Analyzing the Impact of Augmented Reality on Trait Thinking for Electronics Science Learning in Engineering Education

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***Abstract*—This study explores the impact of Augmented Reality (AR) on trait thinking skills among undergraduate students in Electronics Science education at Universitas Negeri Padang in Indonesia. Utilizing a quantitative approach with an online survey and non-probability sampling, the research investigates how AR usage relates to adaptive and critical thinking abilities, influencing students' academic performance. The methods used in this study include Structural Equation Modeling (SEM), Network Analysis, and Fuzzy Clustering analysis with detailed variables that include students' academic performance, learning strategies, information literacy, and trait thinking. The results of this study show that the use of Augmented Reality (AR) significantly enhances students' critical thinking and adaptability—skills that are crucial for solving complex problems and driving innovation in technical fields. This underscores that AR not only helps in understanding difficult concepts but also directly contributes to the development of essential cognitive skills needed for success in technical disciplines.**

***Keywords*—augmented reality, trait thinking, learning strategies, information literacy, academic performance of students, technical education**

I. INTRODUCTION

Technical education is facing extraordinary challenges and opportunities in the 21st century. In fact, technical education is needed to prepare younger generation for the rapidly developing global landscape in a world controlled by technology and innovation [1, 2]. Furthermore, technical education has progressed past teaching traditional mechanical skills, providing students with a strong understanding of information technology, artificial intelligence, modern science, and technology, improving the critical thinking abilities of the learners [3, 4]. This not only has a significant impact on educational standards but also on students' skills and knowledge relevant to the latest technology trends. Consequently, they are better prepared for high academic achievement and ready to face the challenges of the 21st century, which often demand a deep understanding of technology and innovation.

This also impacts the learning process of the Electronics Science course, which requires technological innovation in its implementation. The use of technology facilitates collaboration and discussion between educators and students not only during face-to-face interactions in the classroom but also outside the classroom through online means. Online discussions can deepen knowledge, share ideas, and enable active participation without time constraints [5]. This is because traditional textbooks are no longer the sole source of information literacy in the learning process [6]. Through technology, students can access various educational resources, including e-books, online journals, instructional videos, and e-learning platforms [7, 8]. Additionally, technology enables students to participate in online discussions, collaborate on projects, and share ideas with fellow students and educators from around the world [9]. One technological application that can integrate theory and practice in the classroom is Augmented Reality.

Augmented Reality (AR) is a technology that overlays digital information, such as images, sounds, and videos, onto the real world, enhancing the user's perception of their environment [10]. This technology seamlessly integrates digital content with the physical world, often using cameras and sensors to detect and map the environment [11]. According to Samala *et al.* [12], AR can enhance students' motivation by presenting learning materials in engaging and interactive formats, as well as providing learning experiences tailored to the needs and preferences of individual students. This view is also supported by Wang *et al.* [13], who argues that with the presence of AR, it can bring more interactive and engaging learning experiences, thereby increasing students' motivation to grasp new ideas. The foundation for sustained academic success lies in these skills. When students can explore, understand, and respond to new ideas, it demonstrates strong critical thinking traits in students [14, 15]. Critical thinking encompasses various aspects of perceptual and intellectual understanding, influencing how individuals learn and tackle challenges in learning.

The use of AR can also unearth students' potential for critical thinking. Kao and Ruan [16] argues that through interaction with interactive and dynamic AR content, students are encouraged to analyze, evaluate, and interpret information in the context of the real world. This process prompts students to question, problem-solve, and make informed decisions based on their observations within the AR environment. This engagement not only enhances their problem-solving abilities but also fosters the development of 'trait thinking'. Trait thinking encompasses effective planning, employing appropriate rational strategies, self-monitoring to assess understanding and learning progress, persistent efforts to overcome difficulties, and confidence in their abilities (self-efficacy) [17]. All these components greatly shape the mindset of students, contributing to high academic performance.

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The objective of this research is to examine the effectiveness of AR in enhancing students' academic performance, learning strategies, trait thinking, and information literacy. The proposed AR software aims to develop students' trait thinking skills by enhancing their abilities in argumentation, logical reasoning, and strong interpretation. This research seeks to leverage technology to provide a more unique alternative during the learning process, thereby encouraging students to actively engage in critical thinking. The primary goal of this study is to evaluate the effectiveness of AR in improving students' ability to apply higher-order thinking skills, such as analysis, evaluation, synthesis, and the application of technical concepts in real-world situations. Based on previous studies referenced in this research, the proposed hypothesis is as follows:

1) H_1: Information literacy has an impact on students' academic performance.
2) H_2: Learning strategies has an impact on information literacy.
3) H_3: Learning strategies has an impact on students' academic performance.
4) H_4: Trait thinking has an impact on information literacy.
5) H_5: Trait thinking has an impact on learning strategies.
6) H_6: Trait thinking has an impact on students' academic performance.
7) H_7: Learning strategies moderating information literacy and students' academic performance.
8) H_8: Trait thinking moderating information literacy and students' academic performance.
9) H_9: Trait thinking moderating on learning strategies and students' academic performance.
10) H_{10}: Trait thinking moderating on learning strategies and information literacy.

II. Literature Riview

A. Students' Academic Performance

Students' academic performance is a highly significant topic in education due to its substantial impact on students' futures and the overall achievement of educational goals. The factors influencing academic performance are complex, involving psychological, social, and learning environment aspects. Students' motivation and learning attitudes play a major role in their academic success. Recent research by Vu *et al.* [18] shows that intrinsic motivation, which stems from interest and enjoyment in learning itself, has a positive relationship with students' academic performance.

Additionally, emotional intelligence also plays a crucial role in academic success. Somaa *et al.* [19] found that students with high emotional intelligence are better able to manage stress and adapt to academic challenges, which positively impacts their performance. Social factors are also critically important. Family support, for example, has a significant influence on academic performance. Kristjánsson and Sigfúsdóttir (2009) [20] demonstrate that consistent parental support and involvement in a child's learning process have a substantial positive impact on students' academic achievement. Additionally, social relationships with peers also affect academic performance, both positively and negatively, as revealed by Howard *et al.* [21].

In addition to individual, social, and learning environment factors, educational technology also plays an increasingly important role in enhancing students' academic performance. With technological advancements, many new innovations have been introduced to enrich the learning experience and support academic achievement, one of which is Augmented Reality (AR). Recent research by Kalemkus and Kalemkus (2023) [22] shows that AR can enhance students' motivation and engagement with learning materials, positively impacting their academic performance.

B. Information Literacy

Information literacy is increasingly recognized as an essential skill for students in the digital age, involving the ability to locate, evaluate, and use information effectively and responsibly. It requires a blend of critical thinking, technological proficiency, and an understanding of information ethics. According to Mohamed (2019) [23], information literacy is fundamental for academic success and lifelong learning. Theoretical frameworks such as the Big6 model by Lee *et al.* [24] and the ACRL's Framework for Information Literacy emphasize the importance of inquiry, research, and critical evaluation in the learning process. Research by Sohail and Gupta (2024) [25] shows that students with strong information literacy skills are better equipped to handle complex research tasks and produce high-quality academic work.

Integrating information literacy into the curriculum has proven beneficial for enhancing students' research skills and academic performance. Studies by Rojas-Estrada *et al.* [26] reveal that embedding information literacy into course content and assignments leads to improved research outcomes and better preparation for future academic and professional endeavors. However, there are challenges in teaching and assessing information literacy, such as ensuring that instruction is relevant and engaging for students. Traditional teaching methods may not fully address contemporary learners' needs, leading to innovations such as flipped classrooms, online tutorials, and interactive workshops [27]. These new approaches offer ways to better engage students and enhance their information literacy skills. Overall, information literacy is a vital component of academic success and lifelong learning, and ongoing research and innovative teaching methods are crucial for adapting to the evolving information landscape.

C. Learning Strategies

Learning strategies are techniques or approaches that students use to enhance their learning and academic performance. These strategies play a crucial role in how effectively students acquire, process, and retain information. Novak (1988) [28] highlights that cognitive strategies, such as summarization and keyword mnemonics, improve information retention and comprehension. Metacognitive strategies, including self-regulation and goal-setting, help students plan, monitor, and evaluate their learning processes, as explained by Melissa Ng Lee Yen (2020) [29] and Saadati *et al.* [30]. Research by Teng *et al.* [31] shows that students who effectively use both cognitive and metacognitive strategies are better equipped to handle complex research tasks and produce high-quality academic work.

Integrating learning strategies into the curriculum has been shown to benefit students' research skills and academic performance. Studies by Teng *et al.* [31] indicate that embedding learning strategies into course content and assignments leads to improved research outcomes and better preparation for future academic and professional challenges. However, challenges in teaching and assessing learning strategies remain, such as ensuring that instruction is relevant and engaging for students [32]. Traditional teaching methods may not fully meet contemporary learners' needs, leading to innovations such as flipped classrooms, online tutorials, and interactive workshops [33]. These new approaches offer ways to better engage students and enhance their skills. Overall, effective learning strategies play a vital role in academic success and cognitive development, and ongoing research and innovative teaching methods are crucial for adapting to the evolving educational landscape.

D. Trait Thinking

Trait thinking encompasses various components such as planning, cognitive strategies, self-checking, effort, and self-efficacy, which are critical for academic success. Planning involves setting goals and developing strategies to achieve them, a fundamental aspect for effective learning [34]. Effective planning helps students organize tasks and manage time, facilitating goal attainment. Cognitive strategies, such as summarization and organization, are mental techniques essential for processing and retaining information [35, 36]. Students with strong trait thinking skills are adept at selecting and applying these strategies, which enhances their understanding and academic performance [37].

Self-checking, or monitoring one's own understanding and performance, is crucial for self-regulation and metacognitive control. It allows students to evaluate their progress and adjust their learning approaches as needed [38]. Effort, which involves the persistence and energy applied to achieve academic goals, is closely linked to the growth mindset and significantly influences academic success. Students who consistently apply effort are more likely to overcome challenges and achieve higher performance [39]. Self-efficacy, or the belief in one's ability to succeed, drives motivation and resilience. High self-efficacy enhances goal setting and persistence, leading to better academic outcomes [40]. Overall, these components of trait thinking contribute significantly to how students approach learning and their academic achievements.

III. Methods

This study employs a survey research design with quantitative elements, as it involves online surveys and non-probability sampling to collect data. However, it also includes descriptive elements, as it aims to describe the impact of AR and trait thinking on students' academic performance.

To answer the research questions and hypotheses, the study employs Structural Equation Modeling (SEM), Network Analysis, and Fuzzy Clustering analysis with detailed variables that include students' academic performance, learning strategies, information literacy, and trait thinking. To facilitate a better understanding of the analysis process, Fig. 1 illustrates the various stages involved. This figure outlines the key steps taken during the study, from initial data collection to final analysis. By referring to this figure, readers can gain a clearer overview of the methodology and procedural framework applied in this research.

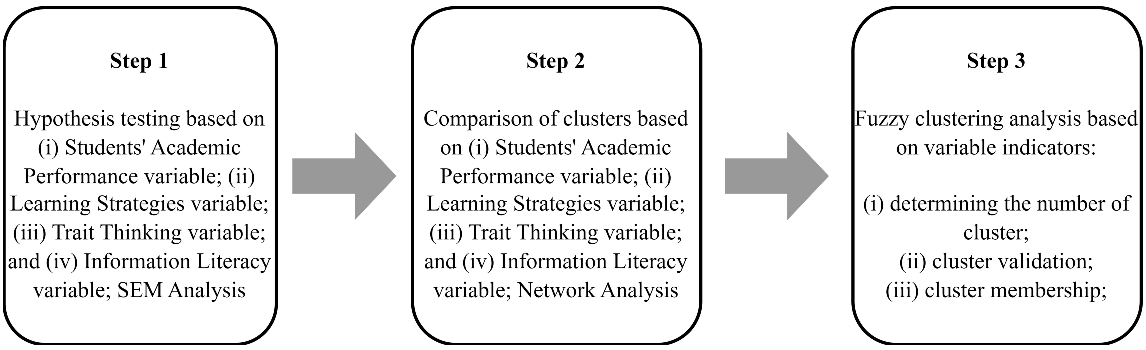

Fig. 1. Summing up of methodological framework [41].

Fig. 1 shows the stages in carrying out the analysis. The first step included testing hypotheses for each variable through SEM analysis, followed by Network Analysis and FCM Clustering [42, 43]. This study aims to investigate various aspects of Augmented Reality (AR) usage and its impact on students' academic performance in technical education. Specifically, it will determine how AR affects academic performance, identify the individual effects of Learning Strategies, Information Literacy, and Trait Thinking Skills on students' performance, and evaluate the mediating roles of these factors.

A. Structural Equation Modeling (SEM) Analysis

In the initial stage, Structural Equation Modeling (SEM) analysis was used to test hypotheses and validate identified relationships in the research [44]. SEM was a statistical method that examined and measured complex relationships between variables in research which integrated multiple statistical analysis techniques, such as factor analysis, path analysis, and regression analysis, into one framework with SEM [45]. SEM was selected as one of the analyses in this study because this methodology enables a deeper analysis of the complex relationships between the observed variables. The observed variables in this research include Students' Academic Performance, Learning Strategies, Trait thinking, and Information Literacy. By utilizing SEM, the study aims to uncover how these variables interact and influence each other, providing a comprehensive understanding of the factors affecting students' learning outcomes in the context of augmented reality and trait thinking.

Furthermore, SEM provides the capability to test pre-designed theoretical models based on existing literature. By incorporating relevant variables into a unified analytical framework, we can test hypotheses regarding the direct and indirect effects of AR usage on students' learning outcomes.

B. Network Analysis

In addition to SEM, Network Analysis will be employed in this study. Network Analysis will allow us to examine how various variables interact within complex networks, offering insights into the interconnectedness and dependencies among factors including students' learning strategies, information literacy, and trait thinking. The network Analysis method was applied in this research which helped to understand and analyze relationships between entities (nodes) in a network and the connections (edges or links) [46]. In the network analysis method, entities, also known as nodes, are the fundamental units or elements within the network. Nodes represent individual items or actors within the network, which can vary widely depending on the context of the study. For instance, in a social network, nodes could represent people, while in a technological network, nodes could represent devices or computers. Nodes are connected by edges (or links), which illustrate the relationships or interactions between them, allowing for the analysis of the structure and dynamics of the network.

Using the method can visually showing patterns of interconnections and interactions among important variables in this investigation. The network Analysis method exposed connections that were not apparent in traditional analyses and it observed how information influenced change among these variables [47]. By combining Network Analysis and SEM PLS, helping to identify relationship patterns not visible with conventional analysis and measure their impact on academic performance, thus enabling more effective educational interventions.

C. Fuzzy C-Means (FCM) Clustering

After discussing the advantages of integrating Network Analysis and SEM PLS to gain a deeper understanding of the relationships among variables and their impact on academic performance, it is essential to examine another critical method employed in this study: Fuzzy C-Means (FCM) Clustering. This approach was chosen to enhance the analysis by facilitating the classification and grouping of data points according to their similarities, thereby offering deeper insights into the underlying patterns and structures within the dataset.

Integrating FCM Clustering into the methodology expands the ability to uncover nuanced relationships and patterns that may not be apparent through traditional analytical approaches alone. Data objects were not completely grouped into one particular cluster but could belong to multiple clusters with varying degrees of membership implying FCM in this research [48]. FCM allowed for a more nuanced analysis and understanding of data difficulties. Therefore, this research took a complete approach to analyzing and understanding relationships among the learned variables and impact on the academic performance of students [49]. By combining SEM PLS, Network Analysis, and FCM, this research required a deeper and more complete understanding of the difficulty of data and the relationships in the exploration setting [50].

D. Participants

The participants in this study are undergraduate students (N = 985) enrolled in the departments of electronics engineering, electrical engineering, mechanical engineering, civil engineering, mining engineering, and automotive engineering at the Faculty of Engineering, Universitas Negeri Padang, Indonesia. Detailed information about the participants will be provided in Table 1.

Table 1. Respondent profile

Sample Characterization		Frequency	Percent (%)
Gender	Male	702	71.27
	Female	283	28.73
	Total	985	100
Age	>24 years old	4	0.41
	23–24 years old	66	6.70
	21–22 years old	283	28.73
	19–20 years old	497	50.46
	17–18 years old	135	13.71
	Total	985	100
NIM/Student ID Number	2022	385	39.09
	2021	205	20.81
	2020	264	26.80
	2019	101	10.25
	2018	26	2.64
	2017	4	0.41
	Total	985	100
Major	Electronic Engineering	110	11.17
	Electrical Engineering	295	29.95
	Mechanical Engineering	135	13.71
	Automotive Engineering	190	19.29
	Civil Engineering	70	7.11
	Mining Engineering	185	18.78
	Total	985	100

Furthermore, stratified random sampling was used to obtain the sample. In contrast to a probability-based sampling process, a non-probability sampling method was employed to conduct an online data-based survey. This approach aimed to provide a comprehensive and representative understanding of the population in the report. In addition, data collection included distributing questionnaires used a Likert scale with response options ranging from (1) strongly disagree/never, (2) disagree/rarely, (3) uncertain/sometimes, (4) agree/often to (5) strongly agree/always to gather information on the academic performance of students, learning strategies, information literacy, and trait thinking.

The mediation analysis used intercession testing procedures to complement the analysis of both direct and indirect effects, signifying the significance [51]. Following this, a classification process produced three groups namely, full mediation, partial mediation, and no mediation.

Full mediation occurs when the mediator variable completely explains the relationship between the Independent Variable (IV) and the Dependent Variable (DV), rendering the direct effect of the IV on the DV non-significant when the mediator is included. Partial mediation happens when the mediator partially explains the relationship, so the IV has both a direct and an indirect effect through the mediator, with the direct effect remaining significant. No mediation is when the mediator does not account for the relationship between the IV and the DV, meaning the IV influences the DV directly without any significant mediation effect. By categorizing mediation as full, partial, or none, researchers can understand the mediator's role in the IV-DV relationship and determine whether the mediator fully, partially, or does not explain this relationship.

E. Instrument and Development

The primary data for this research were collected using a questionnaire adapted based on various findings. The questionnaire consisted of 35 out of 42 validated items, covering elements including students' academic performance [52], learning strategies [53], information literacy [24], and traits related to thinking, covering planning, cognitive strategy, self-check, effort, and self-efficacy [54]. After the questionnaire has been distributed, validity and reliability testing will be conducted using SEM analysis, Network Analysis, and FCM. The instrument's validity was assessed by six experts, with three evaluating aspects of media and language. These experts are professors and doctors specializing in informatics and evaluation at Universitas Negeri Padang.

F. Procedures

According to the established procedures, participants were informed about the objectives and benefits of this research. Students were asked to access and install the Augmented Reality (AR) application "Basic Electronics Application" using the Android platform, which was specifically developed to support the learning process and enhance students' skills. The app likely includes modules on fundamental topics such as circuits, components, and their functions, allowing students to engage with the material in a dynamic and hands-on manner. By integrating the app into the curriculum, students were able to access interactive content that complements traditional learning methods, offering a more immersive and engaging educational experience.

The use of the app aimed to improve students' grasp of basic electronics concepts, facilitate practical application, and ultimately enhance their academic performance in the subject. The app interface can be seen in Fig. 2.

Fig. 2. Implementation of the AR application.

Based on Fig. 2, it can be observed that the "Applications of Basic Electronics" app features a user-friendly interface with several key elements supporting the learning process. Features such as intuitive navigation, a simple interface design, and easily accessible functionalities contribute to the app's user-friendliness. Huang ande Benyoucef [55] supports the claim regarding the effectiveness of user interfaces in similar applications.

Transitioning to the section that discusses the app's main features, the focus is placed on how the app's interface supports interactive learning through its various menus, including materials on electronic components, AR markers for interactive visualization, and an evaluation menu to test students' understanding. The use of AR markers allows students to see virtual representations of the subjects being taught, including diodes and capacitors (units within basic electronic components), directly in their real-world environment, enhancing interaction and understanding of the concepts. Fig. 3 shows students using the app. Permission was obtained from all participants before their photos were published. The researchers ensured that all ethical guidelines were followed, including securing written consent from the students. This consent included the agreement to use their images in any publications or presentations related to the study. The privacy and rights of the students were prioritized throughout the research process.

Fig. 3. Implementation of the AR app by students.

Based on Fig. 3, students used the AR application up to the evaluation feature. This feature is designed to provide immediate feedback to students on their performance, such as quizzes, interactive exercises, or assessments integrated within the AR app. These tools help students gauge their understanding of the material in real-time, allowing them to receive instant feedback and make necessary adjustments to their learning strategies.

IV. Result and Discussion

A. Structural Equation Modeling (SEM) Analysis

The exploration developed factors in the outer model by utilizing measurement variables in the early phase of SEM analysis and these factors were then used to represent the research constructs [56, 57]. During this stage, factor loadings were calculated, and the consistency of measurement variables was calculated to validate the constructs. Convergent validity and discriminant validity were also assessed to ensure that measurement variables accurately measured different constructs. The second stage included structural equation analysis of the inner model, where the created factors were interconnected to test the relationships between variables. Through the path analysis method, PLS-SEM generated path coefficients showing the strength and direction of relationships between these variables.

The SEM process began with developing a theoretical model based on existing literature and the study's hypotheses, incorporating constructs representing key variables, each measured using multiple questionnaire items. The Measurement Model Evaluation was critical, involving the assessment of construct validity to ensure items accurately reflected theoretical concepts through convergent and discriminant validity; reliability, assessing internal consistency using metrics like Cronbach's alpha and composite reliability; and model fit, evaluating overall fit using indices like Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). This rigorous evaluation ensured that constructs were accurately measured, allowing for reliable and valid SEM analysis to provide comprehensive insights into the relationships between academic performance and trait thinking.

1) Measurement model evaluation

The aim of Measurement Model Assessment (MMA) was to ensure that the measurement model used supported the available data and accurately represented the intended concepts. This process included evaluating validity, reliability, and model fit. Firstly, reliability experienced testing by assessing both Alpha of Cronbach (α) and Consistency Reliability (CR), both achieving values >0.7, showing a satisfactory level of consistency. Furthermore, convergent validity was confirmed by observing outer loadings >0.7 and Average Variance Extracted (AVE) values >0.5. Finally, discriminant validity was verified by ensuring that Heterotrait-Monotrait (HTMT) ratio remained below <0.9 and the results of MMA were shown in Table 2.

The results of the measurement model evaluation shown in Table 2 illustrate that most variables and indicators demonstrate good reliability, strong convergent validity, and high composite reliability. Variables such as Cognitive Strategy, Effort, Information Literacy, Learning Strategies, Planning, Self-Efficacy, and Self-checking were all effectively measured constructs supporting respective indicators. However, the Alpha of Cronbach reliability for academic performance variable was slightly below 0.7, requiring additional attention to improve its reliability. Additionally, the trait thinking variable, combining indicators from previous variables, showed an AVE value slightly below the 0.5 threshold, recommending that convergent validity could still be improved. However, these results confirmed that the measurement model was generally valid and reliable, but some variables needed further attention to improve reliability and convergent validity.

Table 2. Measurement model evaluation results (SmartPLS 3)

Variable	Item	Outer Loading	Cronbach Alpha	Composite Reliability	AVE >0.5
Cognitive Strategy (CS)	CS1	0.847	0.915	0.932	0.663
	CS2	0.847			
	CS3	0.833			
	CS4	0.839			
	CS5	0.785			
	CS6	0.837			
	CS7	0.816			
Effort (Ef)	EF1	0.799	0.882	0.914	0.680
	EF2	0.872			
	EF3	0.794			
	EF4	0.858			
	EF5	0.797			
Information Literacy (IL)	IL1	0.838	0.878	0.911	0.672
	IL2	0.848			
	IL3	0.806			
	IL4	0.750			
	IL5	0.853			
Learning Strategies (LS)	LS1	0.799	0.898	0.922	0.664
	LS2	0.809			
	LS3	0.842			
	LS4	0.830			
	LS5	0.845			
	LS6	0.760			
Planning (Pl)	Pl1	0.854	0.883	0.919	0.740
	Pl2	0.868			
	Pl3	0.867			
	Pl4	0.852			
Self-Efficacy (SE)	SE1	0.804	0.880	0.913	0.676
	SE2	0.852			
	SE3	0.794			
	SE4	0.840			
	SE5	0.821			
Self-checking (SCh)	SCh1	0.841	0.897	0.924	0.708
	SCh2	0.854			
	SCh3	0.866			
	SCh4	0.828			
	SCh5	0.816			
Academic Performance of the Students (Pe)	Pe1	0.870	0.816	0.891	0.732
	Pe2	0.892			
	Pe3	0.802			
Trait Thinking	CS2	0.795	0.971	0.973	0.592
	CS3	0.770			
	CS4	0.807			
	CS5	0.720			
	CS6	0.802			
	CS7	0.789			
	EF1	0.748			
	EF2	0.796			
	EF3	0.716			
	EF4	0.782			
	EF5	0.723			
	Pl1	0.788			
	Pl2	0.791			
	Pl3	0.747			
	Pl4	0.769			
	SE1	0.709			
	SE2	0.775			
	SE3	0.750			
	SE4	0.747			
	SE5	0.747			
	SCh1	0.791			
	SCh2	0.786			
	SCh3	0.818			
	SCh4	0.760			
	SCh5	0.788			

Table 3 showed the connections between different variables in the research model, including latent variables and Trait Thinking variables. Furthermore, correlation measured the extent to which two variables were related to each other. The results showed that the trait thinking variable had significant correlations with all other variables in the model.

These high correlations recommended that trait thinking played a substantial role in influencing or being related to other variables such as cognitive strategy, effort, information literacy, learning strategies, planning, self-efficacy, self-checking, and academic performance of students. The significant correlation values observed between trait thinking and other variables proposed a significant influence or relationship of trait thinking with those variables in the context of this research and was reasonable to accept the total proposed model.

Table 3. Heterotrait-monotrait ratio (HTMT) results (SmartPLS 3)

Variable	CS	Ef	IL	LS	Pl	SE	SCh	Pe	Trait Thinking
Cognitive Strategy (CS)									
Effort	0.869								
Information Literacy	0.779	0.733							
Learning Strategies	0.915	0.833	0.812						
Planning	0.936	0.878	0.749	0.874					
Self-Efficacy	0.897	0.927	0.733	0.841	0.857				
Self-checking	0.939	0.950	0.771	0.883	0.901	0.900			
Academic Performance of the Students	0.816	0.767	0.697	0.781	0.755	0.807	0.781		
Trait Thinking	0.990	0.990	0.784	0.903	0.970	0.983	1.004	0.819	

2) Structural model assessment

Structural Model Assessment (SMA) played a crucial role in SEM or path analysis and the structural model used to test relationships between latent variables in the research included evaluating and analyzing [58]. Furthermore, SMA aimed to ensure that the proposed structural model associated with empirical data, showed a good fit, and provided meaningful insights into variable relationships in the research setting. The significance of testing research questions was implied by focusing on T-statistic values and *p*-values to measure the statistical significance of data analysis results. However, the research avoided drawing wrong conclusions by showing that inquiry questions were valid when the T-statistic value was >1.96 and the *p*-value was <0.05. These conditions recommended a significant influence between exogenous and endogenous variables, allowing confident conclusions about relevant relationships from a statistical perspective where Fig. 4 showed the T-Statistic values.

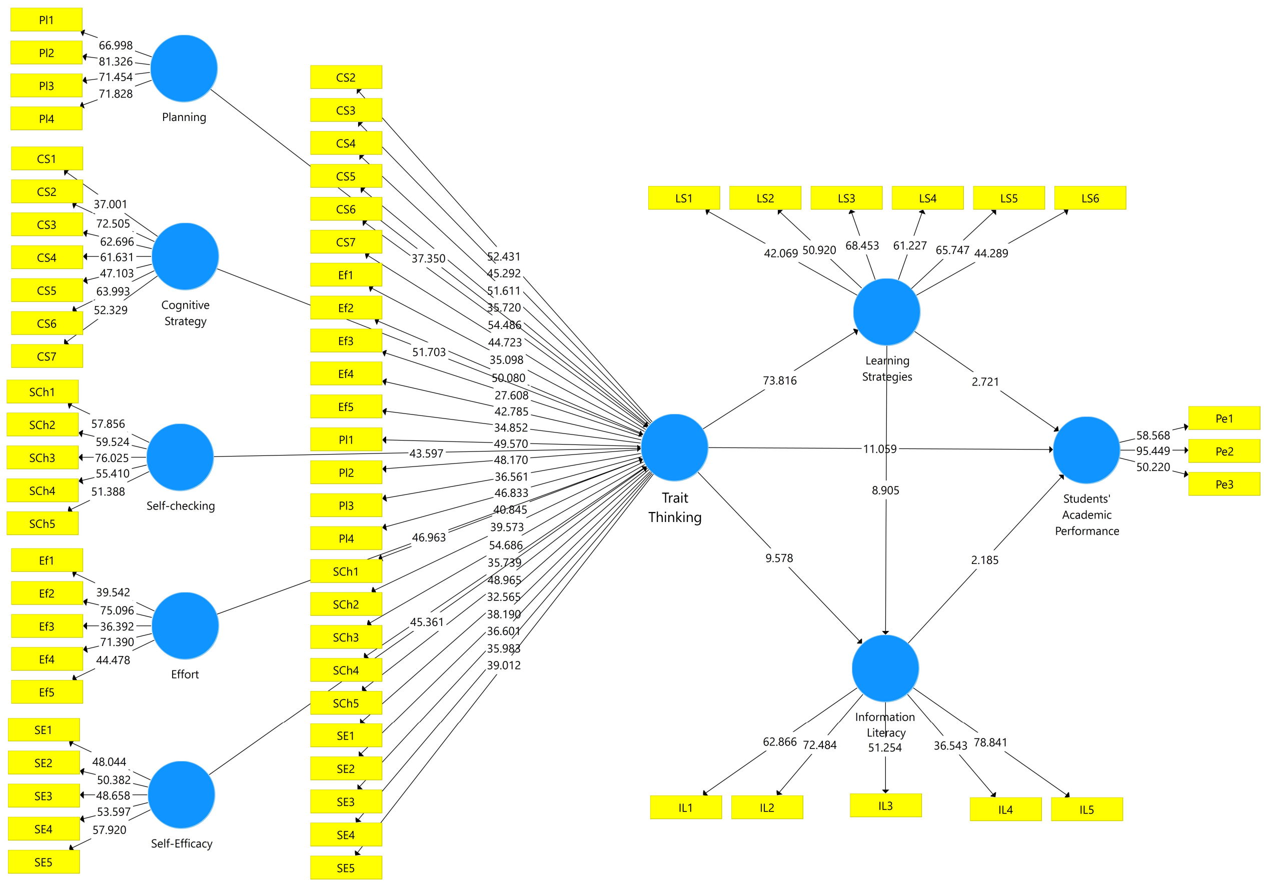

Fig. 4. Model calculation results with T values (SmartPLS 3).

Fig. 4 showed that all T-statistic values obtained were greater than 1.96, signifying strong statistical significance in the relationships between variables and showing a substantial influence, while Fig. 5 showed the corresponding *p*-values.

In Fig. 5, *p*-values <0.05 for all variable relationships showed high statistical significance, supporting the conclusion that these analysis results did not occur by chance. Table 4 showed the results of testing research questions in path analysis.

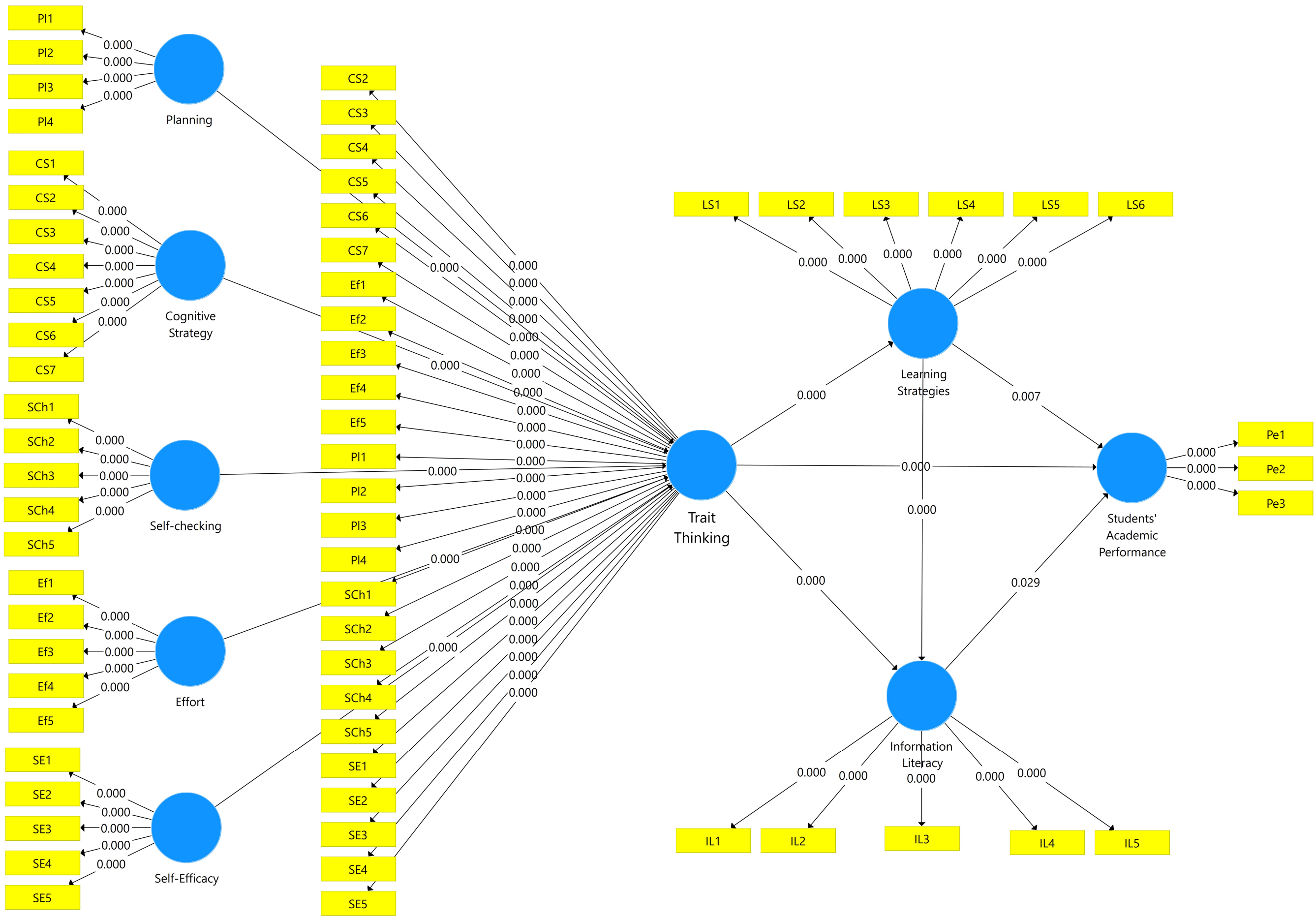

Fig. 5. Model calculation results with *p*-value (SmartPLS 3).

Table 4. Results of the measurement model

Variable	Original Sample (O)	T Statistics	*p*-Values	Hypotheses
Information Literacy→ Academic Performance of Students	0.095	2.232	0.026	H1 Accepted
Learning Strategies→ Information Literacy	0.377	8.780	0.000	H2 Accepted
Learning Strategies→ Academic Performance of Students	0.143	2.618	0.009	H3 Accepted
Trait Thinking→ Information Literacy	0.408	9.217	0.000	H4 Accepted
Trait Thinking→ Learning Strategies	0.846	75.079	0.000	H5 Accepted
Trait Thinking→ Academic Performance of Students	0.542	10.550	0.000	H6 Accepted
Learning Strategies→ Information Literacy→ Academic Performance of Students	0.036	2.198	0.028	H7 Accepted
Trait Thinking→ Information Literacy→ Academic Performance of Students	0.319	8.744	0.000	H8 Accepted
Trait Thinking→ Learning Strategies→ Academic Performance of Students	0.189	4.091	0.000	H9 Accepted
Trait Thinking→ Learning Strategies→ Information Literacy	0.036	2.198	0.028	H10 Accepted

In Table 4, the statistical test results showed strong support for each research hypothesis. Most relationships between tested variables showed high statistical significance, with T-statistic values >1.96 and *p*-values <0.05. This proposed that the relationships were not the answer of chance but had a strong statistical basis. In addition, this research successfully validated the proposed hypotheses, showing that variables such as information literacy, learning strategies, trait thinking, and academic performance of students were interrelated and significantly influenced the research setting. The results provided valuable insights into understanding the factors influencing academic performance.

The Structural Equation Modeling (SEM) analysis in this study revealed complex relationships among variables such as cognitive strategies, effort, information literacy, learning strategies, self-efficacy, self-checking, and students' academic performance. Through measurement model evaluation, it was found that these constructs exhibited good reliability, strong convergent validity, and high composite reliability. Meanwhile, Regression Analysis (RA) confirmed direct predictions of variables such as information literacy, learning strategies, and trait thinking on academic performance. The combination of SEM and RA in this research provided a deep understanding of the intricate interactions among variables and specific predictions of factors influencing academic performance, enriching the interpretation of findings and supporting robust conclusions in the context of educational psychology.

B. Network Analysis

The research applied Network Analysis to visualize and analyze relationships between variables established in the survey in the next stage. Network Analysis helped as a powerful tool for mapping patterns of interaction, relationships, and information flow among these variables [59]. This method provided a straight way to visualize the difficulties in the relationships in the system. The method also enabled the review to understand the flow of information and influence among interconnected variables more easily. However, Network Analysis provided a deeper understanding of the dynamics of the variables in this analysis.

1) Characteristics of edges

In Network Analysis, it is crucial to consider the characteristics of edges, which represented the properties and attributes of relationships between nodes. Comprehending these edge characteristics is crucial as Network Analysis provided perceptions into the strength or weakness of connections between nodes [60]. The weight or value associated with an edge was a significant aspect, showing the intensity or strength of the relationship [61]. Additionally, edges might have direction in some cases, showing the flow of information or influence between nodes. The type of relationship was also crucial in influencing the interpretation of the network in representing a social network with friendship connections or an information network with influence connections. A thorough understanding of edge characteristics helped investigators accurately showed the structure and dynamics of the network in analysis and Fig. 6 showed the domain-level network.

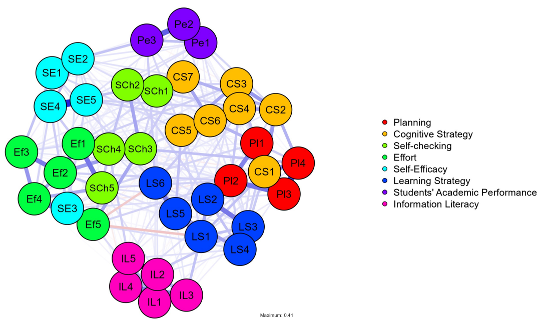

Fig. 6. Network Analysis according to the relationships between Pl, CS, SCh, Ef, SE, LS, IL, Pe.

According to Fig. 6, the analyzed domain-level network had 40 nodes representing entities or variables. Additionally, there were 347 non-zero "edges" in the network, where "edges" refer to connections or bonds between nodes. The number of non-zero edges showed the presence of various relationships or connections between the entities represented by these nodes.

The domain-level network included 40 entities or variables interconnected by 347 different relationships. The network focused on the complexity of relationships between variables, thereby making the domain-level network a subject for in-depth analysis to understand the interactions among these entities. Therefore, it could be concluded that each node represented a variable in each group, such as Pl, CS, SCh, Ef, SE, LS, IL, and Pe.

2) Characteristics of nodes

In Network Analysis, node characteristics referred to various attributes or properties possessed by nodes in the network [62]. Each node represented an object or entity with specific attributes, including labels or names that uniquely identify the nodes, node types determining the role or category in the analysis, and metrics such as centrality measures (betweenness, closeness, degree), distances between nodes, and connections between nodes. Additionally, node characteristics included information about relationships between nodes, such as directly connected nodes and roles in the network. Analyzing node characteristics was a crucial step in understanding the roles, interactions, and total structure of the network, offering valuable insights in the context of the research or analysis being conducted [63]. Table 5 showed the research variables for betweenness, closeness, degree, and influence in the domain-level network.

Table 5. Centrality research variables relationship network

Variable	Betweenness	Closeness	Strength	Expected influence
Pl1	−1.302	−0.081	−0.341	0.016
Pl2	0.494	0.580	0.702	0.572
Pl3	−0.823	0.115	−0.545	−0.176
Pl4	0.793	0.870	0.221	0.546
CS1	−0.224	0.815	−0.226	−1.284
CS2	1.152	0.864	0.876	0.894
CS3	−0.584	0.266	0.357	0.482
CS4	−1.182	−0.066	0.367	0.685
CS5	−0.763	0.519	−1.103	−1.098
CS6	0.853	0.949	1.440	1.697
CS7	0.793	1.010	0.028	0.110
SCh1	−0.584	0.589	0.360	0.677
SCh2	−0.165	0.911	−0.153	0.193
SCh3	2.230	1.670	1.297	1.562
SCh4	0.075	0.586	−0.569	−0.376
SCh5	−0.763	0.142	0.845	0.608
Ef1	−0.703	−0.033	−0.836	−0.934
Ef2	0.135	0.627	1.033	1.313
Ef3	−0.763	−0.322	−1.947	−1.500
Ef4	−0.045	0.473	0.814	1.107
Ef5	3.487	1.670	2.602	−1.262
SE1	−0.584	−1.038	−1.083	−0.685
SE2	−0.284	−1.020	1.236	1.505
SE3	−1.122	0.286	0.068	−0.156
SE4	−0.165	−0.658	−0.286	0.067
SE5	−0.823	−0.903	−0.584	−0.390
LS1	2.409	1.341	0.717	−0.543
LS2	−0.823	0.017	−0.954	−0.563
LS3	0.434	0.086	0.690	0.989
LS4	−0.404	0.187	−0.055	0.286
LS5	0.075	1.027	0.941	1.226
LS6	0.554	0.874	−0.026	−1.330
Pe1	−0.584	−1.464	−0.736	−0.382
Pe2	−0.284	−1.451	−0.008	0.330
Pe3	−0.464	−1.341	−2.537	−2.328
IL1	−0.584	−1.776	−0.273	0.080
IL2	−0.464	−1.791	−0.134	0.211
IL3	0.374	−1.571	−0.886	−0.859
IL4	−0.165	−1.553	−1.917	−2.198
IL5	0.793	−1.405	0.606	0.910

In Table 5, the results of Network Analysis metrics for each report variable were represented as follows: Pl (Planning), CS (Cognitive Strategy), SCh (Self-checking), Ef (Effort), SE

(Self-Efficacy), LS (Learning Strategies), IL (Information Literacy), and Pe (Students' Academic Performance). Each variable was measured across three dimensions of characteristics, namely Betweenness, Closeness, and Strength.

Betweenness showed the extent to which a variable performed as a crucial connector connecting other variables in the network. When the variable had positive values, it showed a substantial connecting role, while negative values showed a more restricted role. Closeness measured the proximity of a variable to others in the network, with higher values showing closer connections. Strength measured the influence one variable had on others, positive values indicated a strong relationship, while negative values recommended a weak one.

The metric results presented additional insights into the difficulty of relationships between variables in the research network. Variables with high Betweenness values could be measured as important connectors, and those through high Strength values might have used significant influence. Analyzing the metrics helped the review to understand the roles and influences of variables in the network established in the research.

From the results of network analysis, AR has the potential to present information in a more visual and interactive manner. For example, AR can be used to visualize the network relationships between these variables in a more concrete and direct context for users, such as students or researchers. By utilizing AR, users can directly observe how each variable is interconnected and interacts within a complex system, which may be challenging to grasp solely through numerical data or network analysis graphs.

More specifically, AR can provide a deeper learning experience by allowing users to visually explore how variables such as cognitive strategies or self-efficacy influence academic performance in simulated or augmented situations. This capability enhances understanding of the complex dynamics among these variables, facilitating a deeper and more practical understanding of network analysis results in educational or psychological research contexts.

C. Fuzzy C-Means Clustering Analysis

Following the stages of SEM analysis and Network Analysis, the subsequent step was FCM Clustering Analysis. Cluster validity was measured using the Dunn index, supported by the elbow method to determine the optimal number of clusters. Additionally, t-SNE (t-distributed Stochastic Neighbor Embedding) map was used for data visualization in high-dimensional space to check the validity of the cluster solution. This combination of methods confirmed that the generated cluster divisions were showed and associated with the actual data structure, strengthening the reliability of cluster analysis results in this research.

1) Determining the number of clusters

To determine the number of clusters using FCM analysis, the elbow method was used [64]. This method was highly useful in clustering analysis, helping identify the optimal number of clusters by finding the point on the graph where there was a significant change in the decrease of intra-cluster variance as the number of clusters increased. Common pointers used in this method included Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Within-Cluster Sum of Squares (WSS).

AIC and BIC were used as statistical measures to compare different statistical models, including clustering models with different numbers of clusters [65]. The aim was to select the most appropriate model that accurately showed the optimal cluster structure in the data. However, BIC tended to favor simpler models with fewer parameters, aiming to prevent more suitable and improve the generalizability of the model.

In the graph, the y-axis points represented AIC, BIC, and WSS values for different numbers of clusters tested on the x-axis. When the graph showed an elbow, the number of clusters at this elbow position was considered the optimal number of clusters, referred to as the elbow point. Increasing clusters outside this point would not significantly reduce AIC, BIC, or WSS values, making the elbow point the most rational choice.

The elbow method was a valuable tool for determining the appropriate number of clusters in clustering analysis. Fig. 7 showed the graph for establishing the number of clusters.

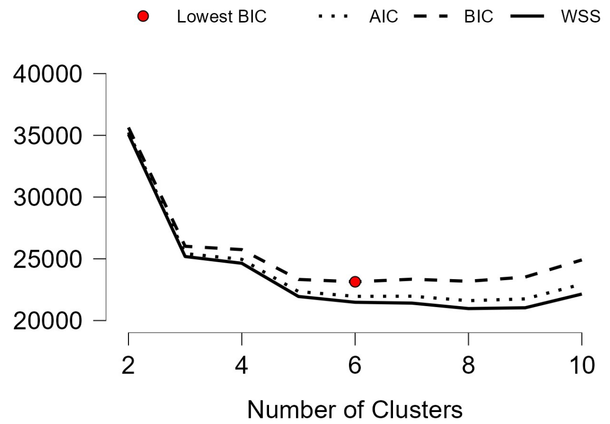

Fig. 7. The Elbow Method for determining the number of clusters [66].

In Fig. 6, the first elbow point was at number three and this showed that the optimal number of clusters in cluster analysis, using the elbow method, was three clusters. Three clusters were the most suitable choice based on the significant change in the reduction of intra-cluster variance as the number of clusters increased. Therefore, for datasets or analyses using this method, the optimal number of clusters was three. Furthermore, in Table 6, pointers AIC, BIC, and Silhouette for FCM Clustering solution were shown. These pointers measured the extent to which data could be consistently interpreted in clusters.

Table 6. AIC, BIC, and Silhouette indicators of Fuzzy C-Means clustering solution

Clusters	N	R^2	AIC	BIC	Silhouette
6	1,004	0.500	22,317.370	23,496.190	0.130

Referring to Table 6, the results of cluster analysis with 6 clusters showed key information. Firstly, 1,004 data points were used, and secondly, the coefficient of determination (R^2) was 0.500, showing that this clustering model could explain about 50% of the variation in the data. While this was good, there was still a significant amount of unexplained variation. The AIC at 22,317.370 and BIC at 23,496.190 were used for model comparison, where lower values showed a preference for a better model. The Silhouette value of 0.130 measured the degree of similarity in the same cluster and dissimilarity from other clusters. Although, the positive value was relatively low, proposing some ambiguity in cluster separation. These results provided understandings into understanding of the data structure in the setting of clustering with 6 clusters. Table 7 showed additional evaluation metrics for the cluster solution, γ of Pearson, the Calinski-Harabasz index, the Dunn index, and entropy.

Table 7. Evaluation metrics of Fuzzy C-Means clustering solution

Metrics	Value
γ of Pearson	0.375
Dunn index	0.052
Entropy	1.526
Calinski-Harabasz index	167.109

Referring to Table 6, the uniform characteristics of clusters could be measured, as the quality of separation between clusters, the successful differentiation among objects in different clusters, and the variation disparity between clusters. Key pointers such as γ value of Pearson of 0.375, Dunn index of 0.052, Entropy of 1.526, and Calinski-Harabasz index of 167.109 played a crucial role in evaluating the clustering quality. Higher values of these metrics showed better clustering quality, providing an understanding of how effectively the data was grouped into meaningful clusters.

2) Cluster validation

t-SNE functioned as a non-linear technique for reducing dimensionality, used to visualize high-dimensional data in two or three dimensions [67]. This method maintained the relative relationships between data points in high dimensions, ensuring that similar data points retained similarity in the lower-dimensional space [68]. t-SNE achieved this by modeling probability distributions based on distances in both the original high-dimensional space and the lower-dimensional space being visualized. Using unsupervised machine learning algorithms, t-SNE captured both local and global structures of high-dimensional data, including clustering at various scales and Fig. 8 showed a t-SNE cluster plot representing the clustering solution.

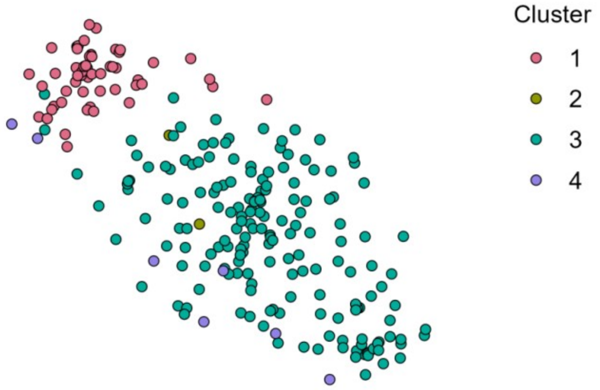

Fig. 8. t-SNE cluster plots for cluster solutions [69].

Analyses of Fig. 7 showed that cluster members, represented by different colors, were closely positioned, confirming the validity of this clustering solution. The results signified several crucial factors influencing the academic performance of students in technical education. However, thinking characteristics (trait thinking) had a significant impact on academic achievement. This signified the importance of developing critical, analytical, and adaptive thinking abilities in the technical education curriculum. Educators should have focused on supporting the development of trait thinking to better prepare students for higher education and the complexities of the workforce.

This research signified the role of learning strategies and information literacy in reaching high academic performance. Furthermore, effective learning strategies and strong information literacy ability were essential in helping students navigate complex information in the digital age. To address the challenges of the 21st century, technical education had to be transformed by integrating relevant learning strategies and information literacy into the curriculum. This ensured that students became independent, critical students ready to face a future characterized by change.

The use of analysis methods, including SEM, Network Analysis, and FCM Clustering in this research, offered a deep understanding of the difficult relationships among the variables going through scrutiny. The variables had the potential to significantly contribute to the improvement of education strategies in the technical education domain. By gaining a clearer understanding of the interactions among variables such as thinking characteristics, learning strategies, and information literacy, educators and policymakers could formulate more appropriate curricula and create adaptive learning experiences.

When discussing Trait Thinking in relation to the use of Augmented Reality (AR) in learning Basic Electronics, our findings reveal several specific aspects that demonstrate how AR effectively supports the development of these skills and enhances students' academic performance.

Firstly, the use of AR in the "Basic Electronics Application" allowed students to interact directly with virtual models of diodes and capacitors. This interaction required students to employ their critical thinking skills to analyze how these components function within electronic circuits. For instance, students had to understand and evaluate the effects of connecting diodes in a particular way within a circuit, as well as analyze the results displayed through AR simulations. This process of analysis and evaluation strengthened students' critical thinking skills, as they had to identify problems and formulate solutions based on their observations.

Secondly, the evaluation feature within the AR application provided immediate feedback that helped students develop problem-solving abilities. When students made mistakes in constructing or analyzing circuits, the application offered hints and corrections, enabling students to rectify their errors in real-time. This process encouraged students to think logically and systematically when resolving issues, thereby enhancing their reasoning skills. For example, if a circuit did not function as expected, students needed to reassess their steps, identify mistakes, and make necessary adjustments to achieve the desired outcome.

Additionally, the AR application facilitated a deeper understanding of concepts through immersive visualization.

Students could see and interact with electronic components in ways that were not possible with traditional textbooks. For instance, they could visually observe how electric current flows through a circuit, which helped them grasp abstract concepts more effectively. This experience fostered active engagement and curiosity, which are critical aspects of Trait Thinking. Overall, the integration of AR in learning Basic Electronics provided an effective platform for developing students' Trait Thinking skills. Through direct interaction, real-time feedback, and immersive visualization, AR helped students to think critically, solve problems effectively, and understand concepts more deeply, all of which contributed to their improved academic performance.

Findings of previous research by Tuli *et al.* [70] on the use of Augmented Reality (AR) can specifically influence trait thinking skills and academic performance of students through several mechanisms. Firstly, AR provides an interactive and engaging learning environment that stimulates students' interest and motivation to learn. By presenting information in a visual and dynamic format, AR helps students to better understand complex concepts. For example, in technical fields, students can use AR to view 3D models of machines or structures, allowing them to analyze and evaluate these components in greater detail. Secondly, interaction with AR content encourages the development of critical and creative thinking skills.

Students are invited not only to passively receive information but also to engage in the processes of analyzing, evaluating, and synthesizing information. This strengthens their ability to plan, solve problems, and make decisions based on the data and observations gathered through AR. A paper submitted by Cai *et al.* [71] explained the use of AR can enhance students' self-efficacy, as they feel more confident in understanding and mastering the subject matter presented in an interactive manner. All these components significantly shape students' mindsets and contribute to higher academic performance. Thus, AR not only enriches the learning experience but also deepens the trait thinking skills essential for long-term academic success.

Based on several similar research references [72], in developing learning media for electronics, a development study on a mobile AR application, incorporating a novel approach that has not been widely explored or developed in existing publications, was conducted. Therefore, this represents a new opportunity and solution for researchers to advance AR technology as an interactive medium and enhance trait thinking skills in electronics courses at the Engineering Education.

V. Conclusion

The research successfully validated the proposed hypotheses, demonstrating that variables such as information literacy, learning strategies, trait thinking, and academic performance of students were interrelated and significantly influenced the research setting. Additionally, Network Analysis enhanced the understanding of the relationships between variables, highlighting the central and influential nodes within the network. To provide a comprehensive view, it is essential to link these findings to the effects of using Augmented Reality (AR) in education.

AR tools enhance students' engagement and interaction with digital information, leading to improved information literacy. AR allows students to visualize complex information, interact with 3D models, and access multimedia content that enriches their understanding. The significant relationship between information literacy and academic performance suggests that using AR can enhance information literacy, which, in turn, positively impacts academic performance. AR can support diverse learning strategies by providing immersive and interactive learning experiences. Students can use AR to perform virtual experiments, participate in simulations, and access interactive content that caters to different learning styles. The strong influence of learning strategies on information literacy and academic performance indicates that AR can improve learning strategies, thereby enhancing both information literacy and academic performance. Additionally, AR promotes critical and creative thinking by offering immersive problem-solving environments. Students can engage in activities that require them to think critically and creatively to navigate AR simulations and scenarios. The significant influence of trait thinking on information literacy, learning strategies, and academic performance suggests that AR can enhance trait thinking, which in turn positively impacts these variables.

Network Analysis revealed the central and influential roles of variables such as Planning, Self-checking, Learning Strategies, Information Literacy, and Academic Performance within the network. These variables can be further enhanced through the integration of AR. AR tools can assist students in planning and organizing their learning activities by providing interactive schedules, reminders, and visual aids. Planning, identified as a central node with high degrees and closeness centrality, can be significantly improved through AR, leading to better academic outcomes. AR applications can provide immediate feedback and self-assessment opportunities, allowing students to self-check their understanding and progress. Self-checking, with high betweenness centrality, plays a crucial role in facilitating learning processes. Enhancing self-checking through AR can improve overall learning efficiency. AR can also motivate students to put in more effort and build their self-efficacy by providing engaging and rewarding learning experiences. Effort and Self-Efficacy, with moderate centrality measures, are important for sustaining student motivation and confidence, which can be boosted through AR applications.

By linking the results of data analysis to the effects of using AR, it becomes evident that AR has the potential to enhance key variables such as information literacy, learning strategies, trait thinking, planning, self-checking, effort, and self-efficacy. Integrating AR into educational practices can create more immersive, interactive, and effective learning environments, thereby positively impacting academic performance. Future research should focus on empirically testing the effects of AR on these variables to validate and expand upon these findings, providing a deeper understanding of AR's role in education.

Conflict of Interest

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Muhammad Anwar: Concept and design, Drafting manuscript, Supervision, Technical and material support. Zulwisli and Yeka Hendriyani: Collecting data, Supervision and Statistical analysis. Hendra Hidayat: Statistical analysis and Supervision. Elsa Sabrina: Drafting manuscript, Collecting Data, Statistical analysis. All authors had approved the final version.

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