Augmented Reality in Computer Network Learning: How to Improve Students' Self-Efficacy?

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***Abstract*—This study aims to develop and test a conceptual model comprising six hypotheses focusing on the impact of Augmented Reality (AR) on students' academic self-efficacy. The research addresses the need to explore how AR technology can improve students' academic self-efficacy by examining the relationships between AR technology features, task value, usage intention, and personal cognitive approach. A total of 340 students participated in this research, completing online questionnaires as part of a controlled experiment. The Structural Equation Modeling-Partial Least Square was used to assess, test, and analyze the conceptual model. The results of this study indicate that the personal cognitive approach, tech features, and task value implemented by students all positively affect their academic self-efficacy in learning. The personal cognitive approach directly contributes to influencing task values and technological features. Task value and tech features contribute to improving usage intention in students while learning with AR. The personal cognitive approach and the usage intention of use contribute directly and significantly to enhancing students' academic self-efficacy. Overall, implementing a personal cognitive approach, tech features, task value, and usage intention positively boosted students' academic self-efficacy in learning with AR.**

***Keywords*—augmented reality, computer networks, self-efficacy**

I. INTRODUCTION

Technology encourages the integration of innovative learning in higher education, which aligns with the era of the Industrial Revolution 5.0, which focuses on collaboration between humans and technology. This transformation is marked by an increasing variety of media, teaching materials, and learning tools based on virtual technology, which connects advanced technological capabilities with human creativity and understanding [1–4]. The presentation of information in learning is not only limited to a two-dimensional environment because technological advances are directing learning towards a three-dimensional environment that is increasingly realistic and in-depth, allowing for a more immersive learning experience [5–7].

Augmented Reality (AR) has become a popular technological innovation in education this decade. This technology offers realistic visualization to enrich the student learning process through the interaction between real and virtual environments [8, 9]. AR allows students to see and interact with objects of various sizes in teaching, replacing 2D visualization with 3D [10]. This supports clearer and deeper interpretation of objects, provides an immersive learning experience and helps students understand abstract concepts more easily [11]. AR has been shown to improve the overall quality of learning, particularly through better engagement and understanding [10, 12].

In the context of computer network learning, AR plays a significant role. This technology allows visualization of network devices in 3D, making it easier for students to understand complex material more intuitively [13, 14]. With AR simulation, students can virtually design computer networks and explore the functionality of each component, which directly supports their learning process [15]. AR also reduces errors during exercises, as the 3D view helps students understand the system in a more structured and precise way [16, 17]. Research also shows that learning AR-based computer networks can significantly improve student learning outcomes [18]. The integration of multimedia and network simulators in computer learning is key to improving the learning experience and student engagement [19–21]. AR supports realistic visualization skills, contributing to interactive learning, especially in computer networking courses [22, 23]. With AR features that allow students to display network objects in a 3D environment, students can develop understanding and active engagement in each learning session [24, 25].

Various studies have reported quantitative research on the impact of AR on learning outcomes. The integration of AR provides a positive experience for students and supports the exploration of their abilities to enhance learning outcomes [26]. AR helps improve learning results compared to traditional methods [27]. The AR method offers superior improvements in delivering the integrity of realistic learning in constrained learning environments [28]. The success of AR in enhancing learning outcomes presents significant potential in developing various skills and attitudes among students in their learning [29]. However, only a few studies have explored aspects of student self-efficacy.

Several previous studies have shown that self-efficacy implemented through traditional methods remains low. Earlier learning methods that are still teacher-centred tend to limit active student engagement, thereby impacting their self-efficacy negatively [30]. Traditional approaches often render students passive, merely receiving information without the opportunity to explore and develop understanding independently. Furthermore, using non-interactive learning media hinders students from developing self-efficacy, especially in exploring more complex concepts in depth. [31, 32]. This limitation is further exacerbated by the lack of direct feedback, the less meaningful learning experiences, and the minimal opportunities to practice and develop skills in a safe environment [33]. As a result, students experience high dependence on teacher instructions, lack confidence in completing academic tasks, and have negative perceptions of their own abilities.

The low self-efficacy of students and the need for new technological innovations create an urgency to investigate their effects on learning. The integration of AR technology in education to support self-efficacy has still been limitedly studied in various influencing factors. Various factors influence the causes of self-efficacy throughout the learning process, and the integration of AR in education introduces a range of factors that can support the enhancement of students' self-efficacy. The personal cognitive approach is a key factor in technology-based learning [34]. This factor plays a role in influencing students' task value and tech features beliefs during learning [35].

The personal cognitive approach and AR-based learning complement each other in enhancing learning effectiveness. AR facilitates personalized learning by presenting interactive 3D visualizations, allowing students to understand abstract concepts more clearly according to their cognitive styles. Furthermore, AR supports independent exploration and provides immediate feedback, reinforcing the metacognitive process and assisting students in organizing their learning strategies. With a more engaging and simulation-based learning experience, AR enhances motivation and self-efficacy, making students more confident in understanding and applying the material. Additionally, AR integration encourages users' intention to adopt AR in the learning process, making AR a contributing factor to improving students' self-efficacy.

However, the diverse factors and accompanying variables that affect students' self-efficacy in AR implementation create a research gap regarding the specific factors that play a role in enhancing self-efficacy. The limited investigation into these influencing factors highlights the need for deeper research to optimize the implementation of AR in effectively supporting students' self-efficacy. Therefore, these aspects are increasingly urgent to be researched as the application of AR in education increases.

This research aims to investigate the contextual factors that influence the use of AR in computer network learning. A conceptual model is developed to test the research objectives. There are five variables in this conceptual model, which consist of Personal Cognitive Approach (PCA), Task Value (TV), Tech Features (TF), Academic self-Efficacy (ASE), and Usage Intention (UI). The form of the conceptual model and the six hypotheses used to achieve the research objectives are presented in Fig. 1.

Fig. 1 displays the conceptual model in this study. There are five interconnected variables: personal cognitive approach, task value, tech features, academic self-efficacy, and usage intention. This study focuses on investigating the relationships and effects among these variables. Therefore, to maintain the consistency of the research results, the study aims to answer the research questions.

1) Does the personal cognitive approach affect improving task value?
2) Does a personal cognitive approach affect improving tech features?
3) Does the personal cognitive approach affect increasing academic self-efficacy?
4) Does task value affect improving usage intention?
5) Does the tech feature affect intention usage improvement?
6) Does usage intention affect improving academic self-efficacy?

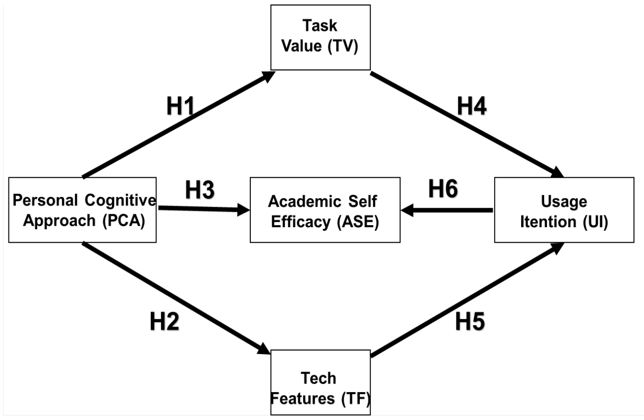

Fig. 1. Conceptual model.

II. Literature Review

A. Augmented Reality

Augmented Reality (AR) is a technology capable of simulating objects in real-world environments with realistic visuals. This technology enables the presentation of information in a virtual form while maintaining its original conditions [7]. The reliability of AR simplifies information delivery, making the learning process more effective. Additionally, AR is utilized as a medium to explain abstract concepts more clearly. With its ability to model objects, AR allows learners to understand materials without needing the physical objects themselves [36, 37]. As a result, AR is widely used to explain complex phenomena and equipment.

In computer network learning, AR contributes by simulating hardware components. This technology enables the detailed visualization of electronic components, which not only increases cost efficiency but also minimizes the risk of component damage when studying and analyzing even the smallest parts of electronic devices [6, 38]. Furthermore, AR enhances learning experiences through interactive presentations, making lessons more engaging.

AR helps to enhance the learning experience by exploring phenomena in the 3D visualization of electronic components in computer networks. [39]. AR enables students to explain complex phenomena in a way that presents interactive and realistic visuals as if they appear before the users. [40, 41]. The interactivity of the visualization presented by AR can enhance students' confidence in conveying complex topics to an audience. [42]. In computer network system learning, AR is designed to assist students in simulating the components of computer networks, including the framework structure and its operational system, so that they can better understand the relationships between elements in computer networks. Furthermore, AR can configure and manipulate computer network elements in interactive simulations. [43]. With this feature, students can observe, explore, and analyze various aspects of computer network systems directly, thereby enhancing their conceptual understanding and presentation skills in explaining network topologies and configurations to others. Consequently, AR significantly improves students' academic understanding and is becoming increasingly popular in educational implementation [44].

The reliability of AR in supporting students' academic performance provides positive contributions to education [36]. However, research on the impact of AR in enhancing academic achievement remains limited. One aspect that has not been extensively explored is the relationship between AR use and students' self-efficacy. Therefore, further analysis is needed to examine the factors influencing students' self-efficacy in AR-based learning.

B. Academic Self-Efficacy (ASE)

ASE is every individual's belief in completing a job [16]. Each individual has a different level of confidence in his or her ability to complete tasks, so self-efficacy is not global but has a different scale depending on the subject [45]. In education, ASE is associated with confidence in completing academic tasks. This belief is determined based on the standard of each person's ability to achieve certain academic goals [46, 47]. ASE correlates with the improvement of students' academic ability [48]. In addition, ASE plays a role in developing students' skills towards new knowledge [49]. The achievement of good academic ability and student motivation is influenced by high efficacy in students in the learning process [50]. High confidence in students in doing a task tends to encourage student persistence in completing difficult tasks [51, 52].

Self-efficacy in computer network learning reflects students' confidence in understanding and applying concepts in a computer network system. Key characteristics include completing complex tasks, resilience in facing technical challenges, and critical thinking and problem-solving skills. AR technology enhances students' self-efficacy by providing interactive simulations, real-time feedback, and independent exploration, enabling students to understand computer networks more deeply without real risks. AR encourages active engagement, where students with high self-efficacy are more confident in attempting solutions. By integrating AR, computer network learning enhances technical understanding and builds students' self-efficacy in the technology field.

C. Personal Cognitive Approach (PCA)

The ability to remember, explain and analyze is part of PCA [53]. Cognitive strategies in learning can be in the process of observing and processing information in each individual. Students need several strategies to understand facing exams, such as studying before exams [34]. The order applied to each individual can be done by arranging a cognitive strategy and something general towards something specific or vice versa [54]. Special strategies tend to require special tools to complete a task [55].

The selection of inappropriate strategies tends to damage student learning outcomes, such as not preparing before exams and postponing assignments [56]. This strategy is negative, known as academic self-handicapping (ASH), which expects failure [57, 58]. ASH aims to protect the self-esteem and perception of others through narratives about failure by blaming a variety of other factors [56]. The selection of positive strategies in learning leads to an increase in academic self-efficacy [35].

The integration of AR in computer network systems learning supports the development of cognitive aspects, particularly in learning and assessment based on Higher-Order Thinking Skills (HOTS). A personal cognitive approach for each student supports the development of these cognitive aspects. AR enables students to analyze, evaluate, and create computer network solutions through interactive visualization, real-time simulations, and direct feedback. In the learning process, AR is designed to assist students in analyzing network structures and configurations, evaluating various network scenarios through simulations, and creating innovative solutions in designing network systems. In terms of assessment, AR supports performance-based evaluations, such as project assessments and real-task simulations, which enhance students' critical thinking skills and self-confidence. Thus, the integration of AR aims to support the development of a personal cognitive approach in the learning process within computer network systems.

D. Task Value (TV)

Task value refers to the extent to which students perceive the assigned assignment or material to have value or relevance to their learning objectives [51]. Research indicates that learning that involves assignments will encourage more effort from students in learning and achieving [59]. The research also proposes the benefits of assignments in building knowledge, insight, motivation, student involvement in using technology and intention in learning [60–62]. ASE can be improved by giving students the freedom to learn new abilities through assignments, thus encouraging students to be competent in achieving the best results from the assignment [52]. In education, to support the completion of assignments, students tend to involve digital technology to encourage critical thinking skills and the ability to process information [63].

E. Tech Features (TF)

Each technology used in learning has a different TF according to the purpose of its use. TF relates to the appearance, usability, and specifications of the technology. AR can produce various forms of learning for students, such as narrative, quantitative, aesthetic, logical, and experimental learning for students in the learning process [37, 64]. AR, as a 3D object visualization technology, has a general characteristic in the form of the incorporation of virtual objects present in the real environment, utilizing the camera as a medium to bring out objects. AR can be presented with cameras in various digital devices, such as smartphones. Each AR developed has a feature specification that is presented. AR can be developed to present zoom, rotation, and movement features. In presenting AR in the environment, there are several forms of presentation, including utilizing markers, utilizing real objects, utilizing flat planes, and appearing directly in the air. Research informs that technology's various features and conveniences encourage user intent to use it [65].

In computer network systems, AR is designed with various features that enhance students' self-efficacy in learning. 3D interactive visualization allows students to understand abstract concepts more clearly, such as seeing real-time simulations of computer network topologies. Additionally, the simulation and self-exploration features allow students to experiment with various scenarios without real risks, for instance, virtual configuring electronic devices on computer network systems. AR in computer network systems is designed to provide real-time feedback by presenting explanatory information about the observed objects, enabling students to immediately identify the mistakes they make and correct them quickly, thereby boosting their confidence in completing tasks.

Gesture-based interaction or virtual control also assists students in becoming more engaged in the learning process, such as disassembling or assembling devices in AR simulations. Gamification in AR, such as challenges, levels, and virtual rewards, can enhance student motivation and confidence in completing tasks effectively. Moreover, collaborative features in AR enable students to work together in a virtual environment, share ideas, and solve problems collectively, which can strengthen their self-efficacy through social learning.

AR also supports personalized learning, where the materials can be tailored to the students' levels of understanding, allowing them to learn at their own pace without pressure. With these various features, AR creates a more supportive, interactive, and responsive learning environment, ultimately enhancing students' confidence in understanding and mastering the learning material.

F. Usage Intention (UI).

Ajzen (1980) proposed the concept of UI by using a technology known as reasoned action theory (TRA) [66]. TRA has evolved to create tangible results that support the relationship of user intent in utilizing technology in education [67, 68]. AR technology has the ability to support students in achieving optimal academic ability. The determination of goal achievement in accordance with individual abilities provides evidence of an increase in academic self-efficacy [69].

The use of AR integrated into computer network system learning is still limited. Learning innovations by adopting this technology aims to enhance students' self-efficacy through various AR features developed in educational products. In computer network systems, the application of AR presents interactive 3D visualization features, real-time simulations, instant feedback, and gesture-based interactions, which play a role in helping students develop exploration, visualization, and simulation skills regarding network concepts. The advantages of these features are designed to support the improvement of students' self-efficacy in learning, enabling them to learn in a more interactive, independent, and confident manner in understanding computer network systems.

III. METHODS

This study was quantitative research using a controlled experimental method aimed at developing and testing a conceptual model consisting of six hypotheses, focusing on the impact of AR on students' academic self-efficacy. The analysis in this study was conducted using Structural Equation Modelling-Partial Least Square (SEM-PLS) to investigate the relationships between variables, processed using the SMART-PLS 4.0 application. This application was used to test the relationships between variables in the conceptual model. The results of this analysis were used to conclude the impact of AR on students' academic self-efficacy.

A. Participants

The total sample in this study consists of 340 students, and each student has completed the survey. The sample distribution in this study is categorized based on gender, age, and year of study. This distribution serves as a representation of the respondents' characteristics in the research. Information regarding the sample distribution can assist in understanding the participants' profiles in more depth. The results of the sample distribution in this study are presented in Table 1.

Table 1. Distribution of sample

Category	Information	Percentage (%)	Count
Gender	Male	74%	250
	Female	26%	90
Age	18 years	18%	60
	19 years	30%	102
	20 years	29%	99
	21 years	23%	79
Year of Study	First Year	28%	93
	Second Year	26%	90
	Third Year	27%	92
	Fourth Year	19%	65

B. Instrument and Procedures

The instrument used in this study was a questionnaire that covered personal cognitive approach, task value, tech features, academic self-efficacy, and usage intention. The questionnaire instrument consisted of 16 items with a Likert scale answer choices, ranging from 1 (strongly disagree) to 5 (strongly agree). Data collection was conducted using Google Forms after the learning process in the controlled experiment. The stages of the research implementation process are presented in Fig. 2.

Fig. 2 presents a diagram of the research process stages. The research process was carried out through a controlled experiment. A total of 240 students were prepared for this study. The controlled conditions in this study involved preparing students who participated in the experiment, specifically those who had smartphones, to access AR media and were engaged in direct classroom learning. During the controlled experiment, the learning process was guided by a lecturer to facilitate its implementation. The lecturer distributed the AR product used in the learning process. The students then installed the distributed product. To ensure controlled outcomes, information related to learning and research was kept confidential from students to obtain genuine results. The learning session lasted 50 minutes using AR technology on computer network material. After the learning session, students were given an instrument in a Google Form to collect information on the personal cognitive approach, task value, tech features, academic self-efficacy, and usage intention. Information related to the features and access of the AR product used in the learning process is presented as follows.

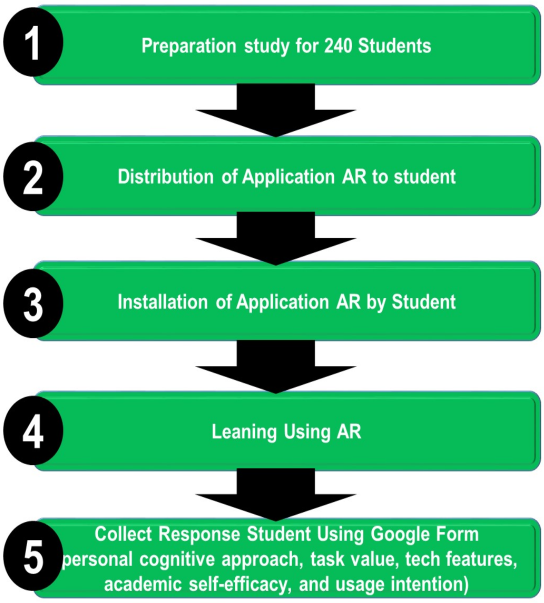

Fig. 2. Diagram of research stages.

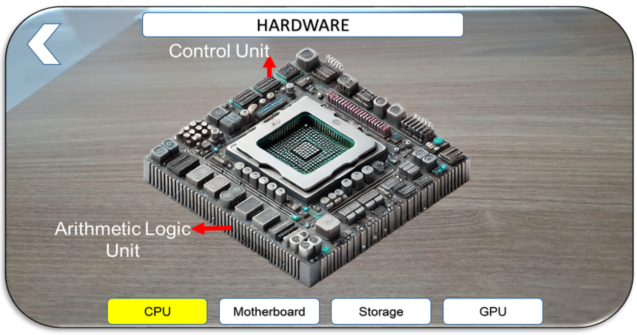

Fig. 3. AR computer network.

1) The AR application is available on the App Store and can be accessed through the following link: [https://bit.ly/4kGGBSs] or by scanning the QR Code.
2) The application is installed on smartphones to present computer network materials. This application displays AR objects implemented in learning, as seen in Fig. 3.
3) AR is presented with zoom, rotation, and direct interaction features with AR objects.

C. Data Analysis

The Structural Equation Modeling – Partial Least Square (SEM-PLS) approach, which is based on component estimation to analyze data, is used in this study. This approach was chosen because it can simultaneously analyze the measurement and structural models. Statistical analysis was conducted using SMART-PLS 4.0 software, which supports path modelling with latent variables through the SEM-PLS method. In evaluating measurement models, it is important to test the reliability and validity to ensure the accuracy of the results obtained. The reliability of a construct can be measured through several methods, such as Cronbach's alpha, composite reliability, AVE, and VIF [70, 71]. Meanwhile, the analysis of the relationships between variables is based on t-test results or p-values.

IV. Result

The conceptual framework was tested to examine the relationships between variables in the conceptual model. The conceptual framework aims to identify factors related to enhancing academic self-efficacy. Therefore, this conceptual model was tested to determine the validity and accuracy of the construct variables [72, 73]. The results of this model testing were analyzed using SEM-PLS, considering the outcomes of Cronbach's alpha (α), Composite Reliability (CR), loading factor, Average Variance Extracted (AVE), and variance inflation factor (VIF) tests [70]. The conceptual model's presentation and the model analysis results are shown in Fig. 4 and Table 2.

Table 3 presents the results of the conceptual model testing analysis. In the multicollinearity test, the model developed through the relationships of each indicator is accepted if no multicollinearity occurs, which is indicated by a VIF value < 5 (J. F. Hair, Risher, Sarstedt, & Ringle, 2019). The analysis results show that the VIF values for each indicator are below this threshold, indicating no multicollinearity exists. The AVE value is used to investigate the convergent validity of each variable. Convergent validity is met when the AVE value is > 0.5. The analysis results indicate that all variables meet this threshold, with the following AVE values: personal cognitive approach (0.775), task value (0.696), tech features (0.719), academic self-efficacy (0.826), and usage intention (0.759). Additionally, the results of the loading factor and CR tests show that all indicators have values above 0.7, indicating that these indicators are valid and reliable. A Fornell-Larcker analysis was also conducted to ensure discriminant validity and strengthen the model's validity. The results of the discriminant validity test are presented in Table 4.

Table 2. Discriminant validity

Variable	ASE	PCA	TV	TF	UI
Academic self-efficacy (ASE)	0.909				
Personal Cognitive Approach (PCA)	0.070	0.880			
Task Value (TV)	0.008	0.056	0.834		
Tech Features (TF)	0.016	0.071	0.043	0.848	
Usage Intention (UI)	0.593	0.024	0.005	0.063	0.871

Table 3. Results of model analysis

Latent Variables	Code Item	Description Item	VIF	Loading Factor	α	CR	AVE
Personal Cognitive Approach (PCA)	PCA1	I apply the knowledge from lectures and textbooks to new assignments.	2.113	0.854	0.858	0.907	0.775
	PCA 2	I tried to understand the tutor's explanation even though it was difficult.	2.093	0.910			

Latent Variables	Code Item	Description Item	VIF	Loading Factor	α	CR	AVE
	PCA 3	When programming, I connect reading with existing knowledge.	2.282	0.877			
Task Value (TV)	TV1	I enjoyed the material taught in this lab session.	2.081	0.748	0.879	1.308	0.696
	TV2	The material of this lab session felt useful to me.	2.292	0.789			
	TV3	I found this lab session material interesting.	2.329	0.949			
	TV4	This lab session learning helped me with network installation projects.	2.112	0.839			
Tech Features (TF)	TF1	AR applications for computer network system materials are easy to use.	2.154	0.895	0.875	0.944	0.719
	TF2	The various functions in the AR app are well integrated.	2.119	0.792			
	TF3	I feel confident using AR applications for this material.	2.324	0.858			
	TF4	AR applications are interactive and interesting.	2.053	0.844			
Academic Self Efficacy (ASE)	ASE1	I am confident as a student in this class.	2.157	0.892	0.897	0.926	0.826
	ASE2	I believe that I can complete this task well.	4.665	0.944			
	ASE3	I am confident that I can master the material taught in this lab session.	4.307	0.890			
Usage Intention (UI)	UI1	I feel that understanding the material of this lab session is very important.	1.955	0.836	0.845	0.919	0.759
	UI2	I prefer lab sessions that use AR applications to those that don't.	1.996	0.855			
	UI3	I hope to use AR applications often to learn this material.	2.150	0.920			

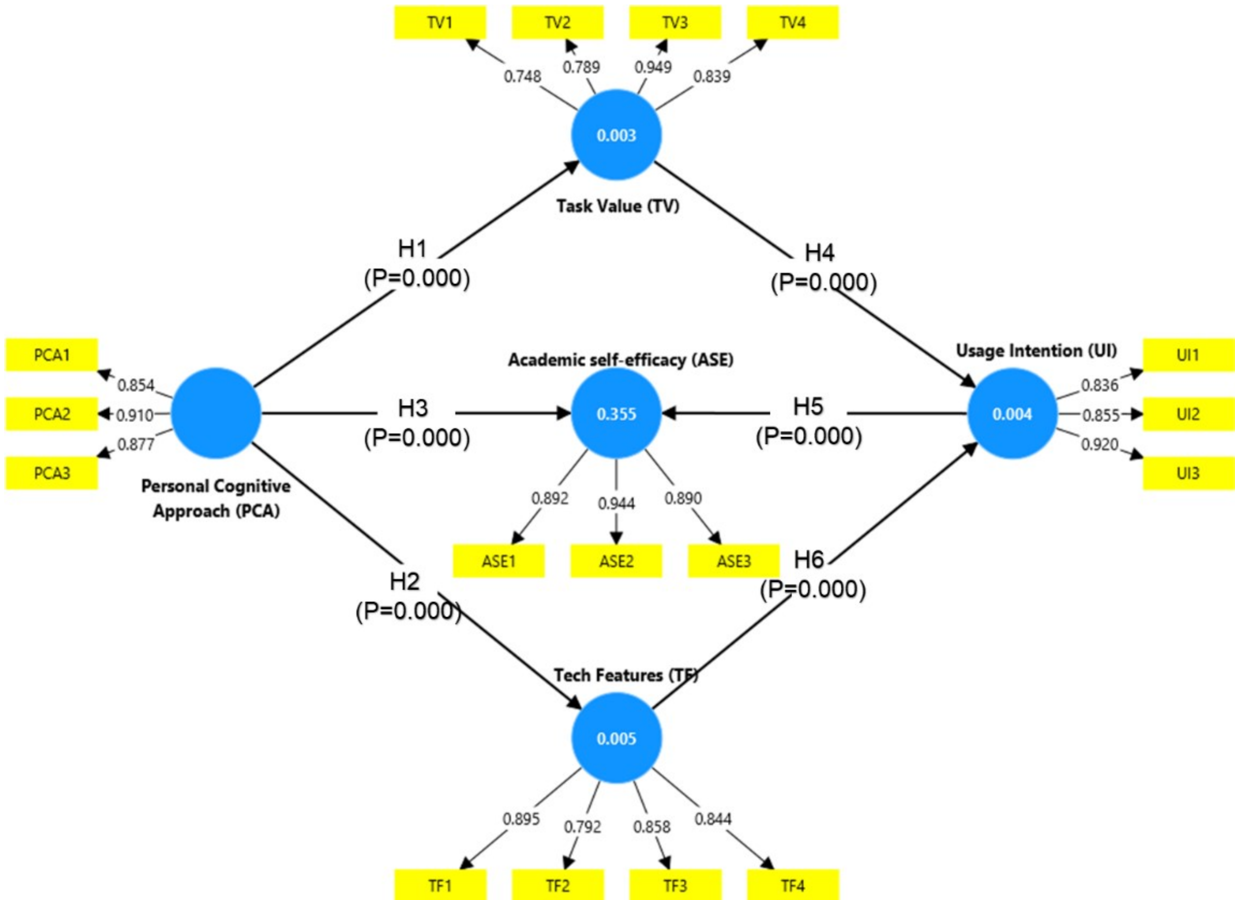

Fig. 4. Result of conceptual model.

Table 4. Discriminant validity

Variable	ASE	PCA	TV	TF	UI
Academic self-efficacy (ASE)	0.909				
Personal Cognitive Approach (PCA)	0.070	0.880			
Task Value (TV)	0.008	0.056	0.834		
Tech Features (TF)	0.016	0.071	0.043	0.848	
Usage Intention (UI)	0.593	0.024	0.005	0.063	0.871

Table 4 presents the results of the Fornell-Larcker criterion validity analysis. A conceptual model is considered valid if it meets the requirement that the square root of the AVE (diagonal values) is greater than the correlations between constructs (off-diagonal values). The AVE values for each construct show good results, with ASE (0.909), PCA (0.880), TV (0.834), TF (0.848), and UI (0.871), all of which are above 0.50. The correlations between constructs show that the relationship between ASE and UI (0.593), PCA and TV (0.056), and TF and UI (0.063) are smaller than the square root of the corresponding AVE values, indicating that all relationships in the model have good discriminant validity. Based on the testing results, the developed conceptual model is valid and reliable and shows no multicollinearity. Therefore, the model was analyzed significantly to determine its effect on each variable. The results of the inter-variable relationship testing are presented in Table 5.

Table 5. Hypothesis testing results

Variable	T-test	P-values	Result
H1: Personal cognitive approach affects improving task value	36.512	0.000	Supported
H2: Personal cognitive approach affects improving tech features	9.705	0.000	Supported
H3: Personal cognitive approach affects improving academic self-efficacy	4.970	0.000	Supported
H4: Task value affects improving usage intention	8.494	0.000	Supported
H5: Tech features affect improving usage intention	40.624	0.000	Supported
H6: Usage intention affects improving academic self-efficacy	14.557	0.000	Supported

Table 5 displays the results of hypothesis testing for the conceptual model. The hypothesis testing results showed that all relationships in the conceptual model had significant effects. Based on the T-test results and p-values, hypothesis H1, which tested the effect of the personal cognitive approach on improving task value, showed a significant result (T-test = 36.512, p = 0.000), indicating that the personal cognitive approach significantly influenced task value. The same was true for hypothesis H2, which tested the effect of a personal cognitive approach on improving tech features, with a significant result (T-test = 9.705, p = 0.000), showing that personal cognitive approach influenced tech features. Hypothesis H3, which tested the effect of the personal cognitive approach on improving academic self-efficacy, also showed a significant result (T-test = 4.970, p = 0.000), meaning that the personal cognitive approach significantly influenced academic self-efficacy. Next, hypothesis H4, which tested the effect of task value on improving usage intention, showed a significant result (T-test = 8.494, p = 0.000), meaning that task value influenced usage intention. Hypothesis H5, which tested the effect of tech features on usage intention, also showed a significant result (T-test = 40.624, p = 0.000), indicating that tech features significantly influenced usage intention. Lastly, hypothesis H6, which tested the effect of usage intention on improving academic self-efficacy, showed a highly significant result (T-test = 14.557, p = 0.000), meaning that usage intention significantly affected academic self-efficacy. Overall, all hypotheses in this model showed significant effects.

V. Discussion

This study revealed the results of a conceptual model test that identified the influence of personal cognitive approach and usage intention on using technology to improve students' academic self-efficacy. These findings support previous research that states that implementing positive learning strategies can support the success of academic self-efficacy [74]. In particular, the personal cognitive approach has significantly improved academic self-efficacy in the learning process [46, 75]. Wang & Wu [76] stated that students with high academic self-efficacy levels tend to apply a personal cognitive approach more effectively in learning because they can choose the right approach in dealing with difficulties or failures. In contrast, students with low academic self-efficacy often put in less effort and choose ineffective strategies. Our research offers a different view by showing the possibility of a reciprocal relationship between personal cognitive approach and academic self-efficacy, which shows the dynamic interaction between the two.

This research also revealed the positive relationship between usage intention technology and academic self-efficacy. These findings are reinforced by the study results, which show that modern technology improves students' academic self-efficacy and abilities [77]. Other research reveals that the availability of technology in learning plays an important role in increasing student engagement, motivation, and satisfaction in the learning process [78, 79]. In particular, technology supports increased student motivation and a more in-depth understanding of learning structures and concepts [33].

In addition, these findings highlight the importance of usage intention in AR technology in supporting the improvement of academic self-efficacy. This strong intention to use technology acts as a driving factor that increases student engagement in learning. When students are motivated to utilize AR, they are more likely to be active in learning and feel more confident in completing tasks. This is in line with Bandura's (1997) theory, which states that an individual's belief in their ability to control the situation they face affects their actions [46]. Thus, an effective personal cognitive approach and a robust intention to use technology contribute to academic achievement and increase students' confidence in overcoming the learning challenges they face.

Task value and tech features play an important role in influencing students' cognitive approach in the context of learning. Based on previous research, students' perception of task value is closely related to applying effective cognitive strategies in achieving learning goals. Lawanto et al. (2014). A positive perception of task value can increase students' motivation to try harder in learning [80]. In this case, students who value the value and relevance of assignments will tend to use more targeted and efficient learning strategies, thereby increasing their chances of academic success.

This study also revealed a relationship between the personal cognitive approach applied by students and their perception of task value. Students who use a better personal cognitive approach tend to better understand the importance of the tasks they are working on, which in turn can improve their learning effectiveness. This corroborates the finding that a positive personal cognitive approach contributes to better academic achievement and increases students' understanding of the task value provided.

However, this study's results show that task value's influence on usage intention to use technology, especially in the context of AR, is not as strong as expected. This is in contrast to other research findings that suggest that task value plays a significant role in motivating students to use technology [81, 82]. To further understand these differences, qualitative studies can provide more in-depth insights into the factors that influence task value in the context of AR technology [83]. More research is needed to unearth the reasons behind these different findings and provide a more comprehensive explanation of the relationship between task value, personal cognitive approach, and usage intention.

In the context of this study, usage intention shows significant relevance to previous studies' findings that identify a positive relationship between good learning attitudes and the application of AR technology in the learning process. Research by Cai *et al*. (2014) suggests that AR technology can affect students' attitudes and learning interests, which in turn increases learning effectiveness [84]. Furthermore, research by Asoodar *et al*. (2016) found that tech features in learning can influence cognitive strategies used by students [85]. This confirms that technology is a tool and an important factor in shaping how students think and solve problems.

It is important to further investigate the relationship between personal cognitive approach and tech features to understand how technology can serve as a clue or aid in improving students' problem-solving, self-motivation, and academic self-efficacy in learning. Research by Kao & ruan (2022) shows a strong relationship between using AR technology and increasing students' motivation to learn [86]. Learning that utilizes AR can create a more engaging and immersive experience, encouraging higher student engagement than traditional methods. In addition, Zumbach *et al*. (2020) also supported these findings by showing that the interactive learning environment provided by technology can strengthen students' cognitive drive [87]. Therefore, the characteristics of good technology not only affect how the material is delivered but can also stimulate active engagement and improve the results.

The relationship between personal cognitive approach and tech features was strengthened by findings that showed a relationship between tech features and usage intention when using ar (H5). Previous research has also revealed that tech features have a positive relationship with usage intention to use technology in learning [68, 88]. Simple features with systematic and easy-to-understand instructions increase students' intention to use technology in learning. Conversely, complex features and misinformation in AR technology can reduce student and learning engagement.

Identifying tech features, including features and student needs, is critical in optimizing the use of media in learning. The realistic display of AR images can increase students' usage intent because it fosters curiosity in the learning process. In addition, the interactivity and feedback provided by AR technology improve learning outcomes, resulting from students' higher intentions of using technology. The AR technology interface's unique, engaging, and innovative features also spark students' interest in using it in the learning process.

VI. Conclusion

This conceptual model shows that personal cognitive approach has an important role in influencing various AR learning aspects. The personal cognitive approach applied by students can improve their understanding of the material and tasks given, increasing the task value achieved. In addition, a good personal cognitive approach also helps students better understand and utilize AR technology, which strengthens their view of the tech features and the usage intention to use it. A strong usage intention to use AR plays an important role in improving students' academic self-efficacy, as the use of AR can improve students' confidence in completing academic tasks. Overall, the implementation of a personal cognitive approach, tech features, and usage intention is proven to improve students' academic self-efficacy, strengthen their engagement in learning, and support better academic achievement.

The innovation in this study develops a conceptual model that examines the relationship between AR technology and its impact on students' academic self-efficacy. AR technology affects students' usage intention, which encourages active engagement in learning and increases their confidence in their ability to achieve academic outcomes. The use of AR also increases motivation and creates a more engaging and effective learning experience. In the context of computer network learning, the relevance of the material to the assignment grade motivates students to use AR, while the personal cognitive approach applied during learning increases their academic self-efficacy. Tech Features AR, such as realistic 3D visualization, high interactivity, immediate feedback, and exercise-based simulations, significantly enhance students' self-efficacy. The interactivity and realistic visualization features allow for a deeper exploration of computer networking material, while immediate feedback aids in better understanding. Additionally, simulation-based exercises provide opportunities for students to practice without risk, increasing their confidence in mastering skills. Based on existing data, the application of AR can strengthen students' self-efficacy, so it is highly recommended that educators integrate AR to improve the quality of education and academic achievement of students.

This study successfully addresses the main objective of investigating the relationship between the variables of personal cognitive approach, task value, usage intention, and tech features on academic self-efficacy in the implementation of AR in computer network learning. However, there are several limitations that need to be considered. The study does not cover important aspects such as individual learning styles, independent learning time, and different students' cognitive strategies, even though these factors can affect how students understand computer network materials through AR. In addition, environmental variables such as parental guidance and student learning behaviour, which have the potential to affect the effectiveness of AR use, are not discussed in depth. From a demographic standpoint, this study has not investigated the differences that may arise regarding gender, age, and the level of immersion in AR technology, which could provide a deeper understanding of the effectiveness of AR in different groups of students. In terms of infrastructure readiness and the initial capabilities of students, this research has not comprehensively addressed these two aspects in the usage and representation of AR, which includes the availability of compatible devices, accessibility of AR platforms, internet connection stability, data storage capacity, device power requirements, available technical support, and the institutional network's readiness to handle AR technology playing a crucial role in the success of AR-based learning. Additionally, the level of students' familiarity with AR, their skills in operating this technology, the institution's preparedness to provide supporting facilities, and university policies regarding integrating AR into the curriculum may also affect learning outcomes and their level of engagement.

Future research is suggested to explore these factors in more detail. An analysis of learning styles and self-study time, for example, can provide a more accurate picture of how AR can be optimally utilized for different types of learners in the context of computer networks. Comparative studies between genders and age differences can also provide insights into how these factors affect students' acceptance and understanding of the concept of computer networks through AR. In addition, testing various levels of AR immersion, from basic to advanced, as well as the readiness of infrastructure and the initial capabilities of students, is important for understanding how these factors affect student engagement and their ability to comprehend complex computer network material. With a broader scope of these aspects, future research is expected to strengthen the understanding of the role of AR in improving the effectiveness of computer network learning as well as creating a more adaptive approach for different types of students.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

IPM contributed to developing the research idea, writing the article, and collecting data. HH and DI played a role in data collection and the development of research instruments. MD and SAB contributed to writing the article. Meanwhile, AA and AB were responsible for designing the research and providing constructive feedback at every stage of the study. All authors had approved the final version.

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References

[1] A. Deguchi *et al.*, "What is society 5.0," *Society*, vol. 5, no. 0, pp. 1–24, 2020. doi: 10.1007/978-981-15-2989-4

[2] F. Mufit, Y. Hendriyani, and M. Dhanil, "Design Immersive Virtual Reality (IVR) with cognitive conflict to support practical learning of quantum physics," *Journal of Turkish Science Education*, vol. 21, no. 2, pp. 369–388, 2024. doi: 10.36681/tused.2024.020

[3] I. P. Dewi, "How effective is immersive ar continental food course for vocational education? analyzing knowledge gains and learning outcome effects," *International Journal of Information and Education Technology*, vol. 15, no. 1, pp. 127–136, 2025. doi: 10.18178/ijiet.2025.15.1.2225

[4] R. Marta, A. R. Riyanda, A. D. Samala, I. P. Dewi, and N. H. Adi, "Innovative learning strategies:project-based learning model for excelling in visual programming," *TEM Journal*, pp. 581–598, Feb. 2024. doi: 10.18421/tem131-61

[5] M. Vásquez-Carbonell, "A systematic literature review of augmented reality in engineering education: Hardware, software, student motivation & development recommendations.," *Digital Education Review*, no. 41, pp. 249–267, 2022. doi:10.1344/der.2022.41.249-267

[6] I. P. Dewi, A. Ambiyar, H. Effendi, M. Giatman, H. F. Hanafi, and S. K. Ali, "The impact of virtual reality on programming algorithm courses on student learning outcomes," *International Journal of Learning, Teaching and Educational Research*, vol. 23, no. 10, pp. 45–61, 2024. doi:10.26803/ijlter.23.10.3

[7] M. Dhanil and F. Mufit, "How virtual reality impacts science learning? A Meta-analysis," *International Association of Online Engineering*, vol. 18, no. 22, pp. 77–96, 2024. doi:10.3991/ijim.v18i22.49989

[8] C. Avila-Garzon, J. Bacca-Acosta, J. Duarte, and J. Betancourt, "Augmented reality in education: an overview of twenty-five years of research," *Contemporary Educational Technology*, vol. 13, no. 3, 2021. doi: 10.3390/mti5070037

[9] S. Vaidya, P. Ambad, and S. Bhosle, "Industry 4.0–a glimpse," *Procedia manufacturing*, vol. 20, pp. 233–238, 2018. doi: 10.1016/j.promfg.2018.02.034

[10] S. Dargan, S. Bansal, M. Kumar, A. Mittal, and K. Kumar, "Augmented reality: A comprehensive review," archives of computational methods in engineering," *Archives of Computational Methods in Engineering*, vol. 30, no. 2, pp. 1057–1080, 2023. doi: 10.1007/s11831-022-09831-7

[11] D. Roopa, R. Prabha, and G. A. Senthil, "Revolutionizing education system with interactive augmented reality for quality education," *Materials Today: Proceedings*, vol. 46, pp. 3860–3863, 2021. doi:10.1016/j.matpr.2021.02.294

[12] M. Raja and G. G. L. Priya, "Using virtual reality and augmented reality with ICT tools for enhancing quality in the changing academic environment in COVID-19 pandemic: An empirical study," in *Technologies, Artificial Intelligence and the Future of Learning Post-COVID-19: The Crucial Role of International Accreditation*, Springer, 2022, pp. 467–482. doi:10.1007/978-3-030-93921-2_26

[13] M. L. Hamzah, F. Rizal, and W. Simatupang, "Development of augmented reality application for learning computer network device," *International Journal of Interactive Mobile Technologies*, vol. 15, no. 12, 2021. doi:10.18502/kss.v7i19.12488

[14] Y. Zhang, Y. Yang, Y. Chu, D. Sun, J. Xu, and Y. Zheng, "Virtual Laboratories in science education: unveiling trajectories, themes, and emerging paradigms (2013-2023).," *Journal of Baltic Science Education*, vol. 23, no. 5, pp. 990–1009, 2024. doi: 10.33225/jbse/24.23.990

[15] A. Kumar, A. Mantri, and R. Dutta, "Development of an augmented reality based scaffold to improve the learning experience of engineering students in embedded system course," *Computer Applications in Engineering Education*, vol. 29, no. 1, pp. 244–257, 2021. doi:10.1002/cae.22245

[16] B. Herbert, G. Wigley, B. Ens, and M. Billinghurst, "Cognitive load considerations for augmented reality in network security training," *Computers & Graphics*, vol. 102, pp. 566–591, 2022. doi: 10.1016/j.cag.2021.09.001

[17] N. H. Adi, A. L. Lubis, A. Basriadi, I. P. Dewi, and Y. W. Wahdi, "Augmented reality learning media application in computer networking courses," *Sinkron*, vol. 8, no. 3, pp. 1641–1650, Jul. 2024. doi: 10.33395/sinkron.v8i3.1370

[18] A. A. Syahidi and A. Mohamed, "Mobile augmented reality application with multi-interaction for learning solutions on the topic of computer network devices (effectiveness, interface, and experience design)," in *Proc. 2020 Third International Conference on Vocational Education and Electrical Engineering (ICVEE)*, pp. 1–6, 2020. doi: 10.1109/icvee50212.2020.9243292

[19] M. F. Mohd, S. K. Ali, P. S. Sulaiman, A. J. Ishak, and I. P. Dewi, "Muscle-synergy for human-robot control, wearable devices and computer animation: A survey," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, 2024. doi: 10.37934/araset.XX.X.146158

[20] M. Prvan and J. Ožegović, "Methods in teaching computer networks: a literature review," *ACM Transactions on Computing Education (TOCE)*, vol. 20, no. 3, pp. 1–35, 2020.

[21] A. Mubai, A. Ambiyar, D. Irfan, and M. S. Rasul, "Flipped Direct Instruction (FDI): A new practicum learning model in vocational education," *International Journal of Learning, Teaching and Educational Research*, vol. 22, no. 7, pp. 547–565, 2023. doi: 10.26803/ijlter.22.7.29

[22] F. Arena, M. Collotta, G. Pau, and F. Termine, "An overview of augmented reality," *Computers*, vol. 11, no. 2, p. 28, 2022. doi: 10.1007/978-3-319-54502-8_4

[23] S. Criollo-C, D. Abad-Vásquez, M. Martic-Nieto, F. A. Velásquez-G, J.-L. Pérez-Medina, and S. Luján-Mora, "Towards a new learning experience through a mobile application with augmented reality in engineering education," *Applied Sciences*, vol. 11, no. 11, p. 4921, 2021. doi: 10.3390/app11114921

[24] I. P. Dewi *et al.*, "Virtual reality in algorithm programming course: practicality and implications for college students," *JOIV : International Journal on Informatics Visualization*, vol. 8, no. 3–2, p. 1720, Nov. 2024. doi: 10.62527/joiv.8.3-2.3113.

[25] V. P. Oleksiuk and O. R. Oleksiuk, "Assessing augmented reality possibilities in the study of school computer science," in *Proc. the Symposium on Advances in Educational Technology,* 2020. doi: 10.5220/0010927900003364

[26] G. Lampropoulos, E. Keramopoulos, K. Diamantaras, and G. Evangelidis, "Integrating augmented reality, gamification, and serious games in computer science education," *Education Sciences*, vol. 13, no. 6, p. 618, 2023. doi: 10.3390/educsci13060618

[27] J. Buchner and M. Kerres, "Media comparison studies dominate

comparative research on augmented reality in education," *Computers & Education*, vol. 195, 104711, 2023, doi: 10.1016/j.compedu.2022.104711
[28] N. A. Ali, M. H. Sadiq, A. A. Albabawat, and R. M. Salah, "Methods and applications of augmented reality in education: A review," in *Proc. 2022 International Conference on Computer Science and Software Engineering (CSASE)*, IEEE, 2022, pp. 175–181.
[29] Y. Koumpouros, "Revealing the true potential and prospects of augmented reality in education," *Smart Learning Environments*, vol. 11, no. 1, 2024. doi: 10.1186/s40561-023-00288-0
[30] A.-S. Ulfert-Blank and I. Schmidt, "Assessing digital self-efficacy: Review and scale development," *Computers & Education*, vol. 191, 104626, 2022.
[31] P. Peciuliauskiene, G. Tamoliune, and E. Trepule, "Exploring the roles of information search and information evaluation literacy and pre-service teachers' ICT self-efficacy in teaching," *International Journal of Educational Technology in Higher Education*, vol. 19, no. 1, p. 33, 2022.
[32] S. Bonanati and H. M. Buhl, "The digital home learning environment and its relation to children's ICT self-efficacy," *Learning Environments Research*, vol. 25, no. 2, pp. 485–505, 2022.
[33] A. D. Samala, I. P. Dewi, and L. Mursyida, "' E-labsheet project' 4cs-based supplementary media for flexible learning: Is it well implemented?" *International Journal of Online & Biomedical Engineering*, vol. 19, no. 1, 2023. doi: 10.3991/ijoe.v19i01.35523
[34] K. Madhusudhana, "The cognitive dimension and course content modeling: An ontological approach.," *International Journal of Emerging Technologies in Learning*, vol. 12, no. 5, 2017. doi: 10.3991/ijet.v12i05.6854
[35] S. Brooman and S. Darwent, "'Yes, as the articles suggest, I have considered dropping out': self-awareness literature and the first-year student," *Studies in Higher Education*, vol. 37, no. 1, pp. 19–31, 2012. doi: 10.1080/03075079.2010.490580
[36] F. Mufit, W. S. Dewi, S. Riyasni, and M. Dhanil, "Augmented reality with a cognitive conflict model and STEM integration on newton's universal law of gravitation: Does practicing practical learning support scientific literacy?" *International Journal of Information and Education Technology*, vol. 15, no. 2, pp. 255–271, 2025. doi: 10.18178/ijiet.2025.15.2.2239
[37] F. Mufit and M. Dhanil, "Effectiveness of augmented reality with cognitive conflict model to improve scientific literacy of static fluid material," *International Journal of Information and Education Technology*, vol. 14, no. 9, 2024. doi: 10.18178/ijiet.2024.14.9.2149
[38] H. Hidayat *et al.*, "The influence of augmented reality mobile app on electronics engineering students' self-competence," *TEM Journal*, vol. 13, no. 3, p. 2310, 2024. doi:10.18421/tem133-58
[39] W. Tong *et al.*, "Exploring interactions with printed data visualizations in augmented reality," *IEEE Transactions on Visualization and Computer Graphics*, vol. 29, no. 1, pp. 418–428, 2022.
[40] M. Z. A. Muthalif, D. Shojaei, and K. Khoshelham, "A review of augmented reality visualization methods for subsurface utilities," *Advanced Engineering Informatics*, vol. 51, 101498, 2022.
[41] B. Lee, M. Sedlmair, and D. Schmalstieg, "Design patterns for situated visualization in augmented reality," *IEEE Transactions on Visualization and Computer Graphics*, vol. 30, no. 1, pp. 1324–1335, 2023.
[42] Y. O'Connor and C. Mahony, "Exploring the impact of augmented reality on student academic self-efficacy in higher education," *Computers in Human Behavior*, vol. 149, 107963, 2023. doi: 10.2139/ssrn.4406066
[43] J. Grodotzki, B. T. Müller, and A. E. Tekkaya, "Introducing a general-purpose augmented reality platform for the use in engineering education," *Advances in Industrial and Manufacturing Engineering*, vol. 6, 100116, 2023.
[44] H. D. Ahmed and G. Asiksoy, "The effects of gamified flipped learning method on student's innovation skills, self-efficacy towards virtual physics lab course and perceptions," *Sustainability*, vol. 13, no. 18, 10163, 2021.
[45] A. Bandura, "Guide to the construction of self-efficacy scales," *Self-Efficacy Beliefs of Adolescents*, pp. 307–337, 2006.
[46] A. Bandura, *Self-Efficacy in Changing Societies*, Cambridge University Press, 1997.
[47] G. Nasa, "Academic Self-efficacy: A reliable predictor of educational performances," *British Journal of Education*, vol. 2, no. 3, pp. 57–64, 2014.
[48] K. Bartimote-Aufflick, A. Bridgeman, R. Walker, M. Sharma, and L. Smith, "The study, evaluation, and improvement of university student self-efficacy," *Studies in Higher Education*, vol. 41, no. 11, pp. 1918–1942, 2016. doi: 10.1080/ 03075079.2014.999319
[49] C. Tang, "Physics of life," *A Festschrift in Honor of the CN Yang Centenary: Scientific Papers*, World Scientific, 2022, pp. 345–350. doi: 10.1142/9789811264153_0020
[50] L. Anthonysamy, A.-C. Koo, and S.-H. Hew, "Self-regulated learning strategies and non-academic outcomes in higher education blended learning environments: A one decade review," *Education and Information Technologies*, vol. 25, no. 5, pp. 3677–3704, 2020. doi: 10.1007/s10639-020-10134-2
[51] P. R. Pintrich, "A manual for the use of the Motivated Strategies for Learning Questionnaire (MSQL)," *National Center for Research to Improve Postsecondary Teaching and Learning*, 1991. doi: 10.52340/gpj.2022.08.01
[52] E. A. Linnenbrink and P. R. Pintrich, "Motivation as an enabler for academic success," *School psychology review*, vol. 31, no. 3, pp. 313–327, 2002. doi: 10.1080/02796015.2002.12086158
[53] P. R. Pintrich and E. V De Groot, "Motivational and self-regulated learning components of classroom academic performance," *Journal of Educational Psychology*, vol. 82, no. 1, p. 33, 1990.
[54] J. Neroni, C. Meijs, H. J. M. Gijselaers, P. A. Kirschner, and R. H. M. de Groot, "Learning strategies and academic performance in distance education," *Learning and Individual Differences*, vol. 73, pp. 1–7, 2019. doi: 10.1016/j.lindif.2019.04.007
[55] P. A. Alexander, S. Graham, and K. R. Harris, "A perspective on strategy research: Progress and prospects," *Educational Psychology Review*, vol. 10, pp. 129–154, 1998. doi: 10.1023/A:1022185502996
[56] S. A. Gadbois and R. D. Sturgeon, "Academic self handicapping: Relationships with learning specific and general self perceptions and academic performance over time," *British Journal of Educational Psychology*, vol. 81, no. 2, pp. 207–222, 2011. doi: 10.1348/000709910X522186
[57] D. L. Feick and F. Rhodewalt, "The double-edged sword of self-handicapping: Discounting, augmentation, and the protection and enhancement of self-esteem," *Motivation and Emotion*, vol. 21, pp. 147–163, 1997. doi: 10.1023/A:1024434600296
[58] J. Martín-Gutiérrez, P. Fabiani, W. Benesova, M. D. Meneses, and C. E. Mora, "Augmented reality to promote collaborative and autonomous learning in higher education," *Computers in human behavior*, vol. 51, pp. 752–761, 2015. doi: 10.1016/j.chb.2014.11.093
[59] A. Wigfield, "The role of children's achievement values in the self-regulation of their learning outcomes," *Self-Regulation of Learning and Performance*, Routledge, 2023, pp. 101–124. doi: 10.4324/9780203763353-5
[60] A. R. Artino Jr and D. B. McCoach, "Development and initial validation of the online learning value and self-efficacy scale," *Journal of Educational Computing Research*, vol. 38, no. 3, pp. 279–303, 2008, doi: 10.2190/EC.38.3.c.
[61] C.-M. Chiu and E. T. G. Wang, "Understanding web-based learning continuance intention: The role of subjective task value," *Information & management*, vol. 45, no. 3, pp. 194–201, 2008. doi: 10.1016/j.im.2008.02.003
[62] T.-J. Lin, "Exploring the differences in Taiwanese university students' online learning task value, goal orientation, and self-efficacy before and after the COVID-19 outbreak," *The Asia-Pacific Education Researcher*, vol. 30, no. 3, pp. 191–203, 2021. doi: 10.1007/s40299-021-00553-1
[63] D. Oblinger and J. Oblinger, "Is it age or IT: First steps toward understanding the net generation," *Educating the net generation*, vol. 2, no. 1–2, p. 20, 2005.
[64] E. J. Rozell and W. L. Gardner III, "Cognitive, motivation, and affective processes associated with computer-related performance: A path analysis," *Computers in Human behavior*, vol. 16, no. 2, pp. 199–222, 2000. doi: 10.1016/S0747-5632(99)00054-0
[65] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, pp. 319–340, 1989.
[66] I. Ajzen, "Understanding attitudes and predictiing social behavior," *Englewood Cliffs*, 1980. doi: 10.4324/9781315801780-18
[67] H. Fan, R. Ahmad, and T.-K. Chen, "A study of fuzhou's undergraduate behavioural intentions to use tablet personal computer as replacement of textbook," *International Journal of Data Science and Advanced Analytics*, vol. 1, no. 1, pp. 32–38, 2019. doi: 10.69511/ijdsaa.v1i1.72
[68] S. Lakhal and H. Khechine, "Student intention to use desktop web-conferencing according to course delivery modes in higher education," *The International Journal of Management Education*, vol. 14, no. 2, pp. 146–160, 2016. doi: 10.1016/j.ijme.2016.04.001
[69] D. H. Schunk, "Self-efficacy and academic motivation," *Educational psychologist*, vol. 26, no. 3–4, pp. 207–231, 1991. doi: 10.1207/s15326985ep2603&4_2%0A
[70] J. Hair, C. L. Hollingsworth, A. B. Randolph, and A. Y. L. Chong, "An updated and expanded assessment of PLS-SEM in information systems

research," *Industrial Management & Data Systems*, vol. 117, no. 3, pp. 442–458, 2017.
[71] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research*, vol. 18, no. 1, pp. 39–50, 1981. doi: 10.2307/3150979
[72] R. P. Bagozzi and J. R. Edwards, "A general approach for representing constructs in organizational research," *Organizational research methods*, vol. 1, no. 1, pp. 45–87, 1998.
[73] C. M. Fuller, M. J. Simmering, G. Atinc, Y. Atinc, and B. J. Babin, "Common methods variance detection in business research," *Journal of Business Research*, vol. 69, no. 8, pp. 3192–3198, 2016.
[74] A. A. Hayat and K. Shateri, "The role of academic self-efficacy in improving students' metacognitive learning strategies," *Journal of Advances in Medical Education & Professionalism*, vol. 7, no. 4, p. 205, 2019. doi: 10.30476/jamp.2019.81200
[75] A. A. Hayat, K. Shateri, M. Amini, and N. Shokrpour, "Relationships between academic self-efficacy, learning-related emotions, and metacognitive learning strategies with academic performance in medical students: a structural equation model," *BMC Medical Education*, vol. 20, pp. 1–11, 2020. doi: 10.1186/s12909-020-01995-9
[76] S.-L. Wang and P.-Y. Wu, "The role of feedback and self-efficacy on web-based learning: The social cognitive perspective," *Computers & Education*, vol. 51, no. 4, pp. 1589–1598, 2008.
[77] D. B. Shank and S. R. Cotten, "Does technology empower urban youth? The relationship of technology use to self-efficacy," *Computers & Education*, vol. 70, pp. 184–193, 2014. doi: 10.1016/j.compedu.2013.08.018
[78] C. Lai and M. Gu, "Self-regulated out-of-class language learning with technology," *Computer Assisted Language Learning*, vol. 24, no. 4, pp. 317–335, 2011. doi: 10.1080/09588221.2011.568417
[79] F. Mufit, Y. Hendriyani, M. D. Usmeldi, and M. R. Tanjung, "The effectiveness of smartphone-based interactive multimedia integrated cognitive conflict models to improve 21st-century skills," *International Journal of Information and Education Technology*, vol. 13, no. 11, 2023. doi: 10.18178/ijiet.2023.13.11.1991
[80] O. Lawanto, H. B. Santoso, W. Goodridge, and K. N. Lawanto, "Task value, self-regulated learning, and performance in a web-intensive undergraduate engineering course: How are they related," *Journal of Online Learning and Teaching*, vol. 10, no. 1, p. 97, 2014. doi: 10.9743/jeo.2014.3.2
[81] Á. Di Serio, M. B. Ibáñez, and C. D. Kloos, "Impact of an augmented reality system on students' motivation for a visual art course," *Computers & education*, vol. 68, pp. 586–596, 2013. doi: 10.1016/j.compedu.2012.03.002
[82] Waskito, "Integration of mobile augmented reality applications for engineering mechanics learning with interacting 3d objects in engineering education," *International Journal of Information and Education Technology*, vol. 14, no. 3, pp. 354–361, 2024. doi: 10.18178/ijiet.2024.14.3.2057
[83] D. T. P. Yanto *et al.*, "Innovative laboratory learning: A study evaluating the practicality of integrated e-worksheets with augmented reality in electrical machines course," *International Journal of Information and Education Technology*, vol. 14, no. 7, 2024. doi: 10.18178/ijiet.2024.14.7.2127
[84] S. Cai, X. Wang, and F. K. Chiang, "A case study of augmented reality simulation system application in a chemistry course," *Computers in Human Behavior*, vol. 37, pp. 31–40, 2014. doi: 10.1016/j.chb.2014.04.018.
[85] M. Asoodar, S. Vaezi, and B. Izanloo, "Framework to improve e-learner satisfaction and further strengthen e-learning implementation," *Computers in Human Behavior*, vol. 63, pp. 704–716, 2016. doi: 10.1016/j.chb.2016.05.060.
[86] G. Y.-M. Kao and C.-A. Ruan, "Designing and evaluating a high interactive augmented reality system for programming learning," *Computers in Human Behavior*, vol. 132, 107245, 2022. doi: 10.1016/j.chb.2022.107245
[87] N. J. Zamzami, F. R. Waskito, and A. Sukardi, "The effectiveness of the group investigation project oriented learning model in the internet programming course," *Journal of Positive School Psychology*, vol. 6, no. 8, pp. 6272–6277, 2022.
[88] W. H. DeLone and E. R. McLean, "The DeLone and McLean model of information systems success: A ten-year update," *Journal of Management Information Systems*, vol. 19, no. 4, pp. 9–30, 2003. doi: 10.1080/07421222.2003.11045748