The Influence of Augmented Reality Mobile App on Electronics Engineering Students' Self-Competence

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Abstract – **Augmented reality (AR) is currently becoming educational trend by offering visualization of learning and making abstract concepts more concrete. Therefore, this research aimed to investigate the effect of AR technology based on mobile application on self-competence of electronics engineering students. It also considered the role of self-regulated learning, intrinsic learning motivation, and perceived usefulness as moderating factors. A cross-sectional survey with quantitative method was conducted on 848 electronics engineering education students at Universitas Negeri Padang, Indonesia. The data were obtained through questionnaires, and Structural Equation Model (SEM) analysis was conducted using SmartPLS 3. Furthermore, a fuzzy C-means clustering analysis was carried out using JASP software. The results showed that perceived usefulness had a significant positive effect on students' self-competence and moderated the significant positive relationship between self-regulated learning and self-competence. These empirical results showed that an improved level of self-regulated learning and beneficial application of technology could increase self-competence.**

Keywords – **Mobile application, augmented reality, self-competence, electronics engineering education.**

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1. Introduction

In recent years, the integration of technology into educational environments has revolutionized traditional teaching methods, offering innovative ways to engage and empower students across various disciplines [1], [2]. A technological advancement attracting significant attention is augmented reality (AR). Based on mobile application, AR brings digital content into the physical via a smartphone or tablet [3]. This immersive technology has tremendous potential to improve learning experience, specifically in specialized fields such as electronics engineering education. Electronics engineering is characterized by complexity and dynamic nature, requiring students to have theoretical knowledge, practical skills, and problem-solving abilities. However, classroom approaches like application of PowerPoint and learning modules are still limited in meeting the diverse learning needs of students. This has led to the concerns of developing self-competence, self-confidence, efficacy, and autonomy in applying knowledge and skills in various disciplines.

The emergence of mobile app-based AR presents a promising solution to this challenge by offering interactive and experience-based learning opportunities that bridge the gap between theory and practice [4], [5]. By leveraging AR technology, educators can create immersive simulations, virtual laboratories, and interactive tutorials that allow students to visualize abstract concepts into more concrete concepts, manipulate virtual components, and engage in hands-on experiments, all in a digital environment integrated with physical surroundings.

Despite increasing interest in the potential benefits of AR in education, there remains a glaring gap in understanding its specific influence on self-competence among electronics engineering education students.

This knowledge gap shows the need for empirical investigation on the effectiveness of mobile AR interventions in improving students' self-confidence, problem-solving skills, and competency in electronics engineering education.

Integrating variables such as self-regulated learning, intrinsic learning motivation, and perceived usefulness offers more profound insight into the mechanisms underlying the influence of mobile AR on self-competence. Self-regulated learning is characterized by students' ability to set objectives, monitor progress, and adjust learning strategies, which are essential in fostering autonomy and self-efficacy [6], [7]. Similarly, intrinsic learning motivation, driven by inherent interest and enjoyment in learning, contributes to sustained engagement and mastery orientation, both essential to self-competence. The perceived benefits of mobile AR application in facilitating learning experiences and enhancing understanding the influence students' attitudes and engagement, thereby shaping self-competence beliefs and behaviors [8]. Understanding how these variables interact in the context of mobile AR interventions can show the mechanisms underlying the development of self-competence among electronics engineering education students.

The current research aimed to investigate the influence of mobile application-based AR on self-competence among electronics engineering education students, as well as explore the role of self-regulated learning, intrinsic learning motivation, and perceived usefulness as moderating factors. By examining the complex interactions between these variables, it was crucial to provide a nuanced understanding of the mechanisms underlying increased self-competence in the context of technology-enhanced learning environments, typically informing the design and implementation of effective pedagogical interventions tailored to learners' needs.

1.1. Overview Augmented Reality (AR)

AR is an immersive technology that combines digital content with the physical world, creating an interactive and enhanced user environment. Unlike virtual reality (VR), which replaces the real with a simulated world, AR overlays digital information, such as images, videos, or 3D models onto a user's real-world view in real-time. Integrating virtual elements into the physical environment allows users to interact with the digital and real worlds simultaneously [9]. Moreover, AR technology typically relies on smartphones, tablets, or special AR glasses equipped with cameras, sensors, and shows to seamlessly combine virtual content with the user's surroundings.

By tracking user's position and orientation, AR systems can accurately correlate digital objects with physical objects in the environment, creating a convincing illusion of interaction and immersion.

1.2. Overview of Self-Competence

Self-competence, often referred to as self-efficacy or self-confidence, is a fundamental aspect of human psychology [10], [11]. It entails an individual's belief in the ability to successfully carry out tasks, achieve objectives, and face challenges in various areas of life. Rooted in social, cognitive, and self-determination theories, self-competence influences motivation, behavior, and outcomes in personal, academic, and professional domains [12]. Self-competence is often domain-specific, meaning individuals may show varying levels of self-confidence and efficacy in different areas of life, such as academics, career pursuits, interpersonal relationships, or hobbies [13], [12]. Several factors contribute to the development and maintenance of self-competence, including past experiences, social status, recognition from others, and emotions. Individuals with high self-competence tend to set ambitious objectives, persevere in the face of challenges, and actively demand opportunities for growth and development.

Cultivating self-competence includes developing a supportive environment that encourages risk-taking, provides opportunities for skill development, offers constructive feedback, and promotes a growth mindset the belief that abilities can be developed through effort and persistence.

1.3. Overview of Self-Regulated Learning

Self-regulated learning is a dynamic and multifaceted process where individuals actively control and manage learning experiences, strategies, and behaviors to pursue academic objectives. Rooted in cognitive, metacognitive, and motivational principles, self-regulated learning includes a variety of mental, affective, and behavioral strategies that students use to monitor, control, and adjust learning activities. It comprises three interrelated phases: a) Planning: setting objectives, establishing learning strategies, and creating action plans to guide learning efforts. b) Monitoring: tracking progress, understanding, and performance relative to objectives and standards. c) Control and Adaptation: adjustments and modifications to learning strategies, resources, or objectives to optimize learning outcomes [14]. Self-regulated learning is not a fixed trait but is a dynamic skill that can be developed and perfected through practice, feedback, or deliberate effort [11].

Studies have shown that individuals who show high levels of self-directed learning tend to perform better academically, show remarkable persistence and resilience in the face of challenges, and establish more profound levels of understanding and the ability to transfer knowledge across contexts.

1.4. Overview of Intrinsic Learning Motivation

Intrinsic learning motivation refers to the natural enthusiasm and interest that individuals derive when engaging in learning activities [15]. Unlike extrinsic motivation, which entails pursuing objectives or rewards external to learning activities [17], [18], intrinsic motivation originates from within the individual. It includes factors like curiosity and interest, independence and self-control, mastery of competence, and joy in learning. As a result, individuals tend to be more immersed and engaged in learning activities, experiencing a state of optimal concentration when faced with challenging tasks that match skill level.

1.5. Overview of Perceived Usefulness

Perceived usefulness refers to an individual's subjective assessment of how much a particular technology, tool, or system can improve performance, productivity, or satisfaction in achieving a specific objective or task [20]. This is an essential component of technology acceptance model (TAM) theory and other theoretical frameworks that explore user attitudes and adoption behavior toward technology, as formulated by Fred Davis in 1989 [21]. Crucial aspects of perceived usefulness include:

- The existence of the usefulness of the technology.
- The existence of correlation with needs.
- Positive impact on performance.

Perceived usefulness is essential in shaping attitudes, intentions, and behavior when adopting technology [22], [23].

2. Methodology

Research methods are systematic steps used for collecting, analyzing, and interpreting data to answer questions or test hypotheses [24]. These methods comprise several stages, namely data collection using research instruments, population, samples, and data analysis.

2.1. Data and Instrument Collection

Before data collection, AR technology, "PISA AR PROJECT," was introduced to the learning process of respondents.

The application is shown below:

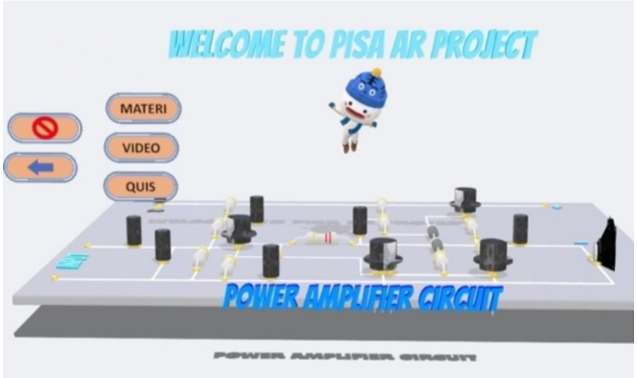

Figure 1. Main menu

Figure 1 shows the main view of PISA AR PROJECT technology. There are several menus that can be clicked on, namely materials, videos, quizzes, and menus for carrying out circuit simulations.

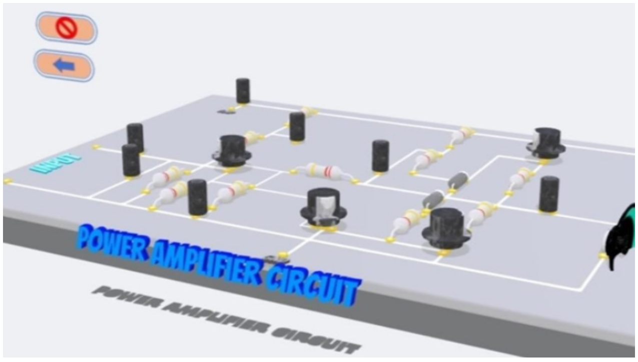

Figure 2. Subject

Figure 2 shows a menu containing learning materials. This section shows materials about electronic circuits in the form of 3D objects.

Figure 3. Video

Figure 3 shows that learning videos can be integrated into AR technology to facilitate students' understanding of the sequences contained in AR environment.

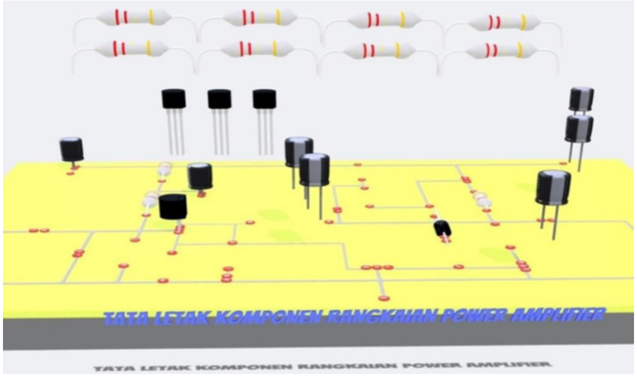

Figure 4. Simulation

Figure 4 shows the circuit simulation menu. Students can drag and drop the available components to assemble electronic circuit, show its functionality in animated form.

Figure 5. Quiz

Figure 5 shows the last menu of PISA AR PROJECT, namely the quiz. In this menu, students can review the learning material studied and evaluate learning with the guidance of lecturers.

Data were subsequently collected from respondents using Google Form questionnaire. The questionnaire was designed to commence with preparatory statements to measure research variables, followed by distribution, and concluding with data analysis. Before the distribution of questionnaire for primary research, a pilot study was conducted to validate data through construct validity testing. The test examined the outer loading value, where the criterion for decision-making is that the outer loading value of each item should be >0.7; eliminating other items. After obtaining a valid instrument, the questionnaire was distributed to electronics engineering students at Universitas Negeri Padang.

2.2. Population and Sample

The population included group members whose characteristics were under consideration [26], namely all students of engineering faculty at Padang State University. Furthermore, the sample size, representing a subgroup of the population, comprised 848 electronics engineering education students whose number was obtained using a random sampling technique.

Table 1. Respondents' profile

Sample characterization		Frequency	Percent
Gender	Male	648	76.42%
	Female	200	23.58%
	Total	848	100%
Age	17 - 18 years old	139	16.40%
	19 - 20 years old	407	47.50%
	21 - 22 years old	250	29.48%
	23 – 24 years old	40	4.71%
	24 years old	12	1.41%
	Total	848	100%
Duration of internet use per day	1 – 3 hours	73	8.61%
	4 – 6 hours	299	35.26%
	7 – 9 hours	232	27.36%
	> 10 hours	244	28.77%
	Total	848	100%
Duration of smartphone use per day	1 – 3 hours	72	8.49%
	4 – 6 hours	272	32.07%
	7 – 9 hours	296	34.91%
	> 10 hours	208	24.53%
	Total	848	100%

Table 1 shows the profile of respondents, totaling 848 students. The majority were men, comprising 76.42%, while only 23.58% were women. The respondents were predominantly aged 19 to 20 years, with an average daily Iinternet usage of 4-6 hours and smartphone usage of 7-9 hours.

3. Data Analysis

Primary data were obtained from a questionnaire, and the analytical method used was a structural equation model (SEM) with SmartPLS 3 software. This model aimed to comprehensively investigate and analyze the relationship between independent and dependent variables [27]. A series of tests were conducted, starting with the convergent validity test by examining the outer loading and AVE values, internal reliability test by assessing Cronbach's alpha and composite reliability values, and concluding with discriminant validity test by examining Fornell and Larcker formula values and heterotrait-monotrait ratio (HTMT) values. Hypotheses were tested using T-statistic and P-values. In addition to data analysis using SmartPLS 3, JASP software was also used for Fuzzy C-means analysis clustering, specifically for grouping data with similar characteristics.

3. Results and Discussion

In this section, the research findings are presented and analyzed. The obtained data are discussed to interpret the findings, evaluate the hypotheses, and connect them with relevant literature.

All instruments used to gather the data have been validated according to scientific research procedures. This ensures the data is credible, valid, and accurate. Subsequently, the findings are compared with previous studies to assess their consistency or differences.

3.1. Validity and Reliability with SEM

The first analysis was construct validity test, which examined the outer loading value with valid criterion of >0.7 and AVE with criterion >0.5 [28]. Subsequently, internal reliability test examined Cronbach's alpha value for reliable decision-making, which was >0.7, and composite reliability >0.7 [29].

Table 2.Validity and reliability

Variables	Items	Outer Loading	Cronbach's alpha	CR	AVE
Self Regulated Learning	SRL1	0.758	0.881	0.910	0.628
	SRL2	0.800			
	SRL3	0.750			
	SRL4	0.818			
	SRL5	0.834			
	SRL6	0.793			
Intrinsic Learning Motivation	ILM1	0.895	0.882	0.916	0.732
	ILM2	0.821			
	ILM3	0.861			
	ILM4	0.843			
Perceived Usefulness	PU1	0.918	0.910	0.943	0.847
	PU2	0.937			
	PU3	0.907			
Self-Competence	SC1	0.887	0.863	0.916	0.784
	SC2	0.868			
	SC3	0.901			

Table 2 shows that all variable items passed the validity and reliability tests, and were valid or reliable as research measuring tools.

Table 3. Formell-Larcker criteria

Variables	SRL	PSAs	PU	S.C
SRL	0.855			
PSAs	-0.001	0.921		
PU	-0.053	0.557	0.885	
S.C	0.019	0.326	0.475	0.793

Table 3 shows the results of Fornell-Larcker discriminant validity test. This statistical method examined whether the variables in a causal model had sufficiently high discrimination between different constructs. The table also shows that the correlation value between the same variables was significantly higher than the correlation value between different variables [30].

Table 4. HTMT ratio of correlations

Variables	SRL	PSAs	PU	S.C
SRL				
PSAs	0.024			
PU	0.055	0.621		
S.C	0.037	0.359	0.541	

Table 4 shows the results of heterotrait-monotrait ratio test, where the criterion for decision-making was a constructed value of <0.90 [31]. Furthermore, all construct values were less than 0.9, showing the satisfaction of discriminant validity.

3.2. Hypothesis Testing

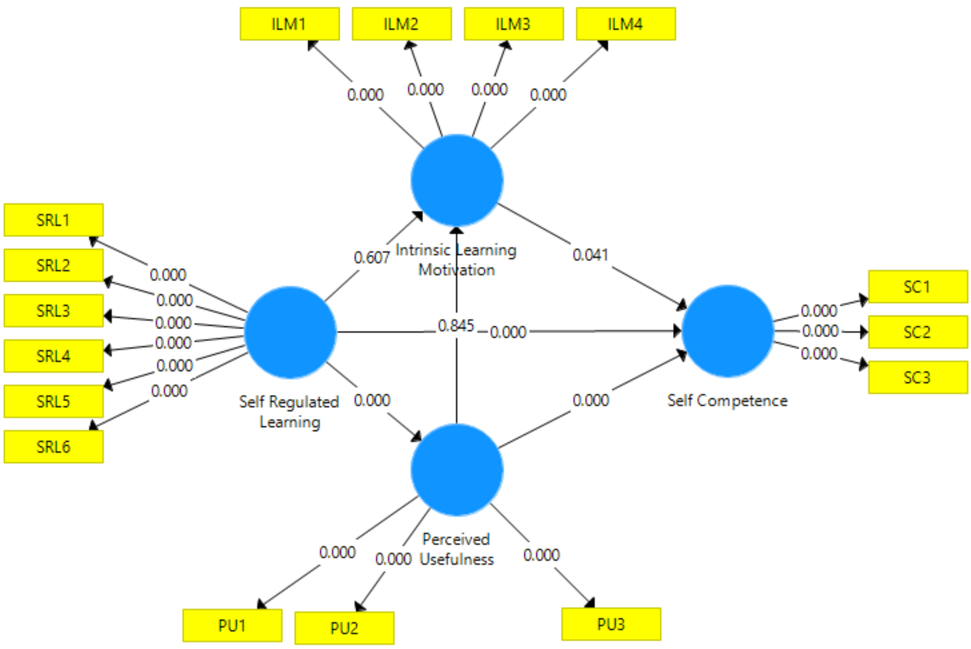

Figure 6. Hypothesis model

Table 5. Hypothesis direct and indirect effects

Hypothesis	β	T-Statistics	P-Value	Results
H1:Self Regulated Learning ->Intrinsic Learning Motivation	0.022	0.515	0.607	Rejected
H2:Self Regulated Learning ->Perceived Usefulness	0.326	8,698	0,000	Accepted
H3:Self Regulated Learning -> Self-Competence	0.330	9,022	0,000	Accepted
H4: Intrinsic Learning Motivation ->Self-Competence	-0.059	2,045	0.041	Accepted
H5: Perceived Usefulness -> Intrinsic Learning Motivation	-0.008	0.196	0.845	Rejected
H6: Perceived Usefulness ->Self-Competence	0.449	13,536	0,000	Accepted
H7:Self Regulated Learning ->Perceived Usefulness ->Self-Competence	0.146	7,713	0,000	Accepted

Table 5 shows the results of hypothesis testing. Out of the seven hypotheses, five were accepted and two were rejected. This was based on T-statistical significance value, which should be greater than 1.96, and P-value less than 0.05 [32], [33].

Hypothesis 1: The relationship between self-regulated and intrinsic learning motivation. T-statistic value of 0.515 and P-value of 0.607 showed insignificant relationship and rejection of hypothesis. However, the empirical results differed from [34], stating that self-regulated learning significantly impacted students' motivation. Several factors might contribute to the differences, one of which lies in the variations of research subjects. The current research focused on university students, while Tri Widiawati investigated elementary school students, facilitating different perspectives from each subject.

Hypothesis 2: The relationship between self-regulated learning and perceived usefulness. T-statistic value of 8.698 and P-value of 0.000 showed a positive significant relationship, as well as the acceptance of hypothesis.

The empirical results supported [35] regarding self-regulated learning's perceived usefulness having a significant correlation with the acceptance of learning management systems. It also correlated with [36], showing that self-regulated learning and perceived usefulness significantly correlated with the acceptance of e-learning.

Hypothesis 3: The relationship between self-regulated learning and self-competence. T-statistic value of 9.022 and P-value of 0.000 showed a positive and significant relationship, as well as the acceptance of hypothesis. Therefore, students' self-regulated learning increased with self-competence.

Hypothesis 4: The relationship between intrinsic learning motivation and self-competence. T-statistic value of 2.045 and P-value of 0.041 showed a negative and significant relationship. The empirical results differed from Suryono's research [37], stating that intrinsic learning motivation positively affected students' competence. One factor that might contribute to this difference was variation in research subjects, with the current research focusing on students and investigating lecturers. This could lead to differences in perspectives and results.

Hypothesis 5: The relationship between perceived usefulness and intrinsic learning motivation. T-statistic value of 0.196 and P-value of 0.845 showed insignificant relationship. Therefore, the ease of using AR did not impact students' motivation.

Hypothesis 6: The relationship between perceived usefulness and self-competence. T-statistic value of 13.536 and P-value of 0.000 showed a positive and significant relationship. The empirical results supported [38], stating that perceived usefulness impacted students' competence in adopting artificial intelligence. Therefore, easy usage of technology tended to have a significant positive impact on students' competence.

Hypothesis 7: The relationship between self-regulated learning and self-competence, moderated by ease of using AR. T-statistic value of 7.713 and P-value of 0.000. Therefore, ease of using AR technology moderated the positive and significant relationship between self-regulated learning and self-competence. The results showed that the usefulness of AR technology could be an effective tool in improving students' self-competence when applied in the context of self-regulated learning.

4. *Fuzzy C-Means Clustering Analysis*

The research items were analyzed using Fuzzy C-means clustering, a method that enables data elements to be assigned to multiple groups with measurable membership levels [39].

In its implementation, each data point was assigned a membership level for each group, resulting in varying membership levels for each data point. This analysis was instrumental for understanding patterns in data, particularly regarding the impact of AR based application on students' level of self-competence in electronics engineering education. Using FCM, this research aimed to investigate the relationship between the use of AR technology and students' independent abilities in educational context.

The first step included determining the optimal number of clusters. Elbow plot method and Bayesian information criterion (BIC) are two approaches to selecting the optimal number of clusters in clustering analysis. Elbow plot method was specifically used to examine where inertia (distortion) in the graph of inertia values against the number of clusters started to decrease significantly [40]. This point, often forming an "elbow" on the graph, showed the optimal number of clusters. On the other hand, BIC is a statistical method that compares values for each number of clusters. The number of clusters that produce a lower BIC value is considered optimal. Despite using different approaches, both methods aim to identify the most suitable number of clusters for the data in clustering analysis.

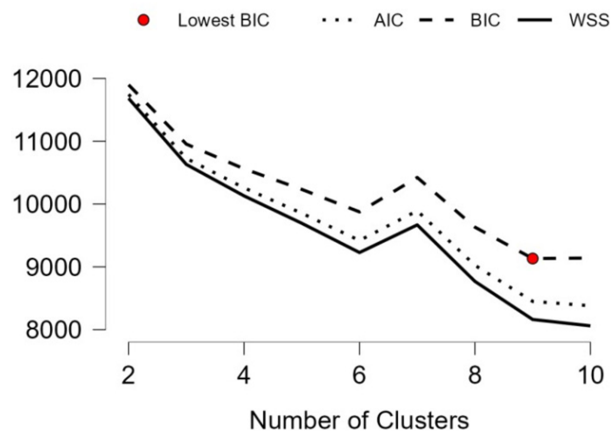

Figure 7. Elbow method plot

Figure 7 shows that the initial elbow plot was reached in nine clusters, a solution considered as the most optimal choice. Elbow method plot analysis showed the optimal number of clusters was nine, as there was a significant change in decreasing inertia at that point. Table 4 presents the AIC, BIC, and Silhouette indicators to evaluate the consistency of data interpretation in clustering solutions using fuzzy c-means clustering (FCM). AIC and BIC indicators provided information about the model's fit to the data, with lower values showing a better fit [41]. Silhouette is a metric for evaluating the quality of resulting clusters, with higher values showing more well-defined clusters.

Therefore, the results of these three indicators were used to ensure the suitability and quality of FCM clustering solution. The final decision regarding the optimal number of clusters was based on elbow method plot analysis.

Table 6. Fuzzy c-means (FCM) clustering

Clusters	N	R2	AIC	BIC	Silhouettes
9	848	0.537	8689.880	9372.850	0.030

Table 6 shows a silhouette score of 0.030 and an internal consistency level achieved through clustering. A Silhouette score measures how well each instance in dataset fits its cluster compared to others. Scores closer to the lower limit of -1 show poor fit, whereas values closer to the upper limit of 1 show more consistent grouping [16]. Maximizing silhouette score is essential to obtaining an optimal cluster solution. In addition, decreasing BIC and AIC values is necessary to achieve desired results. All these indicators showed satisfactory performance under optimal conditions, suggesting that the selected cluster solution had good internal consistency and minimized model complexity.

Table 7. Evaluation matrices

Metrics	Value
Person's γ	0.253
Dunn index	0.080
Entropy	1,959
Calinski-Harabasz index	64,286

Regarding Person's coefficient γ and Dunn index, values close to 1 show good separation between clusters [25]. Therefore, the closer the values of Person's γ and Dunn index are to 1, the better. The table shows a value of 0.253 and a relatively good correlation between the data within clusters and the distance between clusters. However, Dunn index of 0.080 showed that the separation between different clusters and the closeness of data distance within clusters were relatively low. Regarding entropy, a lower value showed lower homogeneity within clusters [19]. Therefore, a lower entropy value was preferable. The table shows a relatively high entropy value of 1.959 and high homogeneity.

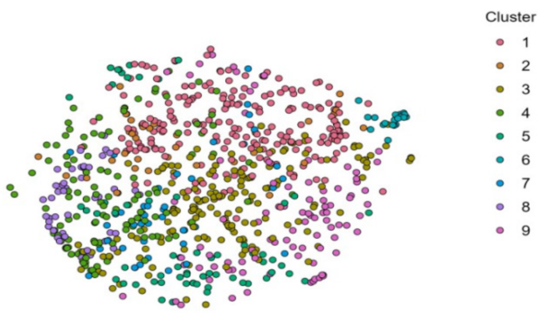

Figure 8. t-NSE plot

Data clustering results could be analyzed based on t-SNE plot using Person's γ, Dunn index, and Entropy values. Person's γ value of 0.253 showed a moderate relationship between data in clusters and the distance between clusters. This correlation showed some level of consistency in cluster formation. However, Dunn index, only reaching 0.080, showed that the separation between different clusters and the closeness of data were relatively low. Furthermore, the high entropy value of 1.959 showed a high diversity level and variations in data.

4. Conclusion

In conclusion, self-regulated learning significantly impacted students' perceived usefulness and self-competence. This showed the importance of developing organized and independently regulated learning skills to increase perception of learning materials' usefulness and self-competence. It was also important to understand students' perceptions of the usefulness of technology or learning materials in improving competencies. The relationship between self-regulated learning and self-competence, moderated by the ease of using AR technology, showed that implementing AR improved the effectiveness of teaching and learning process, specifically in the context of self-regulated learning.

The results had significant implications for developing more effective and efficient learning strategies in educational institutions. Understanding the relationship between factors such as self-regulated learning, perceived usefulness, and learning technology could help educators and policymakers in designing learning programs that are more adaptive and responsive to students' needs.

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