

AI 및 디지털 학습 참여와 디지털 역량: 자기주도적 노력의 역할

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AI and Digital Learning Engagement in Higher Education: The Role of Self-Directed Effort in Digital Competence

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[요 약]

생성형 인공지능(AI)을 포함한 디지털 기술의 급속한 확산은 고등교육에서 요구되는 역량을 변화시키고 있다. 이에 따라 대학생은 단순한 정보 활용을 넘어 디지털 기반 지식의 생성과 적용 능력을 요구받고 있다. 본 연구는 AI 및 디지털 학습 참여가 학생들의 디지털 역량에 미치는 영향을 분석하고, 그 하위 요인의 차별적 효과를 검증하고자 하였다. 서울 소재 한 대학의 교양 교과목에 참여한 학부생을 대상으로 설문조사를 실시하였으며, 수집된 자료는 기술통계, 신뢰도 분석, 상관분석, 회귀분석을 통해 분석하였다. 분석 결과, AI 및 디지털 학습 참여는 디지털 역량에 유의한 정적 영향을 미치는 것으로 나타났다($B = .449, p < .001$). 하위 요인 중에서는 자기주도적 노력이 유의한 영향을 보인 반면($B = .304, p < .001$), 교육 참여 및 제도적 활동 참여는 유의하지 않았다. 이러한 결과는 디지털 역량의 발달이 단순한 기술 접근이나 형식적 참여보다는 학습자의 지속적이고 자기주도적인 참여와 보다 밀접하게 관련됨을 시사한다.

[Abstract]

The rapid expansion of digital technologies, including generative artificial intelligence (AI), is transforming the competencies required in higher education. Accordingly, university students are expected to move beyond information use toward generating and applying knowledge through digital means. In this context, the present study examined the effect of AI and digital learning engagement on students' digital competence, and the differential effects of its subcomponents. A survey was conducted with undergraduate students enrolled in general education courses at a university in Seoul. The data were analyzed using descriptive statistics, reliability, correlation, and regression analyses. The results showed that AI and digital learning engagement had a significant positive effect on digital competence ($B = .449, p < .001$). Among its subcomponents, self-directed effort was significant ($B = .304, p < .001$), whereas participation in training and institutional activities was not. These findings suggest that digital competence is driven less by access or formal participation and more by sustained, self-directed engagement.

색인어 : 인공지능, 디지털 역량, 자기주도적 학습, 고등교육, 디지털 학습 참여

Keyword : Artificial Intelligence, Digital Competence, Self-Directed Learning, Higher Education, Digital Learning Engagement

<http://dx.doi.org/10.9728/dcs.2026.27.5.1311>



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Received 30 March 2026; Revised 17 April 2026

Accepted 08 May 2026

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I. Introduction

The rapid advancement of digital technologies, including generative artificial intelligence (AI), is fundamentally transforming the competencies required in higher education. In the past, the ability to access information and use basic digital tools was considered a key learning competency. Today, however, greater emphasis is placed on higher-order competencies, such as critically searching for information, analyzing and reorganizing it, and ultimately generating new content within digital environments. This shift has led to the growing integration of AI and digital technologies as essential components of university teaching and learning.

Amid this trend, various educational efforts have been made to enhance university students' digital competence (hereafter, DC). However, prior research has largely focused on quantitative indicators, such as the presence or frequency of technology use. Such approaches offer limited insight into whether access to or experience with digital technologies actually translates into meaningful competence. Even within similar technological environments, learning outcomes may differ depending on how learners engage with digital tools and how they experience the learning process. This suggests the need to understand DC development from a more process-oriented perspective.

With the emergence of generative AI, learners are no longer merely consumers of information but also active producers of knowledge. Accordingly, the importance of DC has become more pronounced. In this context, understanding learning outcomes in AI-supported environments requires attention not only to the availability of technology but also to how learners utilize it and the ways in which they engage in the learning process.

In the Korean higher education context, where AI integration and digital education policies have been actively promoted at both institutional and national levels, understanding how learners engage with digital technologies has become increasingly important[1], as highlighted in OECD reports emphasizing the expansion of national digital education strategies and infrastructure[2]. In this regard, AI and digital learning engagement (hereafter, ADLE) can be understood as a multidimensional construct through which learners

develop their DC via participation in training, involvement in institutional activities, and self-directed effort. However, there remains a lack of empirical evidence regarding how ADLE relates to actual DC, and whether its effects differ across types of engagement[1],[3],[4]. In particular, limited attention has been paid to the qualitative aspects of engagement and their role in shaping competence development.

Therefore, this study aims to examine the effect of ADLE on university students' DC in the Korean higher education context, as well as to identify the differential effects of its subcomponents. By focusing on variations in types of engagement rather than merely the level of participation, this study seeks to provide a more nuanced understanding of the process of DC development. The findings are expected to offer practical implications for the design of AI-supported teaching and learning in higher education. This study addresses the following research questions:

RQ 1. What is the effect of ADLE on university students' DC?

RQ 2. How do the subcomponents of ADLE (participation in training, institutional activities, and self-directed effort) differentially affect DC?

II. Literature Review

2-1 Digital Competence (DC)

DC has emerged as a core component of education in response to ongoing socio-economic digital transformation and the expansion of digital learning environments[5]. It is generally understood as a comprehensive construct encompassing the skills, experiences, and attitudes required for the effective use of information and communication technologies (ICT)[3]. Beyond mere technical proficiency, DC refers to the ability to use digital technologies effectively and appropriately across various contexts, including their responsible application for educational purposes[4]. In educational settings, DC is particularly significant, as it shapes how learners process information and how effectively they utilize digital tools and technologies in learning contexts[6]. Learners with higher levels of DC tend to acquire digital tools more quickly, use them more efficiently,

and demonstrate more effective use of digital tools in learning contexts[7].

While traditional educational tools have primarily emphasized functional skills, such as operating devices, AI-based technologies require a more expanded form of digital literacy. The use of AI involves understanding data processing mechanisms, evaluating model reliability, and recognizing algorithm-driven decision-making processes. In this sense, DC in AI-supported environments extends beyond a functional perspective to encompass more complex competencies, including data interpretation and human-machine interaction. Accordingly, examining the relationship between AI use and DC represents an important research agenda.

Previous studies have reported that AI use in learning contexts is positively associated with improvements in DC. This is largely because AI tools provide personalized learning pathways tailored to learners' needs and offer immediate feedback, thereby enhancing both learning efficiency and digital capability[8],[9]. In AI-supported learning environments, learners move beyond passive use of digital tools and actively employ them in problem-solving processes, which can lead to deeper development of DC.

Furthermore, intelligent feedback provided by AI systems supports learners in identifying and correcting errors, thereby strengthening self-directed learning and problem-solving abilities[9]. These competencies are considered core components of DC and become increasingly important in AI-based learning contexts. In addition, interactive learning environments, such as virtual laboratories and online collaborative platforms, promote learner engagement and expand opportunities for meaningful interaction with digital technologies.

Taken together, AI-supported learning activities are closely related to students' DC. However, prior research has tended to focus primarily on the use of AI itself, with relatively limited attention given to how learners engage with these technologies, particularly in terms of participation patterns and self-directed learning processes.

2-2 AI and Digital Learning Engagement (ADLE)

Building on the preceding discussion, ADLE is conceptualized as a multidimensional construct that captures how learners actively participate in and

interact with AI-supported and digital learning environments. Unlike DC, which emphasizes learners' capabilities in digital environments, ADLE focuses on the process-oriented patterns through which learners engage in AI-supported learning activities. Rather than focusing solely on the presence or frequency of technology use, ADLE emphasizes learners' active involvement in digital learning opportunities and experiences.

In this study, ADLE is defined as the extent to which learners participate in AI- and digital-related learning experiences across formal, institutional, and self-directed contexts[9]-[11]. This construct reflects both the quantity and quality of engagement, recognizing that meaningful learning outcomes are shaped not only by access to technology but also by how learners actively participate in and interact with digital learning environments. In this conceptual distinction, DC refers to learners' capabilities in digital environments, whereas ADLE captures the process-oriented patterns of their engagement in AI-supported learning contexts.

Specifically, ADLE consists of three subcomponents[11],[12]. First, participation in AI and digital training refers to learners' involvement in structured educational experiences, such as formal courses, workshops, or training programs designed to develop AI and digital skills. These activities provide foundational knowledge and guided practice, enabling learners to acquire essential competencies in a structured manner.

Second, participation in institutional activities refers to engagement in campus-based or extracurricular activities related to AI and digital technologies, such as student projects, clubs, or competitions. These activities provide opportunities for collaborative and experiential learning, allowing learners to apply digital tools in authentic contexts.

Third, self-directed effort refers to learners' voluntary and autonomous engagement in activities aimed at improving their AI and digital capabilities. This includes independently exploring digital tools, practicing skills, seeking additional learning resources, and continuously refining their abilities outside formal educational settings. Among the three components, self-directed effort is particularly important, as it reflects learners' intrinsic motivation and sustained engagement in learning processes.

Taken together, these three dimensions capture the multifaceted nature of learner engagement in AI-supported environments. By incorporating both structured and self-directed forms of participation, ADLE provides a comprehensive framework for understanding how different types of engagement contribute to the development of DC.

2-3 Digital and AI-Supported Learning Environments and Self-Directed Learning

Contemporary society is experiencing fundamental changes in learning environments driven by the rapid advancement of digital technologies. In particular, the integration of artificial intelligence (AI) has reshaped not only what learners study but also how they learn and the roles they assume. In digital environments, especially those supported by AI, learners are no longer passive recipients of information but are expected to act as active agents who explore, analyze, and reconstruct information using various digital tools.

These changes highlight the increasing importance of self-directed learning (SDL). SDL refers to a process in which learners diagnose their own learning needs, set goals, identify resources, implement appropriate strategies, and evaluate their learning outcomes. It plays a crucial role in fostering learner autonomy and sustaining continuous learning. In rapidly evolving technological contexts, where individuals are required to acquire new knowledge and skills continuously, SDL is closely associated with lifelong learning competencies[12]-[14].

Previous studies have shown that learners with higher levels of SDL tend to achieve better academic outcomes in digital learning environments compared to those who rely on teacher-centered approaches[15],[16]. SDL has also been associated with the development of key competencies, such as problem-solving skills, critical thinking, and adaptability. However, its effectiveness may be constrained by factors such as poor self-management, difficulties in time management, and feelings of isolation.

The importance of SDL can also be explained through Self-Determination Theory (SDT; [17],[18]). According to SDT, autonomy, competence, and relatedness function as core psychological needs that foster intrinsic motivation, which in turn influences the quality and persistence of learning. Here, competence

refers to a perceived psychological need, which is conceptually distinct from domain-specific capabilities such as DC. In particular, autonomy-based learning promotes active engagement and leads to deeper learning outcomes. From this perspective, SDL can be understood not merely as a learning strategy but as a key mechanism underlying effective learning processes[19].

Learning in digital environments is closely linked to SDL, as it requires learners to identify their needs, plan their learning, select appropriate resources, and seek help when necessary[19],[20]. Higher levels of digital literacy and SDL have been associated with increased learning engagement, which ultimately contributes to improved academic performance[20]-[22].

AI-supported learning environments provide important conditions that facilitate SDL. AI technologies can analyze learners' knowledge levels and learning patterns to offer personalized learning pathways[23],[24], while real-time feedback enables learners to monitor and regulate their learning processes. In addition, adaptive learning systems adjust content difficulty based on learner performance, thereby promoting active participation, and learning analytics systems identify engagement patterns and learning difficulties to provide tailored support[25],[26].

Despite these affordances, empirical evidence regarding the effectiveness of AI-supported learning environments remains limited, and discussions on specific instructional design and implementation strategies are still insufficient[27],[28].

In discussing learner autonomy and engagement in such environments, it is also necessary to clarify related conceptual distinctions. SDL and self-regulated learning (SRL) are often used interchangeably, although they refer to different aspects of learning. SDL describes a general approach to learning characterized by learner autonomy, whereas SRL focuses on context-specific cognitive and metacognitive processes involved in task performance[29]. Within this broader conceptual framework, behavior-oriented aspects of engagement, such as effort, can be considered observable elements that reflect learners' active involvement in digital learning contexts.

Taken together, these findings suggest that in digital and AI-supported learning environments, learners'

patterns of engagement play a critical role in understanding both learning processes and outcomes.

III. Method

3-1 Participants

This study was conducted with undergraduate students enrolled at a university in Seoul. Participants were recruited using a convenience sampling method, primarily from general education courses, without restriction to whether the courses were AI- or digital-related or to a specific subject area. The sample consisted of students from diverse academic majors, forming a relatively heterogeneous group. This sampling approach allows the data to reflect, to some extent, a general population of university students rather than being limited to a specific disciplinary background.

The survey was administered at the end of the second semester of the 2025 academic year, allowing participants to reflect on their learning experiences over the course of the semester. Prior to participation, students were provided with information regarding the purpose and procedures of the study. Participation was entirely voluntary, and it was explicitly stated that participation or non-participation would have no impact on academic evaluation. Participants were also informed that they could withdraw from the study at any time without penalty. Only responses from students who provided informed consent were included in the analysis.

A total of 118 valid responses were used for the final analysis. The mean age of the participants was 20.66 years (SD = 1.68), with ages ranging from 19 to 26 years. The sample consisted of 71 male students (60.2%) and 47 female students (39.8%), with a slightly higher proportion of male participants.

3-2 Measures

This study employed a structured questionnaire to measure ADLE and DC among university students. The measurement items were developed based on relevant prior studies and were refined to align with the specific objectives of the present study.

1) AI and Digital Learning Engagement (ADLE)

ADLE was conceptualized as a set of learning engagement behaviors through which learners enhance their capabilities in digital environments. This construct goes beyond mere technology use and reflects learners' modes of participation and their active involvement in the learning process.

In this study, ADLE was operationalized with three subcomponents: (1) participation in AI and digital training, (2) participation in institutional activities, and (3) self-directed effort. Each item was designed to capture learners' actual engagement experiences and behavioral involvement. Rather than focusing on frequency, the items emphasized the extent of participation and engagement. The scale consisted of three items representing these dimensions. Example items include "I participate in AI and digital training programs" and "I engage in institutional AI-related activities." The questionnaire items were developed based on prior studies and were modified and refined to fit the objectives of the present study[11],[30],[31]. In addition, prior studies have conceptualized digital and core competencies as transferable constructs applicable across educational contexts, including higher education[32],[33]. The internal consistency of the scale was acceptable, with a Cronbach's α of .772. Because each subcomponent was represented by a single item, the reliability coefficient should be interpreted as reflecting the overall association among the three engagement dimensions.

2) Digital Competence (DC)

DC was defined as a comprehensive ability to search for, evaluate, reorganize, and generate information in digital environments. This conceptualization is aligned with recent frameworks such as DigComp 3.0, which emphasize the integrated and context-dependent nature of digital competence in contemporary education[31]. This construct extends beyond functional digital skills to encompass higher-order competencies related to information processing and knowledge production.

The scale consisted of 12 items covering multiple domains, including information searching and collection, information evaluation and management, data analysis and representation, and digital content

creation. This structure reflects a multidimensional approach to DC, as suggested in prior research. The scale includes items such as “I can effectively search for information using digital tools” and “I can critically evaluate the reliability of online information,” adapted from prior studies[30]–[34]. The reliability of the scale was high, with a Cronbach’s α of .953, indicating strong internal consistency.

3-3 Data Analysis

The collected data were analyzed using SPSS 28.0. First, descriptive statistics were calculated to examine the basic characteristics of the key variables. Cronbach’s α coefficients were computed to assess the internal consistency of the measurement scales.

Next, Pearson correlation analysis was conducted to examine the relationship between ADLE and DC, allowing for the assessment of the direction and strength of their linear association.

To investigate the effect of ADLE on DC, regression analyses were performed. First, a simple regression analysis was conducted using ADLE as a composite variable to predict DC. Subsequently, to examine the relative effects of the subcomponents of ADLE, a multiple regression analysis was conducted by entering the three subcomponents—participation in AI and digital training, participation in institutional activities, and self-directed effort—as independent variables. All statistical tests were evaluated at a significance level of .05.

IV. Results

4-1 Reliability and Descriptive Statistics

The reliability of the main variables was first examined. The Cronbach’s α for ADLE was .772, indicating an acceptable level of internal consistency, whereas the Cronbach’s α for DC was .953, indicating excellent reliability. These results suggest that both scales measured their respective constructs in a stable and consistent manner.

As shown in Table 1, the descriptive statistics revealed that the mean score for ADLE was 3.43 (SD = 0.76), while the mean score for DC was 3.66 (SD =

0.69). Both variables exceeded the midpoint on a five-point scale, indicating that participants were generally engaged in AI- and digital-related activities and reported relatively positive levels of DC. Notably, the mean of DC was slightly higher than that of ADLE, suggesting that participants tended to perceive their level of DC more favorably than their level of engagement in AI- and digital-related activities.

Table 1. Descriptive statistics

Variable	M	SD
ADLE	3.43	0.76
DC	3.66	0.69

4-2 Correlation Analysis

Pearson correlation analysis was conducted to examine the relationship between ADLE and DC. The results indicated a significant positive correlation between the two variables ($r=.494, p<.001$).

As shown in Table 2, the correlation coefficient between ADLE and DC was .494, indicating a moderate positive relationship. This suggests that higher levels of engagement in AI- and digital-related learning activities are associated with higher levels of DC. At the same time, the magnitude of the correlation indicates that ADLE and DC are related but distinct constructs rather than overlapping measures of the same concept. This supports the conceptual distinction between engagement and competence, while also suggesting that ADLE may serve as a meaningful predictor of DC. Accordingly, the significant correlation between the two variables provides a basis for further examining the effect of ADLE on DC through regression analysis.

Table 2. Correlation matrix

Variable	1	2
1. ADLE	1	.494***
2. DC	.494***	1

Note. *** $p<.001$.

4-3 Regression Analysis

1) Baseline Model

A simple regression analysis was conducted to examine the effect of ADLE on DC. The results

indicated that ADLE had a significant positive effect on DC ($B=0.449$, $t=6.11$, $p<.001$). This suggests that higher levels of engagement in AI- and digital-related learning activities are associated with higher levels of DC. Specifically, a one-unit increase in ADLE was associated with an increase of approximately 0.449 units in DC, indicating a meaningful positive relationship between the two variables.

The explanatory power of the model was $R^2=.244$ (adjusted $R^2=.239$), indicating that ADLE accounted for approximately 24.4% of the variance in DC. Considering that the model included only a single predictor, this can be interpreted as a relatively substantial level of explanatory power.

Furthermore, the overall model fit was statistically significant ($F=37.37$, $p<.001$), confirming that the regression model adequately explains variation in DC.

Taken together, these results demonstrate that ADLE is a significant predictor of DC, suggesting that active engagement in AI- and digital-related learning activities plays an important role in the development of digital competence.

Table 3. Simple regression results for digital competence

Variable	B	SE	β	t
Constant	2.121	0.258	-	8.208***
ADLE	0.449	0.074	.494	6.113

Model fit: $R^2=.244$, Adj. $R^2=.239$, $F=37.37$, $p<.001$
Note. *** $p<.001$.

2) Extended Model

To examine the differential effects of the subcomponents of ADLE on DC, a multiple regression analysis was conducted by entering the three subcomponents—participation in AI and digital training, participation in institutional activities, and self-directed effort—as independent variables (see Table 4). The overall model was statistically significant ($F=14.81$, $p<.001$), with an explanatory power of $R^2=.280$ (adjusted $R^2=.261$), which represents an increase compared to the baseline model ($R^2=.244$). This suggests that disaggregating ADLE into its subcomponents allows for a more fine-grained understanding of their respective contributions to DC. However, given that not all predictors were statistically significant, part of the increase in explained variance may be attributable to the inclusion of additional variables.

Examining the individual effects, only self-directed effort showed a significant positive effect on DC ($B=0.304$, $\beta=.387$, $t=3.99$, $p<.001$). In contrast, participation in AI and digital training ($\beta=.167$) and participation in institutional activities ($\beta=.052$) were not statistically significant predictors. These findings indicate that the effects of ADLE on DC are not uniform across different types of engagement. In particular, the significant role of self-directed effort suggests that learners' active and sustained engagement plays a more critical role in the development of DC than formal or institutionally structured participation alone. Multicollinearity diagnostics indicated that VIF values ranged from 1.24 to 2.88, all within acceptable limits, suggesting no serious multicollinearity issues.

Table 4. Multiple regression results for digital competence

Variable	B	SE	β	t
Constant	1.985	0.262	-	7.570***
AI and digital training	0.135	0.088	.167	1.536
Institutional activities	0.036	0.069	.052	0.513
Self-directed effort	0.304	0.076	.387	3.986***

Model fit: $R^2=.280$, Adj. $R^2=.261$, $F=14.81$, $p<.001$
Note. *** $p<.001$.

V. Discussion

The present study examined the relationship between ADLE and DC among university students and further investigated the differential effects of its subcomponents to better understand the mechanisms underlying the development of digital competence. The main findings are discussed as follows.

First, ADLE was found to have a significant positive association with DC. The baseline model showed a relatively high explanatory power ($R^2=.244$), suggesting that ADLE is a meaningful predictor of DC. This result indicates that DC may be associated not merely with exposure to or use of digital technologies, but with learners' active engagement and accumulated learning experiences. This finding is consistent with prior research conceptualizing DC as an integrated construct involving both ICT use and information

processing abilities[3], as well as studies emphasizing the role of digital information use in shaping learning performance[5].

Importantly, the findings highlight that in AI-supported learning environments, engagement may function as a more critical explanatory factor than mere access to technology. While prior research has often focused on the availability or frequency of AI tool use, the present study provides empirical evidence that learners' active involvement plays a central role in the development of DC.

Second, when the subcomponents of ADLE were examined, only self-directed effort had a significant association with DC, whereas participation in training and institutional activities was not statistically significant. This finding suggests that not all forms of engagement contribute equally to competence development. In particular, learners' voluntary and sustained engagement appears to play a more direct role than externally provided or structured learning opportunities. Although the explanatory power increased in the extended model ($R^2=.280$), the non-significant results for some predictors indicate that the qualitative nature of engagement is more important than mere participation. This pattern may reflect the complex interplay among different forms of engagement in the development of digital competence.

These findings are consistent with previous studies showing that learners with higher levels of self-directed learning tend to achieve better outcomes in digital environments[14],[15],[19],[20], and that digital literacy and self-directed learning are closely associated with learning engagement and performance[20],[21]. However, the present study goes beyond this general association by showing that not all forms of engagement equally contribute to competence development, and demonstrates that self-directed engagement, rather than institutional or training-based participation, is more closely linked to competence development in AI-supported environments.

From a theoretical perspective, these results can also be interpreted through the lens of SDT. According to SDT, autonomy plays a central role in fostering intrinsic motivation and sustaining high-quality learning. The finding that only self-directed effort was significant suggests that DC may be more strongly associated with autonomous engagement than

externally driven participation. In particular, the concept of autonomy provides a useful framework for explaining why self-directed effort emerges as a key predictor of DC, even in technology-rich learning environments.

Furthermore, the findings indicate that formal or one-time participation in AI-related educational programs may not directly lead to meaningful improvements in DC. Even though AI-supported environments offer affordances such as personalized learning and real-time feedback[22],[23], these features alone are insufficient to ensure learning outcomes. Instead, learners' sustained and active engagement appears to be a necessary condition for translating these affordances into actual competence development.

Despite these contributions, this study has several limitations. First, the use of convenience sampling from a single university limits the generalizability of the findings, and common method bias and post-hoc statistical power were not examined. Second, the reliance on self-reported data may not fully capture actual performance in digital environments. Because participants evaluated their own levels of engagement and competence, the results may reflect perceived competence rather than objectively measured digital competence. Therefore, discrepancies between self-perceptions and actual performance may exist. Third, the cross-sectional design based on a single time-point survey limits the ability to draw causal inferences from the observed relationships. Fourth, ADLE was measured using a concise structure in which each subcomponent was represented by a single item, limiting the assessment of internal consistency at the subcomponent level and the application of additional validity analyses. Therefore, the results should be interpreted with caution. Future research should develop multi-item scales with multiple items for each subdimension to provide a more robust assessment of ADLE. In addition, future research should incorporate more diverse samples and employ performance-based assessments to provide a more comprehensive understanding of DC development.

Taken together, this study suggests that in the process of developing DC, learners' self-directed and active engagement may play a more critical role than mere participation in educational activities.

VI. Conclusion

This study empirically examined the relationship between ADLE and DC among university students and further investigated the differential effects of its subcomponents. The results indicated that ADLE significantly predicted DC, with self-directed effort emerging as the most influential factor.

The primary contribution of this study lies in moving beyond a unidimensional view of engagement by differentiating types of engagement and empirically demonstrating their distinct effects. The findings reveal that not all forms of engagement contribute equally to competence development, and that certain types—particularly self-directed effort—are more closely associated with DC.

From a practical perspective, the findings suggest that AI- and digital-based education in higher education should go beyond merely providing programs or increasing participation opportunities. Instead, instructional design should focus on fostering learners' sustained and self-directed engagement. This has important implications for curriculum design and the development of teaching and learning strategies in AI-supported environments. For example, instructors may encourage learners to independently explore AI tools through project-based activities, reflective learning tasks, or personalized digital assignments that require continuous interaction with AI-supported learning environments. Such approaches may support the development of digital competence through active and autonomous engagement rather than passive participation.

Acknowledgments

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2025S1A5A8008 784).

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