less than 0.708. It is recommended that researchers delete items with external loadings between 0.40 and 0.70 to improve composite reliability and average variance extracted (AVE). If an item's external loading is less than 0.40, the item should be removed from the construct (Haji-Othman & Yusuff, 2022).

In the factor loading test, several indicators did not meet the minimum threshold of 0.7 (Hair & Alamer, 2022b). The role of each variable in defining its factor is called its factor loading. Therefore, variables with higher factor loadings are more representative of that factor. In this theory, the number of factor loadings must be carefully considered (Sujati et al., 2020). Therefore, these indicators were declared invalid because they could not adequately represent the construct and were eliminated. A second phase of factor-loading testing was carried out following the removal of invalid indications. A second phase of factor-loading testing was conducted as part of the measurement. The overall factor loading for each indicator is presented in Table 1.

Table 1. Factor Loading Test Results

Variables	Attitude Toward Learning (ATL)	Digital Literacy (DL)	Interest in Learning (IL)	Inventive Thinking (IT)	Category
ATL11	0.833				Valid
ATL12	0.864				Valid
ATL13	0.902				Valid
ATL14	0.897				Valid
ATL7	0.739				Valid
DL1		0.804			Valid
DL2		0.804			Valid
DL3		0.862			Valid
DL4		0.815			Valid
DL5		0.855			Valid
DL6		0.780			Valid
DL7		0.780			Valid
DL8		0.707			Valid
DL9		0.776			Valid
IL2			0.931		Valid
IL3			0.936		Valid
IL6			0.771		Valid
IT10				0.789	Valid
IT19				0.805	Valid
IT20				0.857	Valid
IT21				0.779	Valid
IT22				0.774	Valid
IT23				0.777	Valid
IT6				0.788	Valid
IT7				0.789	Valid
IT8				0.761	Valid

The test results show that all indicators have been declared valid, with loading factors> 0.7. In the Inventive thinking variable, nine indicators (IT10, IT19, IT20, IT21, IT22, IT23, IT6, IT7, IT8) are valid with an outer loading value of 0.761-0.857. In the Attitude toward Learning variable, there are five valid indicators with an outer loading value of 0.739-0.902, namely ATL7, ATL11, ATL12, ATL13, and ATL14. In the digital literacy variable, 9 indicators are declared valid: DL1, DL2, DL3, DL4, DL5, DL6, DL7, DL8, and DL9. In the interest of learning variables, 3 indicators are declared valid: IL2, IL3, and IL6. The factor model with indicators that have satisfied the factor-loading criterion is shown in Figure 1.

Vol. 8, No. 3, December 2025, pp. 331-343

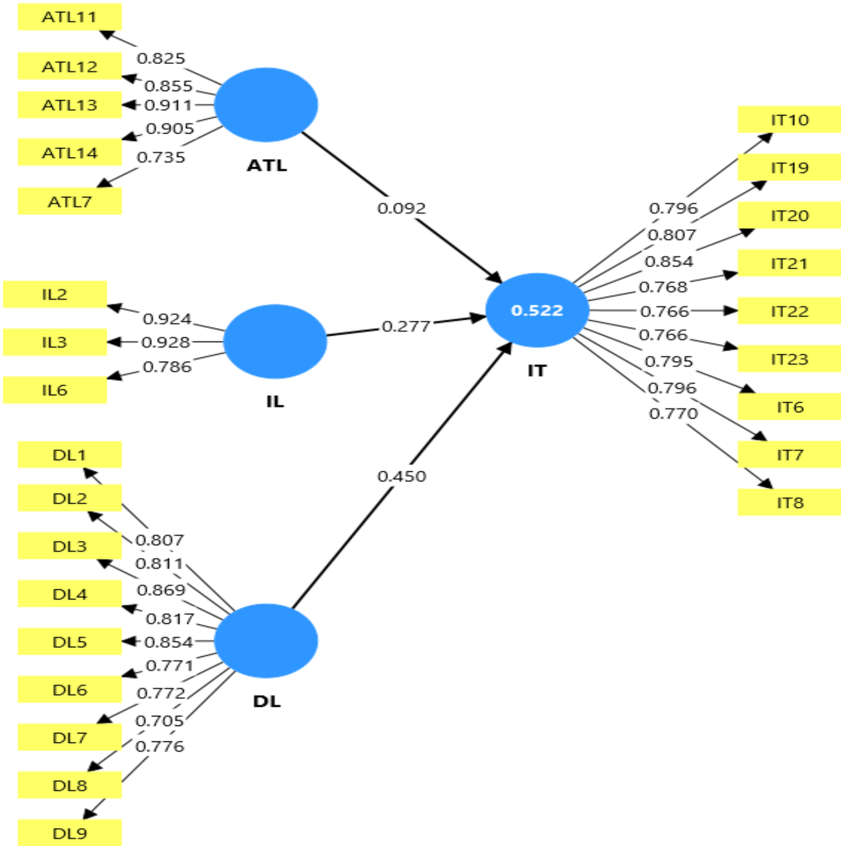

Figure 1. Factor Model

The average variance extracted (AVE) is the average variance explained by a construct in its indicators in relation to the total variance of those indicators. An AVE of at least 0.5, which shows that the latent concept explains at least 50% of the indicator's variance, suggests a suitable degree of convergent validity (Cheung et al., 2024a). The AVE results for each variable are presented in Table 2.

Table 2. AVE Test Results

Variables	Average variance extracted (AVE)	Information
ATL	0.721	Valid
DL	0.639	Valid
IL	0.779	Valid
IT	0.627	Valid

Table 3's AVE test results demonstrate that every variable has an AVE > 0.5, indicating that every variable is deemed genuine. When the construct's AVE value is 0.50 or above, it usually explains more than half of the variance in its indicators. There is usually more inaccuracy in the items than the variance that the construct can explain when the AVE is less than 0.50. A hidden variable or construct's AVE increases with how well it explains the variance in its indicators (Subhaktiyasa, 2024). The average variance extracted (AVE) is calculated as the average variance extracted for the item loadings on a construct. The AVE is the sum of the squared loadings divided by the number of items in the construct (Haji-Othman & Yusuff, 2022).

b. Discriminant Validity

In a structural equation model, discriminant validity guarantees that a construct measure is empirically distinct and captures the phenomenon of interest that other measures are unable to (Henseler et al., 2015). A discriminant validity assessment must be carried out prior to any research utilizing latent variables and the use of items (indicators) to represent constructs. This prevents multicollinearity by ensuring that the latent variables used to quantify the causal relationships under investigation are genuinely unique. If researchers continue to test a proposed model without resolving this problem, they may be mislead or even rendered useless. Consequently, discriminant validity needs to be assessed first (Hamid et al., 2017).

Table 3. Results of Discriminant Validity Test

Variables	Attitude Toward Learning (ATL)	Digital Literacy (DL)	Interest in Learning (IL)	Inventive Thinking (IT)
ATL11	0.834	0.481	0.477	0.380
ATL12	0.864	0.485	0.482	0.371
ATL13	0.902	0.518	0.530	0.508
ATL14	0.897	0.496	0.525	0.503
ATL7	0.739	0.507	0.435	0.393
DL1	0.432	0.803	0.504	0.568
DL2	0.427	0.803	0.518	0.568
DL3	0.496	0.862	0.551	0.605
DL4	0.518	0.815	0.457	0.587
DL5	0.531	0.855	0.510	0.594
DL6	0.466	0.781	0.466	0.490
DL7	0.449	0.781	0.461	0.483
DL8	0.427	0.708	0.442	0.429
DL9	0.466	0.776	0.560	0.499
IL2	0.513	0.519	0.932	0.521
IL3	0.517	0.543	0.936	0.536
IL6	0.499	0.581	0.770	0.547
IT10	0.383	0.474	0.531	0.789
IT19	0.492	0.618	0.503	0.805
IT20	0.511	0.578	0.484	0.857
IT21	0.397	0.495	0.424	0.779
IT22	0.408	0.523	0.392	0.774
IT23	0.357	0.483	0.440	0.777
IT6	0.334	0.587	0.523	0.788
IT7	0.384	0.510	0.493	0.789
IT8	0.375	0.524	0.534	0.761

Thus, discriminant validity ensures that variables truly measure distinct constructs and do not overlap. In this study, discriminant validity was assessed using the cross-loadings shown in Table 3. Table 3 shows that each indicator's cross-loadings correlate more with its own variable than with other variables. This indicates that each indicator reflects only one construct. Thus, based on the results of the convergent and discriminant validity analyses, 26 valid indicators were obtained and can be used for further analysis.

Vol. 8, No. 3, December 2025, pp. 331-343

c. Construct Reliability

Researchers utilized reliability measures as one of the criteria for evaluating convergent validity because the notion of convergent validity stresses the internal consistency of indicators measuring the same construct. However, scholars have contended that evaluating convergent validity requires more than just looking at reliability. Estimating a measurement model is the first step in using SEM to verify convergent validity. This measuring model has no direct connection to any unwanted constructs and includes all indicators associated with the desired construct (Cheung et al., 2024b).

According to others, Cronbach's alpha is "one of the most important and widely used statistics in research involving test construction and use." As a result, it is frequently used in studies where numerous items are measured. When developing measures to evaluate attitudes and other affective dimensions, alpha is commonly reported. Nonetheless, the literature also contains reports on the creation of student knowledge and comprehension assessments that reference Cronbach's alpha as a measure of instrument quality (Cheung et al., 2024b). In this study, two reliability tests were conducted: Cronbach's alpha and composite reliability. The cutoff value for both measures was 0.70. Results of the reliability tests are shown in Table 4.

Table 4. Reliability test results

Variables	Cronbach's Alpha	Composite Reliability (rho_c)	Category
ATL	0.902	0.928	Reliable
DL	0.929	0.941	Reliable
IL	0.853	0.913	Reliable
IT	0.925	0.938	Reliable

Every variable has a value greater than 0.7, according to the Cronbach's alpha and composite reliability test results, so all variables are declared reliable (Hair & Alamer, 2022b).

3.2 Structural Model Evaluation

a. Collinearity Test

The association between two or more independent variables frequently causes issues in multiple linear regression analysis with a large number of independent variables. Multicollinearity is the term used to describe correlated independent variables. The absence of multicollinearity among the independent variables in a linear regression model is one of its underlying presumptions. A correlation or relationship between some or all of the independent variables is known as multicollinearity (Taber, 2018). Multicollinearity occurs when one predictor variable is correlated with another. This can result in inefficient regression coefficient estimates. Multicollinearity in this study was examined using variance inflation factor (VIF) values (Miah et al., 2023). In this study, there were no collinearity problems, and the overall VIF values are shown in Table 5.

Table 5. Collinearity Test Results

Variables	VIF
ATL -> IT	1,771
DL -> IT	2,193
IL -> IT	2,037

b. Coefficient of Determination (R Square)

To evaluate the suitability of a linear regression model, the coefficient of determination (R-square) is used. This value is the square of the multiple correlation coefficient resulting from the sample values for the explanatory and research variables. Only if the observations are correctly observed and there is no measurement error can this value provide valid results. The modified form of the coefficient of determination, or R-square, is referred to as the adjusted R-square. R-square, which is based on the percentage of a research variable's variability that can be explained by knowledge of a particular set of explanatory factors, is used as a summary measure of the fit of any linear regression model. The square of the numerous correlation coefficients between the research variable and each of the current explanatory factors is also known as R-square (Cheng et al., 2014). Table 6 illustrates that the model employed in this investigation fits the measurements well, with a high R-square value. Collinearity is also not a problem.

Table 6. R-square Test Results

Variables	R-square	R-square Adjusted
Inventive Thinking	0.611	0.601

The inventive thinkking variable has an R-square of 0.611 according to the coefficient of determination (R-square). This indicates that 61.1% of the inventive thinking variable, which falls into the high category, comes from the predictor or explanatory power of the link between indicators in the model (Hair et al., 2021; Hair & Alamer, 2022b).

c. Significance of Path Coefficient

Bootstrapping was performed with a resample of 5000 to measure the significance of the path coefficient and the moderator's moderating effect. The t-value needs to be taken into account in order to assess the relationship's significance. Analyze the corresponding t-value and the standardized beta value. A t-value of more than 1.96 or a p-value of less than 0.05 indicates a significant path (Miah et al., 2023).

Table 7. Results of Path Coefficient Significance Test

Variables	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Information
ATL -> IT	0.040	0.040	0.061	0.652	0.514	Not Significant
IL -> IT	0.138	0.136	0.073	1,888	0.059	Not Significant
DL -> IT	0.281	0.278	0.077	3,629	0.000	Significant

The path coefficient significance test results indicate that only Hypothesis 3 has a t-statistic greater than 1.96 and a p-value below 0.05, while Hypotheses 1 and 2 are rejected as insignificant. This indicates that digital literacy has a positive and significant influence on inventive thinking. Additional research findings demonstrate that learning freedom and digital literacy have a substantial impact on student learning outcomes, both partially and concurrently (Setyaedhi & Pramana, 2025). Because it allows us to: (1) think critically, creatively, and innovatively; (2) resolve issues; (3) communicate more fluently; and (4) work with more people, digital literacy is crucial. Additionally, there are several

Vol. 8, No. 3, December 2025, pp. 331-343

advantages to digital literacy, including: (1) time savings due to the ease with which references can be found online; (2) cost savings due to the abundance of free websites and applications on the internet; (3) network expansion due to the ability to add new friends from different countries and regions through social media; (4) better decision making; (5) faster and more efficient learning; (6) quick access to the most recent information; (7) environmental friendliness; and (8) enriching skills (Megasafitri et al., 2023).

4. CONCLUSION

Based on the results and discussion, the measurement model test indicates 26 valid and reliable indicators. The results of the structural model evaluation show that there are no multicollinearity problems, and the indicators' relationships explain 61.1% of the inventive thinking variable, which is in the high category. Only Hypothesis 3 has a t-statistic greater than 1.96 and a p-value below 0.05, according to the path coefficient significance test results, suggesting that only digital literacy is positively and substantially correlated with creative thinking. Improving digital literacy integrated into learning design has practical implications in the form of utilizing technology for creative exploration activities, digital collaboration, and innovative product-based assessments, so that students are encouraged to generate new ideas more effectively. Theoretically, this integration strengthens the framework of constructivism, connectivism, and technology-based learning models such as TPACK, which emphasizes that digital literacy plays a catalyst in the development of inventive thinking through the ability to access, process, and transform information into original and innovative solutions.

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