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RESEARCH ARTICLE

From AI "Disabling" to "Enabling": An Empirical Study on Digital-Intelligent Learning among Students Majoring in Smart Agriculture

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Abstract

Against the backdrop of deep AI-agriculture integration, smart agriculture has become a key direction for agricultural modernization, demanding higher digital-intelligent learning competence from university students. As a core competency for leveraging AI to engage in agricultural information technology learning and solve practical problems, the mechanisms underlying its formation remain underexplored. This study targets undergraduate and graduate students in smart agriculture-related majors, constructing a theoretical model based on the dual dimensions of external technological characteristics and internal learning processes. It systematically investigates how key factors—including the technological suitability of large language models (LLMs), users' information-processing capability, and their capacity to regulate LLM dependence—influence the formation of digital-intelligent learning competence. Based on 166 valid questionnaire responses, reliability and validity tests and factor analysis were conducted in SPSS, and Structural Equation Modeling (SEM) was performed in AMOS. Results indicate that LLM technological suitability and learners' information-processing capability exert significant positive effects on digital-intelligent learning competence, while dependence-regulation capability serves as an important mediating variable. Further analysis reveals that LLMs do not directly enhance learning competence merely by improving efficiency; their enabling effect depends on learners' rational regulation of model usage and deep information processing. These findings uncover the critical pathways underlying the formation of digital-intelligent learning competence, providing theoretical foundations and practical guidance for universities to optimize talent cultivation models and enhance students' digital-intelligent learning competence.

Keywords: smart agriculture, digital-intelligent learning, large language models, structural equation modeling.

1 Introduction

Driven by next-generation information technologies such as 5G, the Internet of Things (IoT), big data, and

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cloud computing, agricultural production is shifting from its traditional experience-driven paradigm to a data-driven one. Smart agriculture has consequently become a key form of agricultural modernization, imposing higher requirements on university talent cultivation in terms of "composite knowledge structures, engineering practice capabilities, sustained learning capabilities." Against this backdrop, large language models (LLMs)—represented by ChatGPT, DeepSeek, and Doubao—have become indispensable learning tools for university students by virtue of their natural language understanding and generation capabilities, providing timely and accurate support in tasks such as clarifying disciplinary concepts, retrieving and integrating reference materials, deducing experimental protocols, and diagnosing problems [1]. It should be noted, however, that generative AI exhibits a "double-edged sword" characteristic: on the one hand, it can enhance learning efficiency and output quality; on the other hand, if learners excessively delegate critical learning activities—such as information filtering, reasoning, and articulation—to the model, cognitive offloading and insufficient deep processing may occur, leading to weakened critical thinking, inadequate knowledge internalization, and constrained competence development [2, 3]. Nevertheless, research also indicates that when learners actively engage in self-regulated strategies during AI-assisted learning, such negative effects can be mitigated [4]. Moreover, LLMs may produce factual errors and "hallucinated" content, requiring learners to discern and verify model outputs [5]. Therefore, in AI-assisted learning contexts, how to reasonably delineate the modes and boundaries of LLM use—promoting their positive support for the development of learning competence while avoiding substitution effects on learners' own capability formation—has become a pressing issue in contemporary higher education research [6, 7].

At the theoretical level, this study moves beyond the conventional "technology-enhanced learning" perspective by introducing intermediate mechanisms such as "information processing" and "dependence regulation," thereby helping to reveal the internal mechanism (i.e., the logical relationships among internal factors) through which artificial intelligence acts on the formation of learning competence.

At the practical level, students majoring in smart agriculture rely heavily on artificial intelligence technologies in their learning processes; in particular, their use of large language models is characterized by high frequency and rich application scenarios, making them a highly representative population. By taking this group as its research subjects, this study possesses strong practical relevance and application value. It can provide empirical evidence for instructional reform and guidance on learning in related disciplines.

To explore cultivation models for digital-intelligent learning competence among students majoring in smart agriculture, this study takes the formation mechanism of this competence among smart agriculture talent as its point of departure. Drawing on the perspectives of the "double-edged sword" effect of artificial intelligence, information processing theory, and self-regulated learning theory, and employing methods including questionnaire surveys, model construction, and empirical analysis via structural equation modeling, this study systematically investigates the formation and enhancement of digital-intelligent learning competence among students in smart agriculture-related majors. It identifies the key factors influencing the development of this competence. It ultimately develops a comprehensive set of strategic recommendations to enhance the digital-intelligent learning competence of smart agriculture students, covering technological suitability optimization, internal capability cultivation, and instructional model innovation. This study makes the following three contributions:

1. It constructs a theoretical model of the factors influencing digital-intelligent learning competence that encompasses both external technological characteristics and internal learning processes, thereby enriching the theoretical framework in the fields of smart agriculture education and digital-intelligent learning.

2. Through empirical analysis, it reveals the mechanisms by which factors such as the technological suitability of large language models, information processing capability, and dependence-regulation capability influence the formation of digital-intelligent learning competence, clarifying the causal relationships and effect magnitudes among these factors.

3. Based on the research findings, it proposes targeted strategies for enhancing digital-intelligent learning competence, offering practical guidance for universities to optimize instructional models in smart agriculture-related majors and for students to engage in efficient digital-intelligent learning.

2 Related Work

Research on "artificial intelligence + higher education learning" has gradually entered scholarly view alongside the development of AI technology. Early studies primarily focused on the role of AI in instructional assistance, learning analytics, and personalized recommendations, with a consensus that intelligent technologies could optimize information presentation and feedback mechanisms, thereby improving learning efficiency and experience [8]. With the emergence of generative AI—particularly large language models—the role of AI in the learning process has gradually shifted from "tool support" to "cognitive collaboration," directly participating in learners' problem comprehension, information integration, and knowledge construction [9]. Large language models, represented by ChatGPT and DeepSeek, have demonstrated significant advantages in university students' learning, providing support in information retrieval, comprehension of complex concepts, text composition, programming, and solution design [1]. In disciplinary learning contexts, LLMs help lower learning barriers and improve learning efficiency. However, the application of AI in learning does not yield exclusively positive effects, and its potential risks have increasingly attracted attention. From the perspective of cognitive psychology, excessive reliance on intelligent tools may trigger "cognitive offloading," in which learners transfer thinking, judgment, and reasoning processes that should be performed by themselves to technological tools, thereby weakening their capacity for deep information processing [10].

Furthermore, when learners lack the capacity for judgment and discernment, they may directly accept model-generated information while overlooking its accuracy and logical soundness, thereby impairing the development of critical thinking and the effectiveness of knowledge internalization [1]. Although generative AI can enhance short-term learning performance to a certain extent, its effects on long-term knowledge mastery and competence transfer remain uncertain, and it may even produce negative effects in some contexts [11]. This line of research indicates that AI is not inherently "enabling"; its learning effects depend largely on learners' usage patterns and regulatory capabilities. Self-regulated learning theory emphasizes learners' active role in goal setting, process monitoring, and strategy adjustment. In AI-assisted learning contexts, "technology-use regulation" is considered an important component of self-regulation. Learners should dynamically adjust their reliance on AI according to task difficulty and learning objectives, to prevent technology from substituting for autonomous cognitive activities [12]. Mehmood et al. found that maintaining independent completion of basic tasks while judiciously introducing AI assistance for complex tasks is more conducive to competence development and knowledge transfer [13]. Accordingly, "dependence-regulation capability" is regarded as a key intermediary factor linking AI use to learning outcomes.

In summary, existing studies have explored the value and risks of AI in university students' learning from various perspectives, yet the following gaps remain. First, most studies emphasize the analysis of technological functions while paying insufficient attention to learners' internal regulatory mechanisms. Second, the pathway through which AI transforms from an "efficiency tool" into an "enabler of competence" has not been adequately elucidated. Third, empirical research remains relatively scarce in application-oriented, technology-intensive disciplinary contexts such as smart agriculture. It is therefore necessary to integrate information processing theory and self-regulated learning theory to conduct an in-depth analysis, within a specific disciplinary context, of the mechanisms through which large language models influence the formation of university students' learning competence.

3 Materials and Methods

3.1 Research Hypotheses and Theoretical Model

The theoretical foundation of this study comprises the following four aspects. First, the "double-edged sword" perspective on AI-enabled learning: while AI tools enhance learning efficiency, they may also induce problems such as "shallow processing" and "over-reliance." Therefore, in AI-assisted learning contexts, the principle of learner-centeredness must be upheld to govern the modes of AI application in education in a reasonable manner [7, 14]. Second, technological suitability and learning support theory: grounded in the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF) theory, this perspective holds that learners' perceptions of a technology's usefulness and ease of use, together with the degree of fit between the technology's functions and learners' task requirements, significantly influence their technology-use behavior and the effectiveness of learning support [15, 16]. Third, information processing and cognitive offloading theory: this perspective posits that information processing serves to avert cognitive offloading and to master knowledge, providing a theoretical basis for examining the mediating role of information processing capability [17, 18]. Fourth, dependence regulation and self-regulated learning theory: learners need to dynamically adjust their learning strategies and resource-use patterns in response to goals and tasks, which constitutes the key mechanism for achieving the core objective of AI technology: "enabling rather than substituting" [19, 20].

Based on the foregoing theoretical analysis, this study contends that the influence of large language models on agricultural information technology learning can be explained along two dimensions: external factors and internal factors. As shown in Figure 1, the external factors primarily comprise the functional characteristics of large language models and their suitability for specific use cases. In contrast, the internal factors comprise information processing capability, agricultural information technology application capability, knowledge mastery, and dependence-regulation capability. On this basis, the following research hypotheses are proposed:

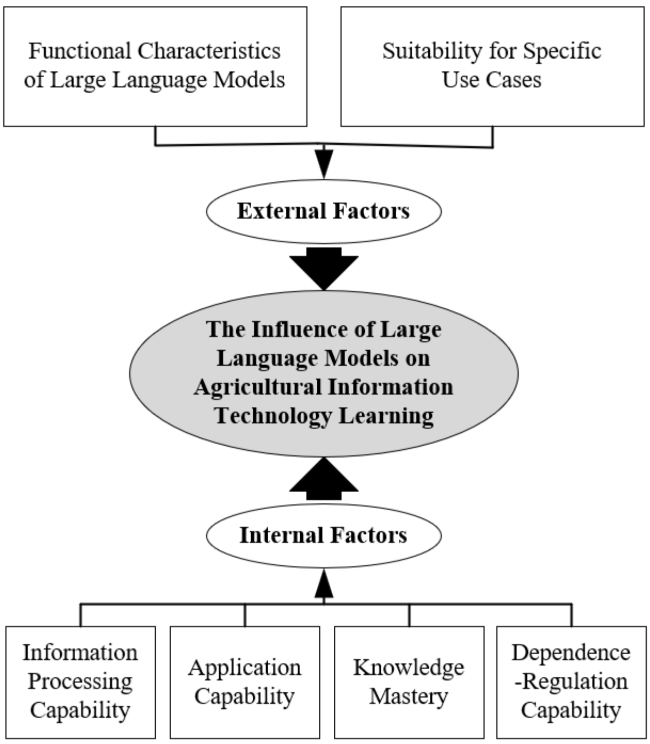

Figure 1. Theoretical model of the influence of large language models on agricultural information technology learning.

Hypothesis 1 (H1): The technological suitability (TS) of large language models has a positive effect on agricultural information technology application capability (AC).

When large language models are well aligned with the learning task requirements, they can provide direct support for students' application of agricultural information technology, thereby enhancing digital-intelligent learning competence [21].

Hypothesis 2 (H2): The technological suitability (TS) of large language models has a positive effect on the formation of students' dependence-regulation capability (DR).

When students perceive that large language models can effectively meet the demands of agricultural information technology learning, they are more likely to develop rational usage cognition and thereby proactively regulate their reliance on these models [21, 22].

Hypothesis 3 (H3): The technological suitability (TS) of large language models has a positive effect on the formation of information processing capability (IP).

Higher model suitability helps provide learners with accurate and reliable information support, reducing the costs of information filtering and discernment, thereby enhancing learners' information-processing capability [23].

Hypothesis 4 (H4): Information processing capability (IP) has a significant effect on knowledge mastery (KM). While effective information processing may support learners in structuring external information into systematic knowledge frameworks [24], excessive reliance on AI-mediated information processing without active cognitive engagement may conversely impair memory consolidation and depth of knowledge mastery [25]. Given the dual-edged nature of AI-assisted information processing, both positive and negative effects on knowledge mastery are theoretically plausible; thus, no directional constraint is imposed on this hypothesis.

Hypothesis 5 (H5): Information processing capability (IP) has a positive effect on the formation of agricultural information technology application capability (AC).

Sound information processing helps learners transform LLM-generated information into capabilities for problem-solving, solution optimization, and innovative practice, which constitute the core manifestation of digital-intelligent learning competence [26].

Hypothesis 6 (H6): Knowledge mastery (KM) has a positive effect on the formation of agricultural information technology application capability (AC).

A stable and systematic knowledge structure in agricultural information technology forms the foundation for its application and innovative practice, directly underpinning the formation of digital-intelligent learning competence [27].

Hypothesis 7 (H7): Dependence-regulation capability (DR) has a positive effect on information processing capability (IP).

Learners who establish reasonable boundaries for LLM use and effectively regulate their reliance on these models can maintain independent thinking during use and avoid mechanically accepting information, thereby improving their level of information filtering, integration, and reprocessing [28].

3.2 Scale Design and Data Collection

3.2.1 Operational Definitions and Item Design

Taking students majoring in smart agriculture as the research subjects, this study first collected baseline data through a questionnaire survey, and then conducted factor analysis using SPSS and Structural Equation Modeling (SEM) using Amos to investigate the influence of large language models on agricultural information technology learning. As shown in Table 1, the scale designed for this study comprises 4 background items and 37 scale items; through dimensionality reduction, the 37 items were grouped into five subscales for analysis: LLM technological suitability, information processing capability, dependence-regulation capability, knowledge mastery, and agricultural information technology (AIT) application capability.

Based on the theoretical research model of the influence of large language models on agricultural information technology learning, the mechanisms by which they affect learning outcomes are elaborated along two dimensions: external and internal factors. The questionnaire developed in this study consists of three parts: an introductory statement, background information, and the main scale. The background information section contains 4 items (grade level, project experience, weekly duration of LLM use, and frequency of use) that describe respondents' basic attributes; descriptive statistical analyses of these items clarify the sample characteristics and provide a basis for subsequent group comparisons. The main section comprises the subscale items, which were designed based on existing scales and disciplinary theory, informed by a literature review and expert consultation, and with measurement scales developed separately for each of the five constructs influencing the effect of large language models on agricultural information technology learning. The questionnaire was scored using a five-point Likert scale, with response anchors ranging from 1 to 5: "1" denotes "strongly disagree," "2" denotes "disagree," "3" denotes "neither agree nor disagree," "4" denotes "agree," and "5" denotes "strongly agree." Respondents conducted self-assessments based on their actual circumstances, and the scores were compiled to capture the relevant data.

3.2.2 Data Collection

The survey targeted undergraduate and graduate students majoring in smart agriculture at multiple universities across China. To ensure questionnaire quality, a small-scale pilot survey was first conducted with 30 students; based on their feedback, ambiguously worded items were revised, and the questionnaire structure was optimized. The formal survey was administered online, yielding 166 valid questionnaires. In the sample, undergraduates accounted for 54.76% and graduate students for 44.84%; only 32.74% of respondents had practical experience in agricultural information technology. Among those who had used large language models, 22.62% had used them for less than 6 months, 16.67% for 1–2 years, and 12.5% for more than 2 years, while 35.71% had never used them. The hierarchical distribution of the sample, together with its practical-experience and tool-use characteristics, largely satisfies the study's requirement of covering different groups.

3.3 Data Processing Methods

This study adopted a quantitative research approach, employing SPSS 26.0 and AMOS 23.0 to perform statistical analysis and model testing on the questionnaire data. The specific analytical procedure was as follows:

1. SPSS 26.0 was used to conduct reliability testing and exploratory factor analysis on the questionnaire data, in order to examine the internal consistency and construct validity of the scale.

2. AMOS 23.0 was used to perform confirmatory

Table 1. Variable description.

Variable	Item	Question No. and Description
Technological Suitability (TS)	TS1	Q5: The agricultural information technology (AIT)-related content output by the large language model (LLM) is accurate in its data and reliable in its sources.
	TS2	Q6: The AIT content output by the LLM suffers from outdated data or "hallucination" problems.
	TS3	Q7: The LLM's algorithms can precisely understand specialized AIT questions and provide logically coherent answers.
	TS4	Q8: When handling AIT problems involving the coupling of multiple factors, the LLM's algorithmic logic exhibits flaws, resulting in internally inconsistent answers.
	TS5	Q9: The LLM responds rapidly and can efficiently support real-time AIT learning needs (e.g., instant QA during experiments).
	TS6	Q10: When handling complex tasks such as agricultural big data analysis, the LLM often lags or produces incomplete answers due to insufficient computing power.
	TS7	Q11: The LLM can adapt to the needs of different AIT learning scenarios (e.g., the differentiated demands of foundational learning versus in-depth research).
	TS8	Q12: In hands-on AIT scenarios (e.g., intelligent equipment commissioning), the guidance solutions output by the LLM lack on-site adaptability.
	TS9	Q13: I cross-validate the AIT content output by the LLM (e.g., against professional textbooks and the literature).
Information Processing Capability (IP)	IP1	Q14: I directly adopt the AIT content output by the LLM without further verification of its authenticity.
	IP2	Q15: I can integrate the scattered knowledge points provided by the LLM into a systematic knowledge framework.
	IP3	Q16: The fragmented information output by the LLM has confused my overall understanding of the AIT knowledge system.
	IP4	Q17: I filter the information output by the LLM according to my learning objectives, focusing on core knowledge points.
	IP5	Q18: The massive volume of information output by the LLM is difficult for me to filter, increasing the cognitive burden of AIT learning.
	IP6	Q19: I optimize and adjust the AIT solutions output by the LLM by drawing on my own disciplinary knowledge.
	IP7	Q20: I directly copy the AIT solutions output by the LLM without personalized optimization.
Dependence-Regulation Capability (DR)	DR1	Q21: For basic AIT tasks (e.g., memorizing core concepts, simple data organization), I prioritize completing them independently without relying on the LLM.
	DR2	Q22: When handling complex AIT tasks (e.g., multivariate analysis of agricultural big data, cross-domain application design), I use the LLM to help organize my thinking but independently optimize the solution (e.g., adjusting experimental parameters, verifying the logic).
	DR3	Q23: If the AIT-related content output by the LLM (e.g., experimental designs, troubleshooting plans) does not fit my research context, I reduce my reliance on it and instead explore solutions independently.
	DR4	Q24: I flexibly control the depth of LLM use according to my AIT learning objectives (e.g., relying on it less when consolidating knowledge, and consulting it moderately when pressed for time).
Knowledge Mastery (KM)	KM1	Q25: The LLM helps me quickly master the core knowledge points of AIT.
	KM2	Q26: Relying on the LLM to acquire knowledge has resulted in insufficient depth in my memorization and understanding of core AIT concepts.
	KM3	Q27: The LLM helps me organize fragmented information into a systematic knowledge framework.
	KM4	Q31: Relying on the LLM for data analysis has left me with an incomplete understanding of the principles underlying analytical methods (e.g., the logic of machine learning algorithms).
AIT Application Capability (AC)	AC1	Q29: Over-reliance on the LLM's experimental plans has diminished my innovative awareness in independently designing AIT experiments.
	AC2	Q30: LLM assistance has improved my agricultural big data analysis skills (e.g., data cleaning, modeling and analysis, visualization).
	AC3	Q28: With the aid of the LLM, my AIT experimental design capability has improved significantly.
	AC4	Q32: The LLM has helped me improve my AIT problem-solving capability (e.g., system troubleshooting, solution optimization).
	AC5	Q33: Relying on the LLM to solve problems has reduced my ability to independently diagnose complex AIT problems.
	AC6	Q34: When faced with AIT content output by the LLM, I proactively question its logical rigor and feasibility.
	AC7	Q35: I fully accept the AIT conclusions output by the LLM without engaging in independent critical thinking.
	AC8	Q36: The diverse perspectives provided by the LLM have stimulated my critical viewpoint in AIT research.
	AC9	Q37: The LLM's one-dimensional answers have constrained my multi-perspective thinking on AIT problems.
	AC10	Q38: Drawing on the LLM's capacity for cross-domain knowledge integration, I am able to propose innovative research ideas in the AIT field.
	AC11	Q39: The LLM's standardized outputs have made my AIT solution designs increasingly homogeneous and lacking in innovation.
	AC12	Q40: The LLM helps me break through fixed thinking patterns and generate new ideas in cross-domain AIT applications (e.g., AI + equipment).
	AC13	Q41: Over-reliance on the LLM's creative outputs has reduced the vibrancy of my own innovative thinking.

factor analysis, testing the goodness of fit and convergent validity of the measurement model.

3. A structural equation model was constructed to analyze the path relationships among the latent variables and to test the research hypotheses.

4. Based on the analytical results, the model was revised and optimized to reveal the mechanism underlying the formation of digital-intelligent learning competence among students majoring in smart agriculture.

4 Results and Analysis

4.1 Reliability Testing

In statistics, hypothesis testing must satisfy the two fundamental quality criteria of reliability and validity; that is, it must pass reliability and validity testing [29]. To assess the quality of the designed questionnaire—whether the items were reasonably constructed, the quality of the sample data, whether respondents completed the questionnaire conscientiously, and whether the resulting data could be used for subsequent structural equation modeling analysis—the sample data were first examined to determine whether they could pass reliability and validity tests. Reliability and validity testing essentially serve as a threshold check on the preceding questionnaire design and data: only after passing these tests can the analysis proceed to the next stage; without this prerequisite, the final analytical results would be of limited significance.

Reliability primarily refers to the dependability, consistency, and stability of measurement results. The internal consistency coefficient—Cronbach's alpha—was adopted as the measure of reliability. This coefficient ranges from 0 to 1, with higher values indicating greater reliability. It is generally held that a coefficient below 0.6 indicates insufficient internal consistency of the scale, whereas a coefficient of 0.7 or above indicates good questionnaire reliability. In this study, SPSS 26 was used to conduct reliability testing on the 37 scale items in the questionnaire; the non-scale items (i.e., the background information section) did not require analysis. The results are presented in Table 2.

Table 2. Reliability test of the overall scale.

Cronbach's α coefficient	Number of items
0.941	37

As shown in Table 2, the Cronbach's alpha coefficient for the entire questionnaire was 0.941, well above 0.7, indicating excellent overall reliability. Reliability testing was then conducted for each subscale, with the results presented in Table 3.

As shown in Table 3, the Cronbach's alpha coefficients for all latent variables in this study exceeded 0.7, except for the "information processing capability" dimension. This dimension was therefore extracted for separate testing, retaining only three items—IP1, IP3, and IP7—with the results presented in Table 4.

As shown in the table above, after retaining the items IP1, IP3, and IP7, the Cronbach's alpha coefficient for this subscale increased from 0.689 to 0.745, thereby improving its overall reliability. At this point, the Cronbach's alpha coefficients for all latent variables exceeded 0.7, indicating that all subscales were well-designed, with good reliability and high internal consistency, meeting the requirements and passing the reliability test.

4.2 Validity Testing

Validity refers to the degree to which a measurement instrument accurately measures the target trait—that is, the degree of congruence between the measurement results and the content under examination; the higher the congruence, the better the validity. Construct validity reflects the degree of consistency between questionnaire results and the theoretical expectations of the research hypotheses. Validity analysis comprises exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

4.2.1 Exploratory Factor Analysis (EFA)

At this stage, exploratory factor analysis was conducted using SPSS. EFA is a dimensionality-reduction procedure that groups all items into distinct dimensions. Commonly used measurement indices include the KMO value, Bartlett's test of sphericity, cumulative variance explained, and factor loadings. The evaluation criteria are as follows: KMO greater than 0.6; a significant Bartlett's test of sphericity ($p < 0.05$); cumulative variance explained by the factors greater than 60%; and, simultaneously, "the item-factor correspondence is consistent with disciplinary knowledge" and "all item loadings on their factors exceed 0.4"—satisfying these conditions meets the requirements of the validity test.

Prior to the exploratory factor analysis, the data were examined to confirm that the sample met

Table 3. Reliability tests of the subscales.

Dependent variable	Independent variable	Number of items	Cronbach's α coefficient
Influence of large language models on agricultural information technology learning	LLM technological suitability (TS)	9	0.847
	Information processing capability (IP)	7	0.689
	Dependence-regulation capability (DR)	4	0.851
	Knowledge mastery (KM)	4	0.758
	AIT application capability (AC)	13	0.864

Table 4. Revised data for the "information processing capability" dimension.

Variable	Cronbach's α coefficient	Number of items
Information processing capability	0.745	3

the requirements for factor analysis. Initially, the factors were extracted with five factors; the results revealed cross-loadings for some items. Analysis identified two principal causes: first, overlap between items measuring "LLM technological suitability" and "dependence-regulation capability," resulting in unclear factor differentiation; and second, ambiguous contextual definition of "complex AIT tasks" in some items, which caused differences in respondents' interpretations and compromised the independence of factor loadings. To optimize the analysis, items were screened according to the criteria of "each item loading on a single factor only" and "loading coefficient ≥ 0.4," resulting in the retention of 17 valid items. The re-test results, shown in Table 5, indicate a KMO value of 0.782 and a significance level of 0.000 for Bartlett's test of sphericity, demonstrating that the data were suitable for validity analysis and could proceed to dimensionality-reduction analysis.

Table 5. KMO and Bartlett's test of sphericity.

Test	Item	Value
Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy	–	0.782
Bartlett's test of sphericity	Approximate chi-square	1382.641
	Degrees of freedom (df)	153
	Significance (Sig.)	0.000

Regarding cumulative variance explained and factor loadings: factors were extracted via principal component analysis with the number of factors fixed at five. The final results show that the cumulative variance explained reached 75.069%, indicating that the extracted common factors adequately captured the information contained in the original data and that the scale possessed good construct validity.

4.2.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis was conducted in AMOS to further examine the construct validity, convergent validity, and overall fit of the measurement model. CFA primarily evaluates the degree of fit between the measurement model and the sample data through model fit indices, thereby assessing the soundness of the scale structure.

To assess overall model fit, commonly used fit indices—including CMIN/DF, RMSEA, GFI, AGFI, CFI, TLI, and NFI—were selected to evaluate the measurement model.

Table 6. Overall fit indices.

Fit index	Test result
χ^2	242.287
CMIN/DF	2.447
RMSEA	0.094
NFI	0.769
IFI	0.849
TLI	0.784
CFI	0.843

The AMOS output, presented in Table 6, shows that the overall model fit indices were generally satisfactory. Specifically, the model chi-square value was $\chi^2 = 242.287$, and the chi-square-to-degrees-of-freedom ratio was CMIN/DF $= 2.447$ (< 3), indicating good overall model fit. RMSEA $= 0.094$, slightly above the ideal threshold of 0.08; however, considering the sample size of 166 and the relative complexity of the model—which contains multiple latent variables and their measurement indicators—this result remains within an acceptable range. Regarding incremental fit indices, NFI $= 0.769$, IFI $= 0.849$, TLI $= 0.784$,

Table 7. Standardized factor loadings for each latent variable dimension.

Latent variable dimension	Item	Standardized factor loading
LLM technological suitability (TS)	TS5	0.817
	TS7	0.844
	TS9	0.730
	TS13	0.602
Dependence-regulation capability (DR)	DR21	0.565
	DR22	0.899
	DR24	0.913
Information processing capability (IP)	IP14	0.721
	IP16	0.706
	IP20	0.662
Knowledge mastery (KM)	KM27	0.974
	KM31	0.678
	KM26	0.826
AIT application capability (AC)	AC40	0.826
	AC34	0.588
	AC32	0.777

and CFI = 0.843. Although NFI and TLI fall slightly below the conventional threshold of 0.90, this is a known consequence of small-to-moderate sample sizes (n = 166), as NFI is particularly sensitive to sample size and tends to underestimate fit in smaller samples [29]. The CFI and IFI values, which are less sensitive to sample size, both approach or exceed 0.85, providing more reliable evidence of adequate fit. Moreover, the CMIN/DF of 2.447 (< 3) and RMSEA of 0.094 (within the acceptable range for models of this complexity) collectively suggest that the model fit is acceptable given the study's constraints. Regarding factor loadings, the standardized loadings of the observed variables on their corresponding latent variables were all statistically significant, with most exceeding 0.6, indicating that the indicators adequately reflected their respective latent variables and demonstrating good convergent validity [30]. The detailed results are presented in Table 7. Overall, the loadings of all measurement indicators on their respective latent variables were statistically significant and reasonably distributed, indicating good internal consistency within each dimension and demonstrating that the measurement model possessed good construct validity and convergent validity.

In summary, the confirmatory factor analysis results indicate that the measurement model constructed in this study exhibited good overall fit, the measurement indicators of each latent variable possessed strong explanatory power, and the scale structure was sound, thereby establishing a reliable measurement foundation for the subsequent structural equation modeling analysis and hypothesis testing.

4.3 Structural Equation Modeling Analysis and Hypothesis Testing

To test the soundness of the research hypotheses, the constructed structural equation model was empirically analyzed using AMOS. To optimize the model, this study removed all correlational paths by introducing residual terms for each exogenous variable; following the model modification suggestions in AMOS, items of limited significance were deleted, and correlations were specified among the five latent variables, thereby completing the model revision and adjustment. The final model estimation results, expressed as standardized coefficients, are shown in Figure 2. The structural model also exhibited acceptable fit, with results comparable to those of the measurement model (see Table 6).

The overall model fit results show $\chi^2 = 242.287$, $df = 99$, $p < 0.001$, with a chi-square to degrees-of-freedom ratio (CMIN/DF) = 2.447, which is below 3, indicating good overall model fit. RMSEA = 0.094, slightly above the ideal threshold of 0.08 but still within an acceptable range. Regarding incremental fit indices, NFI = 0.769, IFI = 0.849, TLI = 0.784, and CFI = 0.843, all of which are markedly superior to the independence model,

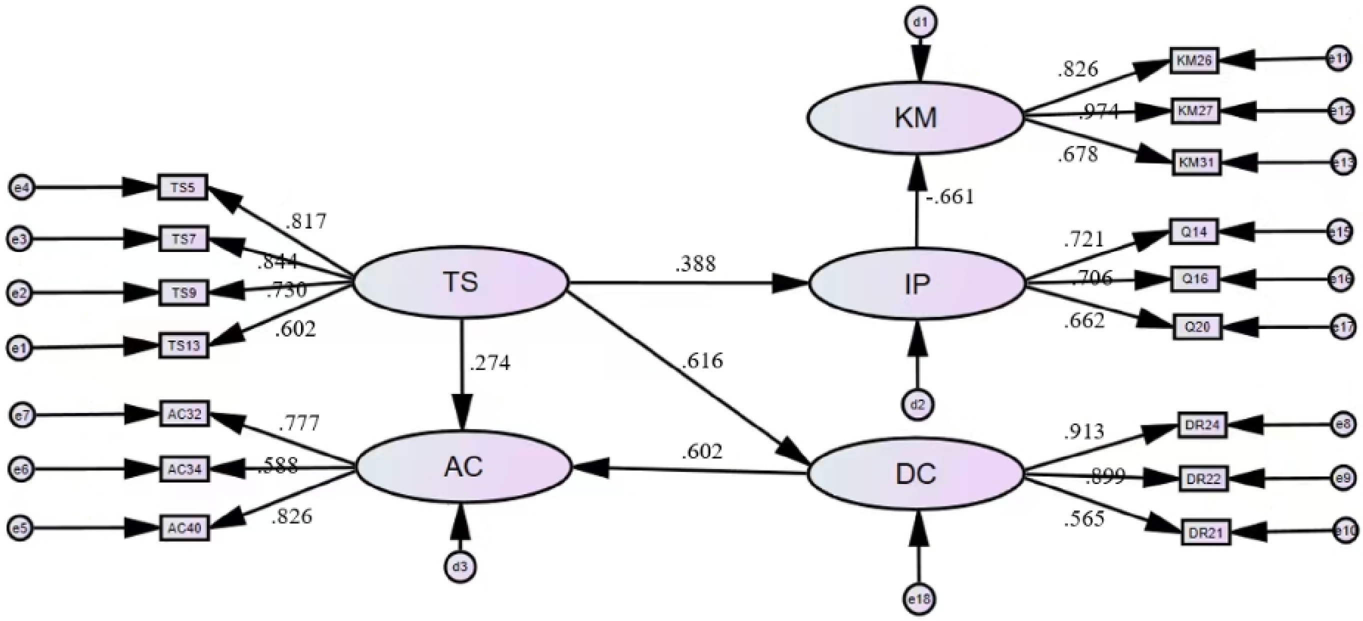

Figure 2. Model estimation results under standardized coefficients.

Table 8. Standardized regression paths of the hypothesized model.

Regression path	Standardized path coefficient (β)	p-value	Result
LLM technological suitability → Information processing	0.388	<0.01	Significant positive effect
LLM technological suitability → Dependence-regulation capability	0.614	***	Significant positive effect
Information processing → Knowledge mastery	−0.661	***	Significant negative effect
Dependence-regulation capability → AI application capability	0.602	***	Significant positive effect
LLM technological suitability → AI application capability	0.274	<0.05	Significant positive effect

Note: *** denotes statistical significance at $p < 0.001$.

indicating that the model fit well and that the overall structure was acceptable.

On this basis, the model's path relationships were tested. The standardized regression paths of the hypothesized model are shown in Table 8.

As shown in Table 8, LLM technological suitability had a significant positive effect on information processing capability ($\beta = 0.388, p < 0.01$), indicating that higher LLM technological suitability is associated with stronger information processing capability. LLM technological suitability also had a significant positive effect on dependence-regulation capability ($\beta = 0.614, p < 0.001$), indicating that the degree of LLM suitability in the learning process can effectively enhance learners' dependence-regulation capability. Meanwhile, information processing capability exerted a significant negative effect on knowledge mastery ($\beta = -0.661, p < 0.001$), suggesting that increased information processing load may inhibit improvements in knowledge mastery. Dependence-regulation capability had a significant positive effect on AIT application capability ($\beta = 0.602, p < 0.001$), indicating that the higher a learner's level of dependence regulation, the stronger their AIT application capability. In addition, LLM technological suitability also exhibited a significant positive effect on AIT application capability ($\beta = 0.274, p < 0.05$), indicating that technological suitability can directly promote the development of AIT application capability. From the measurement model results, the standardized factor loadings for all observed variables exceeded 0.56, with the vast majority exceeding 0.70, indicating good convergent validity. Taken together, the research hypotheses proposed in this study were supported by the empirical data. Accordingly, the hypothesis-testing results from the above data analysis are presented in Table 9.

Table 9. Hypothesis testing results.

Research hypothesis	Hypothesis testing result
H1: LLM technological suitability positively affects AIT application capability.	Supported
H2: LLM technological suitability positively affects dependence-regulation capability.	Supported
H3: LLM technological suitability positively affects information processing capability.	Supported
H4: Information processing capability has a negative effect on knowledge mastery.	Supported
H5: Dependence-regulation capability positively affects AIT application capability.	Supported

The empirical analysis revealed that LLM technological suitability not only directly enhances AIT application capability but also exerts an indirect promoting effect by strengthening learners' information processing capability and dependence-regulation capability, demonstrating that technological suitability plays a pivotal role in the formation of AIT application capability. Further analysis showed a significant negative relationship between information processing capability and knowledge mastery, suggesting that attention should be paid in the learning process to the cognitive load or biases that excessive information processing may induce, which can adversely affect knowledge mastery. Overall, the empirical results of this study largely support the existing research hypotheses and further reveal the pathways and internal mechanisms through which LLM technological suitability influences AIT application capability. These findings provide a useful reference for theoretical research and practical applications of LLM technology in educational settings and offer implications for optimizing instructional design and learning support strategies.

5 Strategic Recommendations

The empirical results of the structural equation modeling reveal that large language models do not influence students' learning competence through the pathway of "merely improving technical efficiency"; rather, they exert complex effects on knowledge mastery and competence development by altering information processing patterns and dependence-regulation mechanisms. Therefore, when guiding students in the use of large language models, universities should adhere to the basic principles of "embracing technology, applying it rationally, and orienting toward competence," thereby promoting the transformation of artificial intelligence from a "tool of dependence" into a "tool of empowerment."

5.1 Proactively Embracing Large Language Models to Unleash Their Learning-Enabling Potential

In technology-intensive disciplinary learning contexts, such as smart agriculture, large language models have become indispensable tools for learning. The research results indicate that the higher the technological suitability of large language models, the more pronounced their promoting effects on knowledge mastery and on learners' capacity to regulate their dependence on these models. That suggests that when a model exhibits high suitability in comprehending disciplinary knowledge, analyzing problems, and matching task scenarios, it is better positioned to fulfill its learning-support function. Accordingly, in instructional practice, universities should not simply avoid or restrict the use of LLMs on account of their potential "disabling" effects; instead, they should adopt an open attitude in guiding students to use large language models judiciously—applying them to auxiliary tasks such as knowledge organization, idea expansion, and solution generation—while preventing them from substituting for learners' own thinking, judgment, and decision-making processes.

5.2 Strengthening Awareness of Rational Use and Reasonably Delineating the Application Boundaries of Large Language Models

The empirical results show that excessive reliance on large language models may weaken students' information-processing capabilities, thereby affecting their degree of knowledge mastery. That demonstrates the importance of reasonably delineating the boundaries of artificial intelligence use in learning. In instructional practice, the use of large language models can be differentially guided according to the type of learning task: at stages such as learning foundational concepts and understanding principles, students should be encouraged to complete tasks primarily through autonomous learning, treating the large language model as a reference tool rather than the primary decision-making agent; in the analysis of complex problems, large language models may be moderately employed to provide ideational support. By differentiating among learning task types, students can be guided to form rational, controllable habits of using artificial intelligence.

5.3 Emphasizing Credibility Analysis and Reprocessing of LLM-Generated Content

Although content generated by large language models is often fluent, problems such as outdated information and logical inconsistencies persist. The results of this study indicate that learners' information-processing capabilities play a critical role in AI-assisted learning. Universities should therefore deliberately strengthen students' capacity to evaluate, verify, and reprocess LLM-generated content during instruction. Specifically, students can be guided to conduct credibility analyses of model outputs through approaches such as cross-comparing multiple information sources and consulting authoritative literature, thereby avoiding indiscriminate direct use. Only content that has undergone learners' active processing and reflection can be genuinely transformed into stable knowledge structures.

5.4 Upholding the Learning Decision-Making Principle of "Human-Machine Collaboration with Human Primacy"

From the perspective of cultivating learning competence, the core role of artificial intelligence lies in assistance rather than substitution. This study demonstrates that moderate reliance on large language models and robust regulatory capacity significantly shape the development of learning competence, indicating that learners' maintenance of their primary role in "human-machine collaboration" is key to realizing AI-enabled learning. Universities should therefore emphasize, in instructional design and evaluation mechanisms, the principle that "final judgments are made by the learners themselves," guiding students to make decisions by integrating their own disciplinary knowledge and judgment with the suggestions obtained from large language models, thereby continuously strengthening their analytical and decision-making capabilities throughout the process of using artificial intelligence.

6 Conclusion

The impact of large language models on university students' data-driven and intelligent learning capabilities is not a simple linear enhancement but rather a dual mechanism characterized by concurrent enablement and impediment. Technological suitability serves merely as a prerequisite for such enablement; whether it translates into tangible learning outcomes depends critically on two intrinsic capacities of the learner: first, information processing ability—the capacity to internalize model outputs into one's own knowledge structures; and second, dependency regulation—the ability to prevent over-reliance on AI that might undermine independent cognition. That implies that among students employing the same large language models, only those engaging in deep cognitive processing while maintaining rational critical reflection can genuinely benefit; otherwise, such technology risks attenuating the depth of learning. Consequently, talent development in higher education should not indiscriminately promote AI tools; instead, it should prioritize the internalization of students' digital-intelligent literacy. The pedagogical focus should pivot from technological empowerment to human-machine collaborative guidance, and from content acquisition to innovation-driven practice and problem-solving informed by decision support systems. This research not only elucidates the mechanisms underlying the development of data-driven and intelligent learning competencies but also provides higher education institutions with actionable empirical evidence for governing artificial intelligence education.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

Wenlong Yi served as an Editor-in-Chief of the *Journal of Digital Intelligence in Education* at the time of manuscript submission. To ensure the integrity of the peer-review process, Wenlong Yi was not involved in the editorial handling, peer review, or decision-making process for this manuscript, which was handled independently by another editor. The remaining authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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