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The impact of AI technology integration and digital innovation self-efficacy on vocational students' adaptability: Dual moderation by innovation competition intensity

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Abstract: This study contributes to the expanding body of research on adaptability development in vocational education by examining the interaction between cognitive, technological, and contextual factors. While existing literature has explored the individual effects of artificial intelligence (AI) integration and digital self-efficacy on learning outcomes, few studies have investigated their combined impact on student adaptability, particularly under varying levels of innovation competition. Drawing on Social Cognitive Theory, this study develops a theoretical model that positions AI technology integration ability and digital innovation self-efficacy as predictors of adaptability intensity, with innovation competition intensity serving as a moderator. A quantitative survey was conducted among 412 students from vocational colleges across China. The data were analyzed using Structural Equation Modeling (SEM) via SmartPLS 4.0. Results demonstrate that both AI integration and digital self-efficacy positively influence adaptability intensity, with innovation competition intensity significantly enhancing these relationships. These findings underscore the importance of embedding AI tools in vocational curricula and fostering learners' confidence in digital innovation within competitive educational environments. Practical implications include the need for institutions to align technology adoption with student-centered strategies and to develop resilience-driven pedagogical models that prepare learners for dynamic, technology-intensive work environments.

Keywords: *Adaptability intensity, AI technology integration, Digital self-efficacy, Innovation competition, Vocational education.*

1. Introduction

As global economies accelerate their digital transformation, vocational education systems face increasing pressure to produce graduates who are not only technically proficient but also highly adaptable. The rapid development of artificial intelligence (AI), automation, and emerging technologies has redefined the skillsets demanded by modern industries. This transformation is especially critical in fast-growing economies like China, where there is a rising need for professionals with strong digital innovation capacity and self-directed learning confidence [1]. However, cultivating such adaptable talent within vocational education remains a significant challenge due to the complexities of aligning pedagogy, curriculum, and technological change.

Recent studies have emphasized the role of AI technology integration in enhancing personalized learning, real-time feedback, and cognitive engagement—factors that contribute directly to the development of adaptability intensity [2]. At the same time, digital innovation self-efficacy has emerged as a key psychological construct that promotes proactive learning, resilience, and readiness for future work environments [3]. Yet, there remains a lack of research that explores how these two constructs interact to shape students' adaptability, especially in vocational education contexts.

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Importantly, adaptation is not shaped solely by internal capabilities. External environmental factors—particularly innovation competition intensity—also exert significant influence over student behavior and outcomes. Institutions operating in highly competitive innovation environments are more likely to adopt advanced technologies and foster experimentation, which in turn places greater adaptability demands on students [4]. However, few empirical studies have systematically examined how such environmental competition moderates the effects of AI and self-efficacy on student adaptability.

Moreover, existing literature often treats AI integration ability and digital self-efficacy as isolated predictors, with limited attention to their interaction under varying contextual conditions. Most studies also focus on higher education settings, while vocational education—despite its growing relevance in future workforce development—remains underexplored. This theoretical oversight limits a comprehensive understanding of how adaptability is developed and sustained among vocational learners.

To address these gaps, the present study draws on Social Cognitive Theory [5] to construct an integrated theoretical framework. It investigates how AI Technology Integration Ability and Digital Innovation Self-Efficacy influence Adaptability Intensity, and how these relationships are moderated by Innovation Competition Intensity. The study seeks to answer two primary research questions:

How do AI integration ability and digital innovation self-efficacy affect vocational students' adaptability intensity?

Does innovation competition intensity moderate these relationships?

To explore these questions, the study applies a survey-based methodology targeting students from vocational colleges in China. Data will be analyzed using SmartPLS 4.0 and structural equation modeling. This research is expected to advance theoretical insight into adaptability formation in digital education, while also providing practical guidance for strengthening learner resilience amid ongoing technological change.

2. Literature Review

This section introduces the theoretical foundation of Social Cognitive Theory (SCT) and outlines the development of hypotheses by integrating relevant empirical findings. The framework provides a lens to understand how individual cognition, technological integration, and external contextual pressures jointly influence adaptability in vocational education settings.

2.1. Theoretical Background

This study is grounded in Social Cognitive Theory (SCT), proposed by Bandura [5] which posits that human behavior is shaped by the dynamic interplay among personal cognitive factors, behavioral patterns, and environmental influences—a model known as triadic reciprocal determinism. SCT emphasizes self-efficacy as a central psychological mechanism through which individuals exercise agency, persist in the face of challenges, and adapt to evolving environments. In the context of vocational education, this theory provides a comprehensive basis for understanding how students develop adaptive capabilities in response to technological and competitive transformations.

Drawing from this framework, AI technology integration ability represents a structured environmental input that enables learners to access new forms of interaction and knowledge, thereby shaping their learning behaviors and adaptive outcomes. Research has shown that AI-integrated learning environments promote engagement, computational thinking, and flexible problem-solving—skills essential for adapting to digital economies Zhang, et al. [6] and Chou, et al. [7]. Mian, et al. [8] further highlight the role of intelligent technologies in enhancing learners' responsiveness to change, indicating that technical environments serve as behavioral facilitators in SCT's triadic structure.

Simultaneously, Digital Innovation Self-Efficacy reflects learners' cognitive beliefs about their capabilities to manage and innovate using digital technologies. It aligns directly with SCT's emphasis on the mediating role of perceived self-efficacy in influencing behavior. Prior studies have demonstrated

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that high self-efficacy leads to stronger adaptability, persistence, and innovation, especially under conditions of technological change [9-11]. SCT posits that such internal beliefs do not act in isolation but interact with external stimuli to determine behavior.

In line with this, the concept of Innovation Competition Intensity is integrated as a moderating environmental factor within the SCT framework. According to Mao, et al. [12] and Qu and Kim [13] higher innovation pressure in institutional or industrial contexts enhances the demand for adaptive behaviors and rapid technological assimilation. Al Dhaheri, et al. [14] further argue that competitive intensity accelerates the functional need for dynamic capabilities, which include both AI adoption and innovation efficacy. These findings suggest that environmental complexity and volatility—key considerations in SCT—amplify the behavioral consequences of both environmental enablers (AI integration) and personal cognitive resources (self-efficacy).

Therefore, by positioning AI Technology Integration Ability and Digital Innovation Self-Efficacy as primary antecedents, and Innovation Competition Intensity as a contextual moderator, this study extends Social Cognitive Theory to explain Adaptability Intensity in the context of vocational education during digital transformation. The model contributes to existing literature by integrating SCT with empirical insights from educational technology, innovation management, and digital competency research.

2.2. Theoretical Framework and Hypothesis Development

The conceptual framework of this study integrates key constructs grounded in educational technology and social cognitive research to explain vocational college students' adaptability intensity in the context of intelligent learning environments. The construct of AI Technology Integration Ability is informed by Huang [15] who empirically examined the integration of artificial intelligence in instructional practices and its impact on learning processes. Digital Innovation Self-Efficacy draws from Pan [16] whose study linked learners' self-perceived technological competence with their motivation and adaptability in digital self-directed contexts. Innovation Competition Intensity references the work of Bylykbashi [17] which operationalized innovation-based environmental pressure as a contextual factor affecting technological behavior. Adaptability Intensity, the outcome variable, is guided by the framework of Martin, et al. [18] who conceptualized adaptability as an individual's ability to respond effectively to uncertainty and change in academic settings. Collectively, these constructs form the basis of the current research model, which explores how cognitive, technological, and environmental factors converge to influence adaptability in vocational education. The complete theoretical model is depicted in Figure 1.

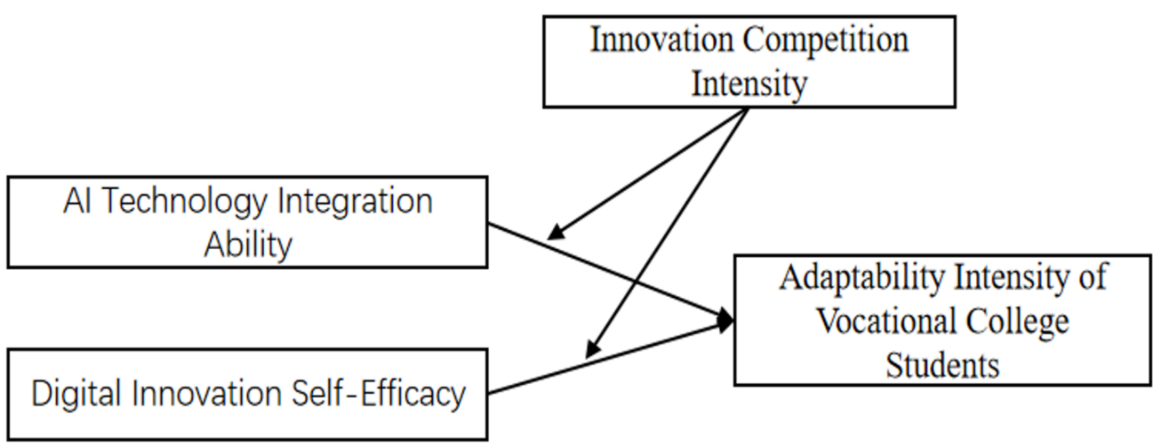

Figure 1.
AI Technology Integration Ability and Vocational College Students' Adaptability Intensity.

The integration of AI technologies into vocational education significantly enhances students' adaptability by fostering career-relevant cognitive, technical, and emotional skills. AI-enriched learning environments promote active engagement, problem-solving, and flexible thinking, which are essential for adapting to rapidly changing work contexts. Zhang, et al. [6] emphasize that AI literacy—especially when combined with ethics and career foresight—cultivates students' ability to navigate future job transformations. Similarly, Chou, et al. [7] highlight that human-computer interaction experiences within AI systems boost students' emotional involvement and learning effectiveness, strengthening their adaptive responses.

Moreover, adaptability in the era of Industry 4.0 relies on students' readiness to work with intelligent technologies and to continuously develop digital competencies. Mian, et al. [8] point out that AI and ICT integration encourages adaptive thinking and computational skills vital for sustainable career development. Therefore, AI technology integration ability can be considered a critical driver of vocational college students' adaptability intensity [6-8].

H_1: AI technology integration ability positively influences the adaptability intensity of vocational college students.

2.3. Digital Innovation Self-Efficacy and Adaptability Intensity of Vocational College Students

Digital Innovation Self-Efficacy, the belief in one's ability to engage with and innovate using digital technologies, is expected to positively influence the Adaptability Intensity of Vocational College Students. Self-efficacy is known to play a pivotal role in enhancing students' confidence and persistence in the face of challenges, particularly in the context of digital innovation and technological integration [9, 10]. As digital self-efficacy strengthens, students are more likely to embrace new technologies, exhibit flexible problem-solving approaches, and adapt to the rapidly evolving demands of the workforce. Furthermore, the capacity for self-efficacy enhances not only innovation capability but also psychological and social adaptability [11]. Therefore, it is reasonable to suggest that higher levels of Digital Innovation Self-Efficacy are associated with increased adaptability intensity, especially in vocational contexts where technological fluency and adaptability are crucial for employability and innovation.

H_2: Digital Innovation Self-Efficacy positively influences the adaptability intensity of vocational college students.

2.4. The Moderating Role of Innovation Competition Intensity

Building upon the works by Mao, et al. [12]; Qu and Kim [13] and Al Dhaheri, et al. [14] the relationship between AI Technology Integration Ability and Adaptability Intensity can be moderated by Innovation Competition Intensity. Specifically, as organizations or institutions experience heightened innovation competition, the ability to integrate AI technologies may become more critical for fostering adaptability within vocational students. The interaction between these variables could potentially amplify the effects of AI Technology Integration Ability on Adaptability Intensity by increasing the demand for quick adaptation and innovative solutions in competitive settings [12, 13].

Moreover, the Innovation Competition Intensity could serve as a catalyst for enhancing the relationship between AI Technology Integration Ability and Adaptability Intensity. High levels of competition in innovation may push individuals or institutions to rapidly adopt and integrate AI technologies to stay competitive, which in turn could lead to a higher intensity of adaptability among students. This aligns with the findings of Qu and Kim [13] which highlight the importance of AI adoption in driving adaptability and innovation, particularly in a competitive environment. Similarly, Al Dhaheri, et al. [14] argue that dynamic capabilities, including AI integration, are crucial for innovation, especially in turbulent, competitive environments.

Thus, the hypothesis can be formulated as follows:

H_3: Innovation Competition Intensity moderates the relationship between AI Technology Integration Ability and Adaptability Intensity.

The relationship between Digital Innovation Self-Efficacy and Adaptability Intensity is influenced by Innovation Competition Intensity, which acts as a moderator. As competition in innovation increases, the ability to adapt to digital changes becomes critical. Digital Innovation Self-Efficacy, which reflects an individual's belief in their ability to innovate in the digital realm, is likely to foster greater Adaptability Intensity in such an environment. Previous studies emphasize that self-efficacy in digital contexts enhances adaptability, creativity, and innovation, especially when innovation competition is high [9, 19, 20]. Innovation Competition Intensity strengthens this relationship by increasing the pressure for individuals to be adaptable, thus amplifying the positive effect of Digital Innovation Self-Efficacy on Adaptability Intensity [21, 22].

Therefore, it is hypothesized that Innovation Competition Intensity moderates the relationship between Digital Innovation Self-Efficacy and Adaptability Intensity, with stronger Adaptability Intensity when Innovation Competition Intensity is high. This hypothesis draws from the literature on the role of self-efficacy in fostering digital innovation and adaptability, particularly in contexts with high innovation competition [9, 19-22].

$H_{4:}$ Innovation Competition Intensity positively moderates the relationship between Digital Innovation Self-Efficacy and Digital Innovation Self-Efficacy.

3. Methodology

3.1. Survey Instrument

The survey instrument was developed based on established scales from previous research, with contextual adjustments made to align with the characteristics of vocational education. All constructs were measured using a seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree), to capture varying levels of respondent agreement on items related to AI technology integration, digital innovation self-efficacy, and interdisciplinary collaboration. The questionnaire was reviewed by domain experts and pilot-tested among a small group of students to ensure clarity, relevance, and appropriateness (see Appendix 1 for the full questionnaire).

3.2. Data Collection

Data were collected through an anonymous online survey distributed to full-time students across multiple vocational colleges in different provinces of China. Dissemination channels included institutional email, WeChat groups, and class communication platforms. A purposive sampling approach was used to ensure that only active diploma-level students from Year 1 to Year 3 participated. To maintain data quality, measures such as IP address monitoring and browser session controls were implemented to avoid duplicate submissions. Responses completed in under two minutes were excluded. After preliminary screening, a total of 197 valid responses were retained for further analysis. Participation was voluntary, and all respondents provided informed consent prior to beginning the survey.

3.3. Common Method Bias

To mitigate potential common method bias (CMB), both procedural and statistical remedies were employed. Procedurally, the survey was anonymous and confidential, and item order was randomized to minimize response bias. Statistically, the marker variable technique was adopted. "Grade level" was selected as a theoretically unrelated marker variable and was linked to all major constructs within the PLS-SEM model. The results revealed that none of the paths from the marker variable to the core constructs were statistically significant ($p > 0.05$), indicating that CMB was not a concern in this study.

3.4. Data Analysis Method

This study applied Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0, following the analytical guidelines proposed by Hair, et al. [23]. Multivariate normality was assessed through Mardia's coefficient of skewness and kurtosis, both of which yielded p-values < 0.05, confirming non-normal data distribution. PLS-SEM was thus deemed appropriate due to its robustness in handling non-normal datasets. The data analysis followed a two-stage approach: the first stage focused on evaluating the measurement model's reliability, convergent validity, and discriminant validity; the second stage assessed the structural model, testing the hypothesized relationships and interaction effects. This method allowed for both theoretical validation and practical insight into how vocational students respond to digital and interdisciplinary learning environments.

4. Results

4.1. Demographic Statistics

This study collected valid responses from 197 vocational college students, providing a well-distributed demographic snapshot of the target population (Table1). The gender composition was nearly balanced, with 51.78% male and 47.72% female participants, ensuring a diverse representation of perspectives across genders.

In terms of age, most respondents (49.75%) were between 20 and 21 years old, followed by 32.49% aged 18–19, and 17.26% aged 22 or older. This distribution reflects a predominantly young cohort in the early to middle stages of their vocational education, likely to be actively engaging with emerging technologies and adaptive learning strategies.

With respect to grade level, second-year students comprised the largest group (40.10%), followed by first-year (36.04%) and third-year students (23.35%). This indicates that the majority of responses were contributed by students with at least one year of academic exposure, offering insights grounded in both classroom and experiential learning.

The field of study data revealed broad academic diversity. Students from Engineering and Manufacturing (21.32%), Information Technology (16.75%), and Finance and Business (14.21%) formed the largest clusters, while other areas such as Medicine and Health, Tourism, and Education were also represented. This distribution ensures that the study captures a cross-sectional view of vocational students with varying degrees of exposure to digital tools and interdisciplinary knowledge.

Overall, the demographic structure enhances the relevance of the findings, offering a robust foundation for examining how vocational students perceive and respond to AI technology integration, self-efficacy in innovation, and collaborative learning environments.

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Table 1.
Demographic Characteristics.

Variable	Category	Frequency (N)	Percentage (%)
Gender	Male	102	51.78
	Female	94	47.72
	Total	197	100.00%
Age	18–19 years	64	32.49
	20–21 years	98	49.75
	22 years and above	34	17.26
	Total	197	100
Grade Level	Year 1	71	36.04
	Year 2	79	40.1
	Year 3	46	23.35
	Total	197	100
Field of Study	Engineering and Manufacturing	42	21.32
	Information Technology	33	16.75
	Finance and Business	28	14.21
	Education and Sports	14	7.11
	Tourism, Hotel and Catering Services	12	6.09
	Medicine and Health	13	6.6
	Arts and Design	12	6.09
	Agriculture, Forestry and Fishery	8	4.06
	Civil Engineering and Architecture	9	4.57
	Transportation	7	3.55
	Public Management and Social Service	6	3.05
	Environmental Protection	4	2.03
	Other	8	4.06
	Total	197	100

4.2. Reliability and Validity

The measurement model demonstrated solid reliability and validity across all constructs, as summarized in Table 2. Internal consistency was evaluated using Cronbach's alpha and composite reliability (ρ_a and ρc), with all values exceeding the threshold of 0.70. Specifically, Cronbach's alpha ranged from 0.835 (AIVCS) to 0.916 (ATIA), indicating satisfactory internal reliability. Composite reliability values were consistently high, with all constructs scoring above 0.90 for ρc, underscoring the coherence of the indicators within each construct.

Convergent validity was confirmed through the Average Variance Extracted (AVE), with all constructs exceeding the recommended threshold of 0.50. AVE values ranged from 0.751 (DISE) to 0.800 (ATIA), demonstrating that each construct captures a substantial portion of variance in its items. Outer loadings for all indicators were above 0.70, further supporting convergent validity.

Discriminant validity was examined using both the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT). As shown in Table 4, the square roots of AVE were consistently greater than the inter-construct correlations, meeting the Fornell-Larcker criterion. HTMT values for all construct pairs remained below the conservative cutoff of 0.90, confirming adequate discriminant validity.

Multicollinearity diagnostics were performed using Variance Inflation Factor (VIF) values. As shown in Table 3, all VIF values ranged between 1.845 and 2.226, which are well below the threshold of 5, indicating no serious multicollinearity issues. The f-square values, though modest (ranging from 0.023 to 0.078), suggest small yet meaningful effect sizes, particularly for the interaction and direct effects of ICI.

Collectively, the reliability and validity assessments confirm that the measurement model is both robust and suitable for further structural analysis, providing a reliable foundation for examining the effects of AI technology integration and digital innovation self-efficacy on vocational students' adaptability.

Table 2.
Construct reliability and validity.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AIVCS	0.835	0.841	0.902	0.754
ATIA	0.916	0.921	0.941	0.800
DISE	0.886	0.886	0.923	0.751
ICI	0.894	0.895	0.927	0.759

Table 3.
Construct variance inflation value and effect size values

	VIF	f-square
ATIA -> AIVCS	2.226	0.040
DISE -> AIVCS	1.845	0.034
ICI -> AIVCS	2.031	0.078
ICI x DISE -> AIVCS	1.872	0.023
ICI x ATIA -> AIVCS	2.120	0.038

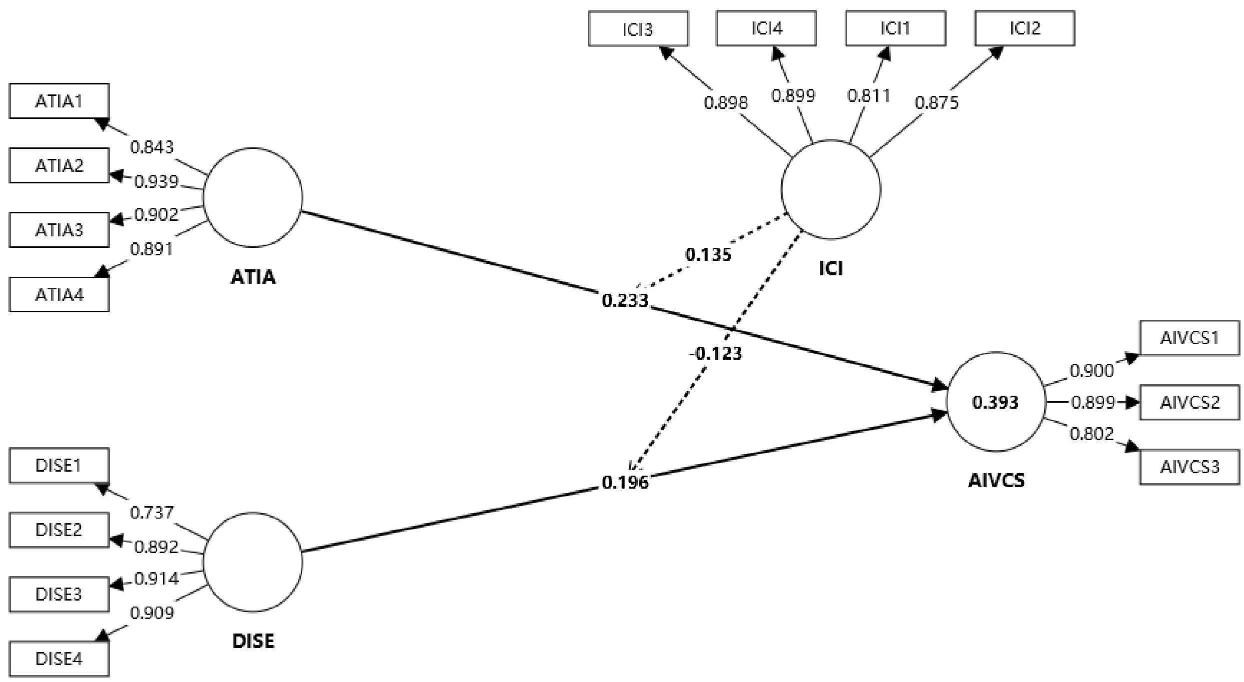

Figure 2.
Theoretical Model.

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Table 4.
Discriminant Validity.

	AIVCS	ATIA	DISE	ICI	ICI x DISE
Heterotrait-monotrait ratio (HTMT) - Matrix					
AIVCS					
ATIA	0.561				
DISE	0.598	0.648			
ICI	0.637	0.721	0.671		
ICI x DISE	0.221	0.235	0.259	0.298	
ICI x ATIA	0.138	0.433	0.193	0.362	0.652
Fornell-Larcker criterion					
AIVCS	0.868				
ATIA	0.495	0.894			
DISE	0.517	0.585	0.866		
ICI	0.55	0.652	0.597	0.871	
Outer loadings					
AIVCS1	0.9				
AIVCS2	0.899				
AIVCS3	0.802				
ATIA1		0.843			
ATIA2		0.939			
ATIA3		0.902			
ATIA4		0.891			
DISE1			0.737		
DISE2			0.892		
DISE3			0.914		
DISE4			0.909		
ICI1				0.811	
ICI2				0.875	
ICI3				0.898	
ICI4				0.899	

4.3. Hypothesis Testing Results

This section presents the structural model results examining the direct and interaction effects of key predictors on vocational students' AI-driven innovation capability score (AIVCS), as detailed in Table 5.

4.4. Direct Effects

Hypothesis 1 (H1) posited that AI Technology Integration Ability (ATIA) positively influences AIVCS. This was supported with a path coefficient of 0.233 ($t = 2.598$, $p = 0.009$), indicating a significant direct effect. Hypothesis 2 (H2) proposed a similar relationship between Digital Innovation Self-Efficacy (DISE) and AIVCS, which was also supported ($\beta = 0.196$, $t = 2.317$, $p = 0.021$), affirming its positive contribution. In addition, Interdisciplinary Collaboration Intensity (ICI) was found to have the strongest direct impact among the three predictors ($\beta = 0.311$, $t = 3.625$, $p < 0.001$), highlighting the critical role of cross-disciplinary engagement in fostering AI-related innovation.

4.5. Moderating Effects

Hypothesis 3 (H3), which tested the moderating role of ICI on the ATIA–AIVCS relationship, was supported ($\beta = 0.135$, $t = 2.244$, $p = 0.025$), suggesting that students with higher collaboration intensity experience a stronger positive impact of AI integration on innovation capability. Conversely, Hypothesis 4 (H4), examining the moderating effect of ICI on the DISE–AIVCS path, was not supported. Although the interaction term showed a negative coefficient ($\beta = -0.123$, $t = 1.799$, $p = 0.072$), it did not reach statistical significance, implying that the influence of digital self-efficacy on innovation capability may be relatively stable across varying levels of interdisciplinary collaboration.

Overall, the results demonstrate that ATIA, DISE, and ICI are significant drivers of students' innovation outcomes, and that the effect of ATIA is further enhanced in contexts of stronger interdisciplinary collaboration. These findings underscore the importance of both technological and cross-disciplinary educational strategies in promoting innovation among vocational learners.

Table 5.
Hypothesis Testing.

		Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	
H1	ATIA -> AIVCS	0.233	0.228	0.090	2.598	0.009	Supported
H2	DISE -> AIVCS	0.196	0.192	0.084	2.317	0.021	Supported
	ICI -> AIVCS	0.311	0.323	0.086	3.625	0.000	Supported
H3	ICI x ATIA -> AIVCS	0.135	0.120	0.060	2.244	0.025	Supported
H4	ICI x DISE -> AIVCS	-0.123	-0.111	0.069	1.799	0.072	Not Supported

4.6. Predictive Relevance Analysis

The predictive relevance of the model was assessed using the Q^2 statistic derived from the blindfolding procedure. As shown in Table 6, AIVCS demonstrated a moderate level of predictive relevance, with a Q^2 value of 0.280, indicating that the model has a meaningful ability to predict vocational students' AI innovation capability based on the selected antecedents.

In contrast, the Q^2 values for ATIA, DISE, and ICI were all 0.000, suggesting that these constructs function primarily as predictors within the model and do not themselves have predictive relevance in this context. This result is expected, as exogenous variables typically serve as inputs rather than predictive targets.

The findings emphasize that the model performs reasonably well in predicting the endogenous construct (AIVCS), reinforcing its applicability in analyzing innovation potential among vocational students. The presence of predictive relevance for AIVCS supports the utility of integrating technological readiness, digital self-efficacy, and interdisciplinary collaboration in forecasting students' innovative outcomes.

Table 6.
Construct cross-validated redundancy.

	SSO	SSE	Q^2 (=1-SSE/SSO)
AIVCS	591.000	425.756	0.280
ATIA	788.000	788.000	0.000
DISE	788.000	788.000	0.000
ICI	788.000	788.000	0.000

5. Discussion

This study offers new insights into how digital competencies and innovation contexts shape adaptability intensity among vocational college students in the era of intelligent education.

First, the results supported Hypothesis 1, confirming a significant positive relationship between AI Technology Integration Ability and Adaptability Intensity. This finding reinforces the theoretical claim that AI-enhanced learning environments foster cognitive flexibility, engagement, and problem-solving—core components of adaptability [6, 7]. The evidence suggests that AI integration promotes not only technical competence but also a mindset conducive to navigating dynamic professional environments.

Second, consistent with Hypothesis 2, Digital Innovation Self-Efficacy was found to positively influence Adaptability Intensity. This supports previous literature on the role of self-efficacy in enabling individuals to manage technological change with confidence and persistence [9, 10]. High levels of

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digital self-efficacy appear to enhance students' readiness to embrace innovation and uncertainty, reflecting its relevance in shaping adaptability within vocational education.

Third, the results affirmed Hypothesis 3, showing that Innovation Competition Intensity moderates the relationship between AI Technology Integration Ability and Adaptability Intensity. The effect of AI integration was amplified in contexts with higher levels of innovation competition, suggesting that competitive pressures heighten the relevance of AI as a catalyst for adaptability [12, 13]. This finding underscores the contextual sensitivity of AI's influence on adaptability outcomes.

Finally, Hypothesis 4 was also supported, indicating that Innovation Competition Intensity strengthens the relationship between Digital Innovation Self-Efficacy and Adaptability Intensity. In more competitive innovation environments, the adaptability-enhancing effect of self-efficacy becomes more pronounced, consistent with prior research linking competitive climates to increased cognitive and behavioral demands on learners [19, 21].

6. Implications

6.1. Theoretical Implications

This study contributes to the literature by extending Social Cognitive Theory (SCT) into the domain of vocational education in the context of AI and digital innovation. First, by empirically validating the role of AI Technology Integration Ability and Digital Innovation Self-Efficacy as significant antecedents of students' Adaptability Intensity, the study highlights the interdependence of environmental affordances and individual cognitive beliefs in shaping adaptive behavior. This complements and extends previous SCT-based research by situating adaptability in a highly digitized and competitive educational context.

Second, the integration of Innovation Competition Intensity as a moderating variable deepens our understanding of how contextual pressures can amplify or condition the effects of technological and psychological variables on learning outcomes. Unlike traditional SCT applications that treat environment as a background factor, this study demonstrates that environmental competitiveness plays an active and dynamic role in influencing adaptability mechanisms. This offers a refined view of the reciprocal determinism between learner, environment, and behavior, especially relevant for educational systems undergoing digital transformation.

6.2. Practical Implications

The findings offer actionable insights for educators, administrators, and policymakers aiming to enhance adaptability among vocational college students. First, promoting meaningful AI integration in teaching practices—not merely as a tool but as an embedded instructional strategy—can significantly strengthen students' ability to cope with rapid changes in technology and workplace demands. Institutions should invest in teacher training, digital infrastructure, and curriculum design that emphasizes practical AI use across disciplines.

Second, building students' digital innovation self-efficacy should be a core focus of vocational training programs. This can be achieved through experiential learning, digital project-based tasks, and self-directed learning modules that empower students to explore and innovate within digital environments.

Finally, schools should recognize the role of innovation competition pressure as both a challenge and an opportunity. In highly competitive environments, it is especially important to foster institutional cultures that support innovation, agility, and psychological readiness. Creating benchmarking systems, digital innovation hubs, and student-led innovation initiatives can further reinforce adaptability and future-readiness among learners.

7. Conclusion

In an era marked by rapid technological disruption and evolving skill demands, vocational education systems are under increasing pressure to cultivate learners who are not only technically competent but also highly adaptable. This study addresses this imperative by examining how AI Technology Integration Ability and Digital Innovation Self-Efficacy influence Adaptability Intensity among vocational college students, and how Innovation Competition Intensity moderates these relationships. Grounded in Social Cognitive Theory, the study integrates environmental, cognitive, and behavioral perspectives into a comprehensive framework to understand the determinants of adaptability in digitally-driven educational settings.

Using structural equation modeling based on data collected from Chinese vocational institutions, the findings confirm that both AI integration and digital self-efficacy significantly enhance students' adaptability intensity. Moreover, Innovation Competition Intensity was shown to strengthen these effects, suggesting that competitive innovation environments act as amplifiers of adaptive behavior. These results not only affirm the critical role of cognitive and technological enablers in shaping student outcomes but also highlight the importance of context in moderating educational interventions.

The study offers valuable implications for educational practitioners and institutional leaders striving to prepare students for uncertain and technologically complex futures. By emphasizing the strategic role of AI-driven instruction and the cultivation of digital self-belief, the findings support a shift toward more innovation-ready, learner-centered vocational education models. In doing so, the study contributes to the broader discourse on how educational systems can evolve to meet the needs of the digital age.

Despite its contributions, the study is not without limitations. Its focus on a single educational context and cultural setting may constrain the generalizability of the results. Future research is encouraged to examine these relationships across diverse institutional types and cultural regions, and to incorporate longitudinal and mixed-method approaches to deepen understanding of how adaptability develops over time. Such future inquiries will be essential for building more resilient and responsive education systems that can empower learners to navigate the complexities of the 21st-century workforce.

8. Recommendations

Based on the findings, future researchers are encouraged to extend this study across diverse cultural and institutional contexts using longitudinal or mixed-method approaches, and to explore additional moderating or mediating variables such as institutional policy or peer support. Cross-disciplinary comparisons and skill-specific measures of adaptability may also yield deeper insights. For practitioners, the study recommends embedding AI literacy into curricula, fostering digital self-efficacy through experiential learning, leveraging innovation competitions, enhancing teacher capacity in adaptive pedagogy, and cultivating a psychologically safe, innovation-driven learning environment to better support vocational students' adaptability in rapidly evolving digital landscapes.

9. Limitations

This study has several limitations that should be considered when interpreting the findings. First, as the data were collected at a single point in time, the results cannot reflect changes in students' adaptability or self-efficacy over time. Future research may adopt a longitudinal approach to better understand how these variables develop. Second, the sample was drawn exclusively from vocational colleges in China, which may limit the generalizability of the findings to other countries or educational systems. Third, although precautions were taken to ensure data quality, the use of self-reported questionnaires may still introduce bias. Lastly, the study focused on a limited number of factors, and did not examine other potential influences on student adaptability, such as teaching methods, institutional support, or access to digital resources.

Institutional Review Board Statement:

The study involving human participants was reviewed and approved by the Research Ethics Committee of Shenzhen Polytechnic University. All participants were informed of the purpose and anonymity of the research, and provided their written informed consent prior to participation.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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Appendix

Appendix 1.
Measurement Items of Variables.

Variable	Items
AI Technology Integration Ability Huang [15]	
ATIA1	The school I attend integrates artificial intelligence related tools into its teaching.
ATIA2	I often use AI systems (such as intelligent Q&A and recommendation systems) in my courses.
ATIA3	The application of AI technology has improved my learning efficiency.
ATIA4	I am proficient in operating AI supported learning platforms or tools.
Digital Innovation Self-Efficacy Pan [16]	
DISE1	I believe I can use digital tools to come up with innovative solutions.
DISE2	I can quickly adapt to new digital platforms.
DISE3	I have the ability to innovate effectively in a technology driven environment.
DISE4	When encountering new technologies, I am confident that I can self-study and master them.
Innovation Competition Intensity Bylykbashi [17]	
ICI1	My school is facing fierce competition in educational technology and innovation.
ICI2	There is a clear pressure for innovation in the educational environment.
ICI3	We often compare our school's innovation ability with other schools.
ICI4	Maintaining technological leadership is an important goal of our school.
Adaptability Intensity Martin, et al. [18]	
AI1	I am able to quickly adapt to new learning or work environments.
AI2	Despite sudden changes, I am still able to maintain efficient performance.
AI3	I am good at learning new skills and methods when needed.
AI4	I exhibit flexibility and a positive attitude when facing uncertainty.