



## **Students' 21st-Century Economic Competencies in the Digital Age: Exploring the Interplay between Artificial Intelligence, Augmented Reality, and Learning Engagement**

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**Abstract:** This study aims to analyze the effect of Artificial Intelligence (AI) and Augmented Reality (AR) on high school students' 21st century economic competencies with learning engagement as a mediating variable. Using a quantitative approach with an explanatory survey design, the study involved 358 public high school students in Bitung City selected through proportional stratified random sampling. Data were collected using a 5-point Likert scale questionnaire and analyzed by Structural Equation Modeling based on Partial Least Squares (SEM-PLS) through SmartPLS 4. Results showed that AI ( $\beta = 0.364$ ,  $p < 0.001$ ) and AR ( $\beta = 0.498$ ,  $p < 0.001$ ) significantly influenced learning engagement, which in turn influenced 21st century economic competence ( $\beta = 0.654$ ,  $p < 0.001$ ). Learning engagement partially mediated the AI-competence ( $\beta = 0.238$ ) and AR-competence ( $\beta = 0.326$ ) relationships. The model explained 51.5% of learning engagement variance and 42.8% of 21st century economic competence variance. The findings resulted in a dual-technology competency development framework that integrates dual technology capabilities through direct and mediated pathways. Research implications emphasize the importance of differentiated learning technology implementation and teacher training that is responsive to the needs of AI-AR integration. The synergistic integration of AI and AR is proven to be a transformative catalyst in shaping students' competencies in the digital era.

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## **Introduction**

The rapid development of digital technology has brought significant changes in the world of education (Shurygin et al. 2022). In the era of digital transformation and industrial revolution, education is required to not only transfer knowledge, but also foster 21st century competencies such as critical thinking, creativity, collaboration, communication, and strong character education (González-Pérez and Ramírez-Montoya 2022; Thornhill-Miller et al. 2023). The utilisation of cutting-edge technologies such as Artificial Intelligence (AI) and Augmented Reality (AR) is becoming highly relevant to support more interactive, personalized, and meaningful learning (Tikader 2023). In addition to general 21st-century competencies, students in the social sciences track are also required to develop 21st-century economic competencies such as financial literacy, economic reasoning, entrepreneurial thinking, and the ability to apply economic concepts in real-life problem-solving.

The Merdeka Curriculum, implemented in Indonesia since 2022, emphasises the importance of learner-centred learning, differentiation of learning, and strengthening

character values and 21<sup>st</sup>-century literacy (Amiruddin et al. 2023). To achieve these goals, the integration of digital technology is one of the main strategies. AI plays a role in providing an adaptive learning system that is able to adjust materials according to students' abilities and needs (Kabudi, Pappas, and Olsen 2021; Strielkowski et al. 2025), while AR enables the visualisation of abstract concepts in a concrete manner through immersive and contextual learning experiences (Crogman et al. 2025). Both are believed to increase student engagement in the learning process (Almusaed et al. 2023; Zouhri and EL MALLAHI 2024).

The integration of AI and AR in education is no longer limited to concepts, but has become a widespread practice in various countries (Fisher and Baird 2020; Wang and Huang 2025). AI enables personalised learning through adaptive systems that tailor materials to students' learning styles and ability levels (Kaswan, Dhatteval, and Ojha 2024), while AR provides immersive, contextual, and interactive learning experiences (Akçayır and Akçayır 2017). In the midst of global challenges such as technological disruption and VUCA (volatility, uncertainty, complexity, ambiguity), high schools are required to prepare students with 21<sup>st</sup>-century competencies. In the context of economics education, AI can provide adaptive simulations for market analysis or personalized financial problem-solving, while AR enables immersive visualization of economic concepts such as supply-demand dynamics, inflation effects, or trade systems in interactive ways. These technological affordances are highly relevant in strengthening students' engagement and economic competencies.

21<sup>st</sup>-century competencies include critical thinking skills, creativity, collaboration, communication, digital literacy, and complex problem-solving abilities (Kennedy and Sundberg 2020; Thornhill-Miller et al. 2023). OECD studies show that countries that successfully adopt technologies such as artificial intelligence (AI), adaptive learning, and interactive digital platforms in the education ecosystem tend to be better able to produce graduates with 21st century competencies such as critical, collaborative, and creative thinking (OECD 2021). This integration is not just about the use of hardware, but rather how technology supports effective pedagogical strategies (OECD 2016). In addition, teachers' ability to utilise technology meaningfully is a determining factor in the success of digital learning, leading to increased graduate readiness in the global labor market (OECD 2023). In Indonesia, digital transformation efforts at the high school level still face obstacles in terms of technology utilisation oriented towards the development of these essential skills.

Despite various initiatives, the implementation of AI and AR technology integration in learning at the high school level is still limited and uneven. This emphasises the importance of empirical studies on how the integration of these technologies can contribute to strengthening 21st century essential competencies through increasing learning engagement as a crucial psych pedagogic variable. This fact confirms the urgency of researching how AI and AR can improve student competencies, especially through learning engagement which is an important internal driver in the educational process.

Various studies have proven the effectiveness of artificial intelligence (AI)-based adaptive learning systems on improving students' cognitive learning outcomes (Wang et al. 2024). A meta- analysis of 45 studies shows that AI-adaptive learning systems have a considerable positive effect ( $g = 0.70$ ), although this effect is affected by several moderating factors such as education level, learning duration, and research design. Meanwhile, other studies emphasise the importance of institutional support and technological self-efficacy in shaping students' perceptions of AI-based learning, with results showing that students' positive perceptions are directly and indirectly influenced by perceived learning outcomes and self-efficacy (Jeilani and Abubakar 2025). Similarly, (Mansour et al. 2024) noted that the



integration of AR in science learning improved students' conceptual understanding significantly.

However, these studies have generally not combined the simultaneous influence of AI and AR in one framework, nor have they deeply explored the mediating role of learning engagement. Learning engagement is an important psych pedagogic factor that bridges the relationship between external stimulus (e.g. learning technology) and long-term learning outcomes, including 21st century competencies (Zhou et al. 2023). Although numerous studies have examined AI or AR in improving learning outcomes, limited attention has been paid to how these technologies simultaneously contribute to students' economic competencies, especially among social science students who explicitly study economics. Addressing this gap is crucial because strengthening 21st-century economic competencies is essential for preparing graduates to face digital-based economic systems, financial decision-making, and global competitiveness.

This research is significant because it addresses the gap in the literature and provides theoretical and practical contributions to the development of AI and AR-based learning strategies at the secondary education level. It is hoped that the results of this research can enrich studies in the field of digital pedagogy and provide references for educators, policy makers, and learning system developers to design learning processes that are adaptive, transformative, and in accordance with the challenges of the 21st century. This study aims to analyse the direct and indirect effects of AI and AR technology integration on high school students' 21st century economic competencies, with learning engagement as the mediating variable. This objective is aligned with efforts to develop innovative learning models that secondary education institutions in Indonesia can widely apply.

## **Research Method**

This study uses a quantitative approach with an explanatory survey design. This design was chosen because it is considered the most appropriate for explaining causal relationships between variables in complex structural models, especially when they involve mediating mechanisms that cannot be explained only through descriptive approaches. The population in this study consisted of all public high school students majoring in Social Sciences (IPS) in Bitung City, North Sulawesi Province, Indonesia. The IPS track was purposively selected because students in this stream explicitly study economics-related subjects, making them highly relevant for measuring 21st-century economic competencies. This city was purposefully chosen selected because it is considered representative, both in terms of demographic diversity, digital infrastructure readiness, and the implementation of technology-based learning that has taken place. The sample in this study was taken using a proportional stratified random sampling technique, where each public high school was treated as a stratum. The number of samples obtained was 358 students, calculated using the Slovin formula with an error rate of 5%. The determination of this sample size also takes into account the principle of minimum sample size in SEM-PLS, as recommended by (Joseph F Hair et al. 2019), which is at least 10 times the number of indicators on the most complex constructs, so that the reliability of the model can be maintained.

Data collection was conducted through a closed questionnaire structured in the form of a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). This instrument was developed based on theoretical indicators that have been empirically validated from various previous studies. Prior to the distribution of the main questionnaire, a pretest was conducted to assess item validity through Corrected Item-Total Correlation analysis and internal reliability using Cronbach's Alpha value. The test results showed that all constructs had alpha

values above 0.70, indicating an adequate level of reliability. The collected data were analyzed using the Structural Equation Modeling method based on Partial Least Squares (SEM-PLS) with the help of SmartPLS software (Ringle, Wende, and Becker 2015). This approach was chosen because it is able to handle complex relationship models with latent variables, and can be used for data with non-normal distributions (Sarstedt, Ringle, and Hair 2021). The stages of analysis include testing the measurement model (outer model) to evaluate construct validity and reliability, and the structural model (inner model) to test the strength and significance of the relationship between variables (Joseph F. Hair et al. 2019).

AI Integration is measured through indicators: content adaptivity, feedback system intelligence, and learning personalization (Adamu and Awwalu 2019; Kochmar et al. 2020). AR Integration is measured through indicators: content realism, visual interactivity, and immersive learning experience (Akçayır and Akçayır 2017; Ibrahim et al. 2018). Learning engagement is measured based on behavioral, affective, and cognitive aspects (Alrashidi, Phan, and Ngu 2016; Fredricks, Blumenfeld, and Paris 2004). Meanwhile, 21st-century economic competencies were operationalized through indicators such as economic literacy, financial literacy, critical thinking in economic decision-making, and creativity in utilizing digital technology for solving economic problems (Thornhill-Miller et al. 2023).

## Results and Discussion

### Results of Measurement Model and Structural Model Evaluation

The measurement model demonstrated strong reliability and validity. All constructs (AI, AR, LE, and COM) showed Cronbach's Alpha values between 0.884–0.916 and Composite Reliability (CR) between 0.912–0.932, exceeding the recommended threshold ( $>0.70$ ), indicating high internal consistency. Average Variance Extracted (AVE) values (0.631–0.685) confirmed convergent validity, as each construct explained more than half of its indicator variance. Discriminant validity was established through HTMT ( $<0.85$ ), Fornell-Larcker ( $\sqrt{\text{AVE}}$  greater than inter-construct correlations), and cross-loading tests, all showing satisfactory results. Indicator loadings ranged from 0.748–0.856 (above 0.70) and VIF values were below 3.0, confirming strong indicator quality and no multicollinearity. Model fit indices also indicated good adequacy, with SRMR = 0.050 ( $<0.08$ ) and NFI = 0.841 ( $>0.80$ ). The structural model revealed substantial explanatory power.  $R^2$  values showed that AI and AR explained 51.5% of learning engagement (moderate–substantial) and together with LE explained 42.8% of 21st century economic competencies (medium). Effect size ( $f^2$ ) analysis highlighted  $\text{AR} \rightarrow \text{LE}$  (0.440, large) as the strongest technological predictor of engagement, while  $\text{LE} \rightarrow \text{COM}$  (0.748, large) was the most influential overall, confirming LE's central mediating role.

### Hypothesis Testing

#### Direct Effect

Direct path analysis in the structural model was conducted to test the strength and direction of causal relationships between constructs. The results of hypothesis testing are presented in the following Table:

**Table 8. Direct Path Analysis Results**

Hypothesis	Path	$\beta$	t-value	p-value	Decision	Effect Size
H1	AI $\rightarrow$ LE	0.364	6.796	0.000	Supported	Medium
H2	AR $\rightarrow$ LE	0.498	11.299	0.000	Supported	Large
H3	LE $\rightarrow$ COM	0.654	22.370	0.000	Supported	Large
H4	AI $\rightarrow$ COM	0.238	6.444	0.000	Supported	Small
H5	AR $\rightarrow$ COM	0.326	9.218	0.000	Supported	Small to Medium



The results of hypothesis testing show that all direct have strong empirical support. All paths have p values <0.001, indicating that the observed effects are highly unlikely to be due to chance and have a solid empirical basis. Hypothesis 1 (AI → LE): The path coefficient of 0.364 with a t-value of 6.796 indicates a significant positive effect of Artificial Intelligence (AI) on Learning Engagement (LE). This finding reinforces the theoretical assumption that the implementation of AI technology in learning substantially increases students' engagement in the learning process. Hypothesis 2 (AR → LE): The path from augmented reality to learning engagement shows a coefficient of 0.498 and a t-value of 11.299, which is the strongest effect among the relationships between technology and learning engagement. This confirms that AR technology has a greater impact on increasing students' learning participation and motivation compared to AI. Hypothesis 3 (LE → COM): The path coefficient of 0.654 with a t-value of 22.370 indicates that learning engagement has a very strong influence on 21<sup>st</sup>-century economic competencies. This finding demonstrates the central role of learning engagement in developing the competencies required in the digital age. Hypotheses 4 & 5 (AI/AR → COM): Both direct pathways from technology to competence show significant but relatively smaller effects, indicating that the influence of technology on 21<sup>st</sup>-century economic competence is largely mediated by learning engagement.

#### Indirect Effects and Mediation Analysis

Mediation path analysis was conducted to evaluate the role of Learning Engagement (LE) construct as an intermediate variable in the relationship between learning technology and 21<sup>st</sup>-Century Competencies (COM).

**Table 9. Mediation Analysis Results**

Mediation Path	Indirect Effect (β)	t-value	p-value	95% CI	Mediation Type
AI → LE → COM	0.238	6.444	0.000	[0.165, 0.311]	Partial Mediation
AR → LE → COM	0.326	9.218	0.000	[0.256, 0.396]	Partial Mediation

The analysis results show that learning engagement (LE) mediates the relationship between learning technology and 21<sup>st</sup>-century economic competencies with significant indirect effects for both paths ( $p < 0.001$ ). Mediation is partial as the direct effects of AI → COM and AR → COM remain significant, although the indirect effects through LE are also significant. Theoretically, these findings reveal complex mechanisms of influence within the structural model. Learning technologies influence 21<sup>st</sup>-century economic competencies through two main pathways, the direct pathway and the indirect pathway through learning engagement. The mediating effect of AR ( $\beta = 0.326$ ) was stronger than that of AI ( $\beta = 0.238$ ), consistent with previous findings that AR has a greater impact in learning contexts. This partial mediation finding strengthens the understanding that learning engagement acts as an important cognitive-affective mechanism that bridge the influence of technology on competency development. From a practical perspective, this implies that learning technology implementation needs to be strategically designed to maximize student learning engagement to optimize 21<sup>st</sup>-century economic competency development.

#### Predictive Relevance Evaluation

**Table 10. Predictive Relevance Evaluation**

Construct	Q <sup>2</sup> value	Predictive Relevance
LE	0.322	Medium
COM	0.265	Small to Medium



Evaluation of the predictive relevance of the model is carried out using Stone-Geisser's  $Q^2$  value, which aims to assess the extent to which the model is able to accurately predict observational data with the criteria that  $Q^2$  values above 0 indicate small predictive relevance, values above 0.25 indicate moderate relevance, and values above 0.50 indicate great relevance (Joseph F. Hair et al. 2019). A positive  $Q^2$  value indicates that the model has adequate predictive ability of the endogenous constructs. The Learning Engagement (LE) construct obtained a  $Q^2$  value of 0.322, which is categorised as moderate predictive relevance. This finding indicates that the model has a good ability to predict student learning engagement based on the implementation of AI and AR technologies. Meanwhile, the 21st Century Competencies (COM) construct shows a  $Q^2$  value of 0.265, which falls into the category of small to medium predictive relevance. This provides evidence that the model has sufficient predictive ability in projecting 21<sup>st</sup>-century competencies based on the predictor constructs used. Thus, the positivity of  $Q^2$  values on both endogenous constructs indicates that the model is not only statistically adequate (through evaluation of fit and path significance), but also has substantively real predictive capabilities. A comparison between constructs reveals that the model's ability to predict the mediator variable (LE) is superior to that in predicting the outcome variable (COM), which is consistent with the complexity of factors influencing the development of 21<sup>st</sup>-century competencies.

### **Technology Convergence Paradigm in 21st Century Economic Competency Transformation**

In the context of the industrial revolution 5.0, which is characterized by the convergence of digital technologies, the demands of developing 21<sup>st</sup>-century economic competencies can no longer be viewed as a linear phenomenon that only refers to the mastery of technical skills. In line with the view of (Schwab 2024), which emphasizes that the industrial revolution 4.0 creates a fundamental transformation in the way humans live, work and learn, the integration of Artificial Intelligence (AI) and Augmented Reality (AR) in learning creates a new paradigm called the immersive-intelligent learning ecosystem.

The learning process is no longer limited to conventional teacher-student-material interactions, but rather evolves into a complex and adaptive human-AI-environment symbiosis (Luckin et al. 2016). This paradigm supports the concept proposed by (Goldie 2016) about learning ecosystems, which emphasizes that modern learning requires the integration of technology that is able to create adaptive learning experiences that are responsive to individual needs.

This research is rooted in the theoretical framework of technology-enhanced learning theory developed by (Dede and Richards 2012), which emphasizes that effective learning technology should be able to create cognitive amplification and metacognitive scaffolding simultaneously. In this case, AI functions as an intelligent tutoring agent capable of providing personalized learning based on data and individual learning patterns. At the same time, AR acts as a contextual reality bridge that transforms conceptual abstractions into meaningful visual-spatial experiences. This framework is reinforced by the technology acceptance model (TAM) developed by (Davis 1989). It has been updated by (Venkatesh, Thong, and Xu 2016) for the context of digital learning, which shows that perceived usefulness and ease of use of technology are the main predictors of technology adoption in learning.

However, this study does not simply adopt the existing theoretical framework, but rather extends it through integration with self-determination theory (SDT) developed by (Deci and Ryan 2000). SDT provides a psychological lens to understand how technology can facilitate intrinsic motivation and autonomous learning engagement, which are fundamental prerequisites for the development of sustainable 21<sup>st</sup>-century economic competencies (Ryan



and Deci 2020). The convergence of these two theories enables research to map how AI-AR integration affects not only the cognitive dimensions of learning, but also the affective and motivational dimensions that determine the quality of learning engagement.

### **Epistemic Revolution in Digital Learning Engagement Constructs**

This study highlights a paradigm shift from the classical concept of learning engagement, which focuses on behavioral, emotional, and cognitive dimensions, to the more complex construct of immersive-intelligent engagement. In this new construct, learning engagement depends not only on students' intrinsic factors or instructional quality but also on the technological affordances provided by AI and AR, which operate separately yet reinforce each other. The concept of technological affordances (Gibson 1979; Norman 2013) offers a theoretical basis for understanding how AI and AR create opportunities and constraints that shape learning actions. Previous research (Bower 2019) categorizes these affordances into cognitive, social, and pedagogical dimensions, each contributing uniquely to engagement.

In this research, AI is defined as a learning technology system that employs adaptive algorithms to deliver personalized content, provide feedback, and create individualized learning paths (Holmes, Bialik, and Fadel 2019). AI enhances engagement through three main mechanisms: personalized learning pathways that adapt to students' abilities, intelligent feedback systems that strengthen self-efficacy, and predictive analytics that identify learning gaps for targeted interventions (Luckin et al. 2016).

AR, meanwhile, is defined as a technology combining virtual elements with real environments to produce immersive and interactive learning experiences (Bacca et al. 2014; Milgram and Kishino 1994). AR strengthens engagement via immersive visualization, interactive manipulation of virtual objects, and contextual learning experiences that link theory to real-world applications (Dunleavy, Dede, and Mitchell 2009).

Empirical findings show that AI and AR complement each other, significantly enhancing students' multidimensional engagement. This supports Gardner's, multiple intelligence theory, suggesting that effective learning accommodates diverse learning styles and intelligences through a multimodal approach (Gardner 2011). Together, AI and AR create a dynamic, responsive, and student-centered ecosystem that enriches behavioral, cognitive, and affective engagement while fostering deeper understanding and mastery of learning content.

### **Theoretical Relevance and Conceptual Novelty**

This study extends Self-Determination Theory (Deci and Ryan 2000) by showing that technology-mediated learning engagement not only increases task involvement but also facilitates the development of 21st-century economic competencies. AI enhances autonomy through personalized learning, enabling students to make informed economic decisions, while AR strengthens competence and relatedness through immersive, collaborative simulations of real-world economic scenarios.

The dual-pathway technology integration model (DPTIM) conceptualizes AI and AR as dual facilitators of competency: directly via technological affordances and indirectly via motivational mediation. Learning engagement functions as a psychological bridge, amplifying and sustaining the impact of technology on economic competency mastery. Without this engagement, even advanced technologies may fail to activate the deep learning required for effective economic reasoning and decision-making.

In the AI-AR context, learning engagement encompasses behavioral, emotional, and cognitive dimensions, forming a stable and observable manifestation of students' interaction with economic learning technologies (Alrashidi et al. 2016; Fredricks et al. 2004). In contrast, 21st-century economic competencies including critical thinking, problem solving,



collaboration, digital literacy, and entrepreneurial creativity, require cumulative development through the transfer of technology-mediated learning into practical economic applications (Thornhill-Miller et al. 2023). These findings highlight that engagement responds immediately to technology, while economic competency develops gradually through repeated, contextualized experiences. AI-AR systems should therefore capture real-time engagement indicators for adaptive support and monitor long-term competency trajectories for strategic intervention, ensuring students acquire actionable economic skills in the digital era.

### **New Conceptual Framework**

This research proposes an innovative conceptual framework called the dual-technology competency development framework (DTCDF), which is designed to integrate the technological capabilities of artificial intelligence (AI) and augmented reality (AR), mediate the psychological process of learning engagement, and lead to competency development outcomes in a unified systematic architecture. The DTCDF represents a layered theoretical structure in line with the multi-layered technology integration framework by (Hughes, Thomas, and Scharber 2006), which emphasizes technology integration on pedagogical, content, and socio-cognitive aspects in digital learning, as follows: (1) AI technology base, this substructure serves as the algorithmic foundation that includes adaptive learning algorithms, predictive analytics, personalized content delivery, and intelligent assessment systems. This layer provides cognitive scaffolding that enables individualized learning pathways and data-driven optimization. (2) AR technology base, this substructure acts as an immersive foundation that includes 3D visualization, spatial interaction, contextual overlays, and embodied learning experiences. This layer provides experiential scaffolding that supports situated learning and multimodal engagement. (3) Engagement amplification layer, this layer describes the psychological process by which intrinsic motivation, curiosity and self-efficacy are shaped through dual technology interactions. This layer formulates engagement mechanisms that transform technology exposure into meaningful learning experiences through different pathways: AI through personalization satisfaction and AR through immersion fascination. (4) Competency synthesis zone, this zone is a convergence space where multiple technological capabilities and engagement processes combine to produce 21<sup>st</sup>-century economic competencies. This zone becomes a conceptual arena for skill development, knowledge construction, and competency mastery through the synergistic interaction of both technology and learning motivation.

To strengthen the conceptual foundation of DTCDF, a theoretical framework is needed that is able to explain in more depth the psychological and pedagogical dynamics that occur in the process of dual technology integration. Dual-technology mediated learning theory (DTML) takes the role as a theoretical extension of the DTCDF structure. Suppose DTCDF describes the systematic architecture and function of each technology layer in learning. In that case, DTML articulates how the interaction between the layers results in meaningful learning engagement and leads to the mastery of 21st century economic competencies. As such, DTCDF and DTML are not two separate entities, but a coherent whole: DTCDF provides the design framework and structure of technology integration, while DTML provides the theoretical lens to understand the layered transformation of technology-mediated engagement and competence. The integration of the two creates a strong conceptual foundation for the development of adaptive, contextualized and transformative multi-technology-based learning strategies.

As the main theoretical contribution, this study formulates the dual-technology mediated learning theory, a theoretical framework that extends the understanding of learning



engagement in the context of multi-technology integration. The theory aims to explain how learning engagement is formed and mediated through the interaction between artificial intelligence (AI) and augmented reality (AR). The dual-technology mediated learning theory conceptual framework builds on the synthesis of several established learning theories, including Social Cognitive Theory (Bandura 2001), Constructivist Learning Theory (Piaget 1977), and Technology Acceptance Model (Davis 1989). In its formulation, DTML identifies four fundamental transformation processes that reflect the dynamic relationship between technology, engagement, and 21st century economic competency development.

- 1) From single-technology to multi-technology engagement, engagement is no longer understood as a response to a single technology, but rather as a composite response to a technology ecosystem consisting of AI and AR, which contribute differently but produce synergistic effects.
- 2) From uniform to differentiated technology impact AI and AR have different patterns of impact on engagement: AI contributes through cognitive personalization, while AR through experiential immersion. These demands differentiated learning design strategies.
- 3) From direct to mediated competency development, 21<sup>st</sup>-century economic competency development does not only occur through direct transfer from technology to competency, but also through a mediated process: from technology-to-engagement-to-competency, indicating multilayered development mechanisms.
- 4) From static to dynamic engagement-competency relationship, the relationship between engagement and competency is dynamic and context-dependent, influenced by technology affordances, individual characteristics, and learning contexts that change over time.

## Conclusion

This research has successfully developed and validated the Dual-Technology Competency Development Framework (DTCDF) and Dual-Technology Mediated Learning Theory (DTML) as significant theoretical contributions in understanding the integration of AI and AR in 21st century learning. The empirical findings show that both technologies have a significant influence on learning engagement and 21st-century economic competencies through different but complementary mechanisms. The dominance of AR in influencing engagement ( $\beta = 0.498$ ) over AI ( $\beta = 0.364$ ) indicates that experiential affordances have a stronger impact on learning motivation than algorithmic personalization. The dual-pathway mediation phenomenon suggests that competency development occurs simultaneously through a direct pathway (technology-to-competency) and a mediated pathway (technology-to-engagement-to-competency). The main theoretical contribution lies in the formulation of the "motivational bridge" concept that explains how learning engagement acts as a psychological amplifier that intensifies the impact of technology on competency development. Asymmetric predictive relevance ( $Q^2$  engagement = 0.322 vs  $Q^2$  competencies = 0.265) confirmed that engagement is a more predictable proximal outcome than distal competency outcomes. Practical implications demand the development of differentiated implementation strategies, specialized teacher training programs, and technology-specific assessment systems that can accommodate the uniqueness of AI and AR in supporting 21<sup>st</sup>-century learning. The paradigm transformation from single-technology to multi-technology engagement requires a fundamental reorientation in learning design, teacher professional development, and technology education policy.



## Recommendation

Future research is recommended to conduct longitudinal studies to examine the stability of the DTCDF and DTML models, explore the moderating effects of individual and contextual factors, develop adaptive algorithms for real-time AI–AR integration, and design authentic assessment tools for measuring 21st-century economic competencies. From a practical standpoint, teachers should be encouraged to utilize AI technologies for providing personalized feedback and employ AR applications to create immersive learning experiences that foster engagement, critical thinking, and collaboration, supported by continuous professional development, adequate infrastructure, and enabling school policies.

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