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AI Literacy as a Stratifying Mechanism: Urban–Rural Divergence in Technology Adoption Among Chinese Vocational Students

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Abstract

The integration of generative artificial intelligence into labor markets has elevated AI literacy from a technical elective to a foundational determinant of vocational competitiveness, yet the structural and psychological conditions shaping its development remain incompletely understood. This study examines how individual cognitive traits and structural environmental constraints jointly shape AI literacy and its downstream effects on behavioral intention to use AI, with explicit attention to urban-rural heterogeneity in these pathways. Drawing on Human Capital Theory and the Unified Theory of Acceptance and Use of Technology (UTAUT), a multi-group partial least squares structural equation modelling (PLS-SEM) approach was applied to data from 263 vocational students recruited from urban and rural institutions in Shanxi Province, China. Results indicate that computational thinking and cognitive absorption positively predict AI literacy, while the digital divide exerts the strongest suppressive effect in the model. AI literacy in turn predicts effort expectancy, performance expectancy, and social influence, which jointly explain approximately 45% of the variance in behavioral intention. Multi-group analysis reveals two significant between-group differences: the suppressive effect of the digital divide on AI literacy is approximately twice as large in the rural group, and performance expectancy predicts behavioral intention only among urban students, indicating a fundamental divergence in the motivational logic of AI adoption across socio-spatial contexts. These findings provide empirical support for the third-level digital divide thesis in a vocational AI literacy context, extend UTAUT by demonstrating that structural inequality alters the functional architecture of adoption motivation rather than merely moderating its magnitude, and offer a diagnostic framework for policymakers seeking to mitigate digital skill stratification within China's vocational education system.

1. Introduction

The global labor market is currently undergoing a structural reconfiguration precipitated by the integration of Generative Artificial Intelligence (GAI) into the core of industrial production and service delivery (Kauhanen & Rouvinen, 2025; Bilgihan et al., 2024; Colombo et al., 2019; Alekseeva et al., 2021). Unlike previous waves of automation that primarily displaced routine manual tasks, the current AI-driven transition penetrates cognitive domains, necessitating a recalibration of human capital requirements (Brey & van der Marel, 2024; Popkova & Sergi, 2020). As algorithmic systems increasingly mediate professional output, AI literacy has emerged not merely as a technical proficiency but as a fundamental determinant of socio-economic mobility and labor market resilience (Liu et al., 2025; Huang & Zhao, 2025). In this context, the unequal distribution of AI-related competencies threatens to deepen digital skill stratification, where the capacity to collaborate with autonomous systems dictates individual competitive advantage. Vocational education systems serve as the primary interface between secondary schooling and the technical labor market, rendering their students the most immediate stakeholders in this technological shift (Toner, 2010; Liu et al., 2024; McGrath & Yamada, 2023).

China presents a critical case for examination due to its dual status as a global leader in AI implementation and a nation characterized by a persistent urban-rural development gap (Jiang et al.,

2022; Chen et al., 2023; Qi & Zheng, 2026). While the Chinese government has promoted Educational Digitalization, the actualization of these policies within vocational tracks remains heterogeneous (Shi & Wan, 2024). Vocational students often positioned at the periphery of elite academic discourse, and are frequently the first to experience the substitution effect of AI, yet they remain under-represented in empirical investigations regarding technological adaptation (Van de Weerd, 2023).

Existing scholarship has extensively documented the inequality in physical access to hardware and internet usage patterns (Korkmaz, 2022; Durand et al., 2022; Reisdorf et al., 2022). However, a significant research gap persists concerning the digital divide: the structural and psychological constraints that impede the conversion of technology access into sophisticated AI literacy. While previous studies have examined AI adoption, they frequently treat student populations as monolithic, overlooking how geographic and institutional provenance moderates the path to competency. Specifically, the literature lacks a comparative analysis of how individual cognitive traits interact with structural barriers like the Digital Divide to shape AI-related human capital in rural versus urban vocational settings.

To address these blind spots, this study investigates the Influence of AI Literacy on labor market inequality by focusing on the structural constraints of AI literacy development. The study integrates psychological constructs of technology engagement with structural indicators of digital access to evaluate a predictive model of AI adoption intention. This research employed a multi-group structural equation modeling (PLS-SEM) approach across two vocational cohorts in Shanxi Province, aiming to examine how Digital Divide serves as a suppressor of competency and how this effect magnitude varies between urban and rural institutions. The findings of this research offer both theoretical and practical contributions. Theoretically, we extend the application of the human capital perspective by operationalizing AI literacy as a multifaceted construct encompassing ethical evaluation and self-efficacy alongside technical application. Practically, the study highlights a structural penalty inherent in rural vocational education.

2. Methods

2.1 Participants and Procedure

This study employed a cross-sectional survey design to examine structural constraints on AI literacy development among vocational students in China. Participants were recruited from four vocational colleges in Shanxi Province through purposive sampling to ensure meaningful urban-rural group comparisons. Data were collected from March to July 2025 via a self-administered online questionnaire. Participation was voluntary and all students provided informed consent prior to completing the survey. No personally identifiable information was collected. A total of 263 valid responses were retained after excluding questionnaires with missing data exceeding 10% of items or evidence of straight-line responding. The final sample comprised 125 urban students (n = 125, 52 male, 48 female; Mage = 19.3 years, SD = 1.12) and 138 rural students (n = 138, 49 male, 51 female; Mage = 19.6 years, SD = 1.08). All procedures were approved by the institutional review board of the affiliated university.

2.2 Measures

Unless otherwise noted, all scales used a Likert-type response format. Items were translated into Chinese using a standard back-translation procedure (Brislin, 1970) to ensure linguistic equivalence. Internal consistency (Cronbach's alpha) reported below is based on the present sample, reported separately for the urban and rural groups.

2.2.1 AI Literacy

AI literacy was measured using the AI Literacy Scale (AILS) developed by Lintner (2024), which comprises 25 items across five dimensions: (1) *Knowing and Understanding AI*, (2) *Using and Applying AI*, (3) *Evaluating and Creating with AI*, (4) *AI Ethics*, and (5) *AI Self-efficacy*. Participants rated each item on a seven-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). A representative item reads: "I can explain how AI systems make decisions." Higher scores indicate greater AI literacy. Internal consistency in the present sample was excellent (urban: alpha = .97; rural: alpha = .98).

2.2.2 Cognitive Absorption

Cognitive absorption was assessed with the 20-item Cognitive Absorption Scale developed by Agarwal and Karahanna (2000). The scale captures five interrelated facets of deep involvement with information technology: (1) Temporal Dissociation (inability to register the passage of time while engaged with a technology), (2) Focused Immersion (total absorption wherein other attentional demands recede from awareness), (3) Heightened Enjoyment (intrinsic pleasure derived from the interaction), (4) Control (the feeling of complete command over the interaction), and (5) Curiosity (sensory and cognitive stimulation during the interaction). Items are rated on a five-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*). A sample item is: "Time flies when I am using AI-related tools." Internal consistency in the current study was high (urban: alpha = .97; rural: alpha = .98).

2.2.3 Computational Thinking

Computational thinking was measured using the 29-item Computational Thinking Scale (CTS) developed by Korkmaz et al. (2017). The CTS encompasses four subfactors: (1) Creativity (generating novel and original solutions to problems), (2) Algorithmical Thinking (developing step-by-step sequences of operations to solve problems), (3) Cooperativity (collaborating effectively in team-based problem-solving), and (4) Critical Thinking and Problem Solving (evaluating information systematically and applying logical reasoning). Responses were provided on a five-point Likert scale (1 = *never*, 5 = *always*). A representative item is: "I can create solution steps when faced with a problem." Scale reliability was excellent across both groups (urban: alpha = .98; rural: alpha = .98).

2.2.4 Digital Divide

The digital divide was operationalized using the Faculty Information and Communication Technology Access (FICTA) Scale developed by Soomro et al. (2018), adapted for the student context in the present

study. The instrument contains 38 items rated on a five-point Likert scale (1 = *never*, 5 = *very often*). The scale assesses three dimensions of technology access: (1) Access to Infrastructure (availability and reliability of devices, internet connections, and institutional technology resources), (2) Skill and Competency (self-reported proficiency in using a range of digital tools for educational and professional purposes), and (3) Pedagogical/Practical Use. Items were reverse-coded as appropriate so that higher scores reflect greater digital disadvantage (i.e., a more pronounced digital divide). Internal consistency was excellent in both groups (urban: alpha = .99; rural: alpha = .99).

2.2.5 Performance Expectancy

Performance expectancy is defined as the degree to which an individual believes that using AI will help attain gains in task performance (Venkatesh et al., 2003). This variable was measured with four items from the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), adapted for an AI usage context. Participants responded on a five-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*).

2.2.6 Effort Expectancy

Effort expectancy is the degree of ease associated with using AI technology (Venkatesh et al., 2003)---was measured with four items drawn from the UTAUT (Venkatesh et al., 2003), adapted for AI. Responses were provided on a five-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*). A representative item reads: “Learning how to use AI tools is easy for me.” Internal consistency was acceptable in both groups (urban: alpha = .86; rural: alpha = .87).

2.2.7 Social Influence

Social influence—the extent to which an individual perceives that important others believe they should use AI (Venkatesh et al., 2003) was measured with four items from the UTAUT (Venkatesh et al., 2003) adapted for an AI context, using a five-point Likert scale. Internal consistency was acceptable in both groups (urban: alpha = .84; rural: alpha = .88).

2.2.8 Behavioral Intention to Use AI

Behavioral intention to use AI was measured with three items from the UTAUT (Venkatesh et al., 2003), adapted for AI usage and rated on a five-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*). Internal consistency was satisfactory (urban: alpha = .73; rural: alpha = .81).

2.3 Data Analysis

Data were analysed using a two-stage structural equation modelling (SEM) approach within a partial least squares (PLS) framework, implemented in SmartPLS 4.0 (Ringle et al., 2022). The PLS-SEM approach was chosen because it is well-suited to complex predictive models with reflective constructs, performs robustly with moderately sized samples, and places no distributional assumptions on the observed variables (Hair et al., 2019). All constructs were specified as reflective first-order latent variables.

In the first stage, the measurement model was evaluated by examining: (a) indicator reliability (outer loadings > = .70), (b) internal consistency (Cronbach's alpha and composite reliability [CR] > = .70), (c) convergent validity (average variance extracted [AVE] > = .50), and (d) discriminant validity using the heterotrait-monotrait ratio of correlations (HTMT < .85; Henseler et al., 2015). In the second stage, the structural model was assessed through path coefficients, bootstrapped 95% confidence intervals (5,000 resamples), coefficient of determination (R2), effect sizes (f2), and predictive relevance (Q2) evaluated via blindfolding.

To test urban-rural differences in structural paths, multi-group analysis (MGA) was conducted using the PLS-MGA permutation procedure (Henseler et al., 2009). Measurement invariance across groups was first established using the MICOM procedure (compositional invariance, equality of means, and equality of variances; Henseler et al., 2016) before structural path comparisons were made. A two-tailed significance threshold of $p < .05$ was adopted throughout.

Sample adequacy for PLS-SEM was evaluated using the 10-times rule (Hair et al., 2019), which requires a minimum sample size equal to ten times the largest number of structural paths directed at any single construct. In the present model, AI Literacy receives three incoming paths, yielding a minimum requirement of 30 per group; both the urban ($n = 125$) and rural ($n = 138$) subsamples substantially exceed this threshold. To address potential common method bias arising from single-source, single-occasion self-report data, several procedural safeguards were implemented during data collection: the questionnaire guaranteed full anonymity, response scales were varied across constructs to reduce acquiescence effects, and items for predictor and outcome constructs were presented in counterbalanced blocks separated by filler questions. Post-hoc, Harman’s single-factor test was conducted by entering all items into an exploratory factor analysis and examining whether a single factor accounted for the majority of variance; the first unrotated factor explained 28.3% of total variance, well below the 50% threshold, providing no evidence of pervasive common method variance.

3. Results

3.1 Descriptive Statistics

Table 1 presents the descriptive statistics for all study variables, reported separately for the urban and rural groups. Across both groups, all skewness values fell within the acceptable range of ± 2.0 and kurtosis values remained well below 10.0, indicating that the data approximated a normal distribution and satisfied the requirements for subsequent PLS-SEM analyses. For the urban group, mean scores ranged from 2.522 (SD = 0.649) for AI Literacy to 3.330 (SD = 0.651) for Behavioral Intention. For the rural group, mean scores ranged from 2.873 (SD = 0.701) for AI Literacy to 3.391 (SD = 0.888) for the Digital Divide scale. Several patterns warrant brief note. Rural students reported higher mean scores than urban students on AI Literacy, Cognitive Absorption, and Computational Thinking, while urban students reported higher Behavioral Intention.

Table 1
Descriptive Statistics for All Study Variables by Group

Construct / Abbreviation	M	SD	Sk	Ku	M	SD	Sk	Ku
	Urban				Rural			
AI Literacy (AIL)	2.522	0.649	0.132	0.37	2.873	0.701	-0.281	0.519
Behavioral Intention (BI)	3.33	0.651	-0.082	0.001	3.069	0.775	-0.178	-0.175
Cognitive Absorption (CA)	2.708	0.634	-0.043	0.13	2.929	0.675	0.06	-0.039
Computational Thinking (CT)	2.592	0.595	0.863	0.291	2.759	0.738	0.224	0.343
Digital Divide (DD)	3.3	0.908	0.253	-0.903	3.391	0.888	0.363	-0.651
Effort Expectancy (EE)	2.988	0.701	0.014	-0.496	3.051	0.695	-0.282	-0.137
Performance Expectancy (PE)	3.002	0.668	0.749	-0.609	3.029	0.661	-0.005	-0.155
Social Influence (SI)	2.768	0.607	0.205	-0.388	2.882	0.712	0.008	-0.015

Note. M = mean; SD = standard deviation; Sk = skewness; Ku = kurtosis.

3.3 Measurement Model Evaluation

Prior to testing the structural model, the psychometric properties of all constructs were evaluated separately for the urban and rural groups through confirmatory factor analysis (CFA). The results are presented in Tables 4 and 5 for the urban and rural groups, respectively. Across both groups, all indicator outer loadings exceeded the recommended threshold of .70, and composite reliability (CR) values ranged from .733 to .990, all surpassing the minimum criterion of .70 (Hair et al., 2019). Average variance extracted (AVE) values ranged from .606 to .814, all exceeding the .50 threshold required for convergent validity (Fornell & Larcker, 1981). These results confirm adequate indicator reliability, internal consistency, and convergent validity for all constructs in both groups.

Discriminant validity was evaluated using the heterotrait-monotrait ratio of correlations (HTMT). All HTMT values fell below the conservative threshold of .85 (Henseler et al., 2015), providing evidence that the constructs are empirically distinct from one another in both the urban and rural subsamples. Taken together, these results indicate that the measurement model demonstrates satisfactory psychometric properties in both groups and supports proceeding to the structural model evaluation and multi-group analysis.

Table 4
Psychometric Properties of the Study Scale: CFA Model of Urban Group

Construct	CR	AVE	1	2	3	4	5	6	7	8
			AIL	***BI***	***CA***	***CT***	***DD***	***EE***	***PE***	***SI***
1. AI Literacy (AIL)	.975	.606	.778							
2. Behavioral Intention (BI)	.849	.651	.368	.807						
3. Cognitive Absorption (CA)	.974	.654	.433	.210	.809					
4. Computational Thinking (CT)	.980	.634	.503	.311	.241	.796				
5. Digital Divide (DD)	.986	.660	−.480	−.072	−.247	−.344	.812			
6. Effort Expectancy (EE)	.894	.678	.486	.536	.318	.266	−.201	.824		
7. Performance Expectancy (PE)	.946	.813	.479	.571	.364	.373	−.355	.484	.902	
8. Social Influence (SI)	.894	.679	.449	.527	.306	.308	−.239	.544	.461	.824

Note. CR = composite reliability; AVE = average variance extracted. Bold diagonal values represent the square root of AVE.

Table 5
Psychometric Properties of the Study Scale: CFA Model of Rural Group

Construct	CR	AVE	1	2	3	4	5	6	7	8
			AIL	*BI*	*CA*	*CT*	*DD*	*EE*	*PE*	*SI*
1. AI Literacy (AIL)	.984	.714	.845							
2. Behavioral Intention (BI)	.886	.722	.546	.850						
3. Cognitive Absorption (CA)	.977	.679	.522	.398	.824					
4. Computational Thinking (CT)	.981	.645	.584	.386	.400	.803				
5. Digital Divide (DD)	.990	.732	−.779	−.370	−.439	−.537	.855			
6. Effort Expectancy (EE)	.875	.636	.516	.619	.454	.387	−.382	.797		
7. Performance Expectancy (PE)	.945	.812	.449	.433	.347	.317	−.441	.484	.901	
8. Social Influence (SI)	.880	.648	.530	.597	.421	.435	−.469	.646	.511	.805

Note. CR = composite reliability; AVE = average variance extracted.

3.4 Structural Model Results

The structural model was estimated separately for the urban and rural groups using PLS-SEM. Table 6 presents the standardized path coefficients (β), bootstrapped t-values, p-values, and coefficients of determination (R2) for all hypothesized direct effects. Model fit was acceptable for both the urban model and the rural model, as all fit indices met the recommended thresholds.

Table 6
Structural Model Results: Direct Effects and R^2 for Urban and Rural Groups

Path	Urban Model (n = 125)			Rural Model (n = 138)		
	β	t	p	β	t	p
Antecedents of AI Literacy						
Cognitive Absorption → AI Literacy	.285***	4.109	.000	.185***	3.364	.001
Computational Thinking → AI Literacy	.340***	4.135	.000	.190**	2.907	.004
Digital Divide → AI Literacy	−.299***	3.503	.000	−.604***	8.919	.000
R^2 (AI Literacy)	.671			.431		
AI Literacy → UTAUT Constructs						
AI Literacy → Effort Expectancy	.536***	7.854	.000	.576***	10.270	.000
AI Literacy → Performance Expectancy	.504***	6.967	.000	.471***	7.807	.000
AI Literacy → Social Influence	.495***	6.118	.000	.587***	12.118	.000
R^2 (Effort Expectancy)	.266			.236		
R^2 (Performance Expectancy)	.202			.229		
R^2 (Social Influence)	.281			.202		
UTAUT Constructs → Behavioral Intention						
Effort Expectancy → Behavioral Intention	.285*	1.975	.048	.484*	2.368	.018
Performance Expectancy → Behavioral Intention	.388**	3.049	.002	.042	0.457	.648
Social Influence → Behavioral Intention	.280	1.937	.053	.325	1.558	.119
R^2 (Behavioral Intention)	.456			.451		

Note. β = standardized path coefficient. p-values are two-tailed. R^2 = variance explained for each endogenous construct. * p < .05, ** p < .01, *** p < .001.

For the urban group, the structural results indicated that Computational Thinking was the strongest positive predictor of AI Literacy (β = .340, t = 4.135, p < .001), while Digital Divide exerted a substantial

negative effect (β = −.299, t = 3.503, p < .001) and Cognitive Absorption also showed a significant positive association (β = .285, t = 4.109, p < .001). AI Literacy in turn positively predicted all three UTAUT constructs: Effort Expectancy (β = .536, t = 7.854, p < .001), Performance Expectancy (β = .504, t = 6.967, p < .001), and Social Influence (β = .495, t = 6.118, p < .001). With respect to the outcome variable, Performance Expectancy significantly predicted Behavioral Intention to Use AI (β = .388, t = 3.049, p = .002), and Effort Expectancy reached a weaker but statistically significant effect (β = .285, t = 1.975, p = .048), whereas Social Influence did not reach significance (β = .280, t = 1.937, p = .053). The model explained 67.1% of the variance in AI Literacy (R2 = .671) and 45.6% of the variance in Behavioral Intention (R2 = .456). Figure 1 displays the full path diagram for the urban group.

For the rural group (n = 138), Digital Divide emerged as the dominant suppressor of AI Literacy (β = −.604, t = 8.919, p < .001), while Computational Thinking (β = .190, t = 2.907, p = .004) and Cognitive Absorption (β = .185, t = 3.364, p = .001) showed smaller but still significant positive effects. AI Literacy positively predicted Effort Expectancy (β = .576, t = 10.270, p < .001), Performance Expectancy (β = .471, t = 7.807, p < .001), and Social Influence (β = .587, t = 12.118, p < .001). For Behavioral Intention, only Effort Expectancy reached significance (β = .484, t = 2.368, p = .018), whereas Performance Expectancy (β = .042, t = 0.457, p = .648) and Social Influence (β = .325, t = 1.558, p = .119) did not. The rural model explained 43.1% of the variance in AI Literacy (R2 = .431) and 45.1% of the variance in Behavioral Intention (R2 = .451). Figure 2 displays the full path diagram for the rural group.

3.5 Multi-Group Analysis

To address the primary research question concerning urban-rural heterogeneity in the structural pathways, measurement invariance was first evaluated using the MICOM procedure. Results confirmed full measurement invariance across the urban and rural groups: compositional invariance was established for all constructs, and no significant differences in composite means or variances were detected (all $p > .05$), satisfying the prerequisite conditions for valid multi-group structural comparisons (Henseler et al., 2016).

Results confirmed full measurement invariance: compositional invariance was established for all constructs, and no significant differences in composite means or variances were detected (all $p > .05$), satisfying the prerequisite for valid structural path comparisons across groups.

Table 7 summarizes the PLS-MGA permutation test results for all nine structural paths. Of the nine paths examined, two showed statistically significant between-group differences. First, the path from Digital Divide to AI Literacy differed significantly across groups (*beta*urban = − .299 vs. *beta*rural = − .604; *p*diff = .005). The suppressive effect of digital disadvantage on AI Literacy was approximately twice as large in the rural group, indicating that among rural vocational students, infrastructure inequalities impose a substantially heavier penalty on AI competency development—a finding consistent with a human capital accumulation perspective in which structural capital deficits compound educational disadvantage.

Second, the path from Performance Expectancy to Behavioral Intention differed significantly between groups (*beta*urban = .388 vs. *beta*rural = .042; *p*diff = .033). This path was strong and significant in the urban group but essentially zero and non-significant in the rural group, indicating a fundamental divergence in the motivational drivers of AI adoption intention. Urban students' adoption intent is substantially driven by beliefs about AI's productivity-enhancing value, whereas rural students' intention appears less contingent on performance-related appraisals. This contrast may reflect differing baseline expectations: urban students, operating in more competitive environments, may apply a more calculative utility logic to technology adoption decisions.

Table 7
Multi-Group Analysis: Urban–Rural Path Coefficient Differences

Path	**Urban (n = 125)**		**Rural (n = 138)**			
	β	**t**	**β**	**t**	**Δp**	**Result**
AI Literacy → Effort Expectancy	.536***	7.854	.576***	10.270	.658	NS
AI Literacy → Performance Expectancy	.504***	6.967	.471***	7.807	.710	NS
AI Literacy → Social Influence	.495***	6.118	.587***	12.118	.327	NS
Cognitive Absorption → AI Literacy	.285***	4.109	**.185*** **	3.364	.257	NS
Computational Thinking → AI Literacy	.340***	4.135	.190**	2.907	.157	NS
Digital Divide → AI Literacy	−.299***	3.503	−.604***	8.919	.005	✓
Effort Expectancy → Behavioral Intention	.285*	1.975	.484*	2.368	.397	NS
Performance Expectancy → Behavioral Intention	.388**	3.049	.042	0.457	.033	✓
Social Influence → Behavioral Intention	.280	1.937	.325	1.558	.850	NS

*Note. β = standardized path coefficient from the PLS-MGA unconstrained model. t = bootstrap t-statistic (5,000 resamples). Δp = p-value from the PLS-MGA permutation test for between-group path difference. NS = no significant group difference. ✓ = significant group difference (p < .05). * p < .05, ** p < .01, *** p < .001.*

4. Discussion

The present study examined how AI literacy functions as a mechanism linking individual cognitive traits and structural environmental conditions to technology adoption intention among vocational students in

China. The findings support three overarching conclusions. First, AI literacy operates as a mediating form of digital human capital that translates both internal cognitive endowments and external structural constraints into behavioral outcomes, rather than functioning as an isolated technical proficiency. Second, the process of AI literacy formation is not uniform across socio-spatial contexts; structural disadvantage imposes a substantially heavier penalty on rural students' competency development than on their urban counterparts, providing empirical support for the third-level digital divide thesis in a vocational education setting. Third, the motivational pathways driving AI adoption intention diverge across groups, with urban students showing a more performance-oriented pattern, whereas rural students' behavioral intention is linked more clearly to effort expectancy.

A central finding of this study is that AI literacy functions not as a direct outcome of either cognitive traits or structural access alone, but as the product of their joint operation. Computational thinking and cognitive absorption both showed statistically significant positive associations with AI literacy across both groups, while the digital divide exerted the strongest suppressive effect of any predictor in the model (Shi, 2025). This pattern is consistent with a human capital accumulation perspective in which the capacity to develop AI-relevant competencies depends on the interaction between an individual's cognitive condition and the resource environment in which that infrastructure is deployed (Faucher et al., 2025). The finding aligns with Human Capital theory, which posits that AI does not uniformly augment all labor but instead generates a skill premium for those who possess both the cognitive capacity and the environmental conditions to engage with it meaningfully (Popkova & Sergi, 2020).

Notably, AI literacy in turn predicted all three UTAUT constructs: effort expectancy, performance expectancy, and social influence (Williams et al., 2015). These factors across both groups, and these constructs jointly explained approximately 45% of the variance in behavioral intention. This structural chain, running from cognitive traits and structural conditions through AI literacy to adoption intention, provides a more integrated account of AI adoption behavior than models that treat intention as a direct function of access or attitude alone. The implication is that policies aimed at increasing behavioral intention to use AI are unlikely to produce the intended effects, because intention is downstream of literacy rather than independent of it.

The model also explained substantially more variance in AI literacy for the urban group ($R^2 = .671$) than for the rural group ($R^2 = .431$). This divergence in explanatory power is itself a substantively meaningful result. It suggests that the structural and cognitive factors included in the present model capture the urban AI literacy formation process more completely than the rural one, pointing toward a broader and less legible set of influences operating in rural contexts, including, potentially, peer networks, regional labor market expectations, family educational background, and informal mentorship. This finding should be read not as a limitation to be apologized for but as a diagnostic signal: the rural pathway to AI literacy is more contextually complex and requires theoretical frameworks that go beyond the variables inherited from urban-centered technology adoption research.

The most theoretically consequential finding in this study is the result of the multi-group analysis, which revealed that the suppressive effect of the digital divide on AI literacy is approximately twice as large in the rural group as in the urban group, a difference confirmed as statistically significant. This finding goes beyond simply documenting that rural students are more digitally disadvantaged; it demonstrates that each unit of digital disadvantage imposes a greater competency penalty in rural settings than in urban ones. The divide is not merely in the stock of digital resources but in the efficiency with which whatever resources exist are converted into skill.

This pattern can be interpreted through the lens of compensatory capital theory. In urban vocational institutions, students who face individual-level digital disadvantage may still benefit from ambient structural resources, such as high-tech campus environments, industry partnerships, digitally proficient peer networks, and accessible institutional support (Woronov, 2011). These environmental effects absorb some of the penalty that digital disadvantage would otherwise impose on AI literacy development. In rural institutions, such buffers are largely absent. The consequence is that digital disadvantage operates more directly and more forcefully on individual competency, with little systemic mediation to attenuate its effect (Kretschmer & Winkler, 2024). This mechanism corresponds to what the literature has described as “fragmented digitalization”, a condition in which access to technology exists but is insufficiently embedded in a pedagogical and institutional context that can convert access into genuine competency (Kazakova, 2020).

The finding thus provides empirical grounding for the third-level digital divide thesis in a domain where it had not previously been examined with comparative longitudinal rigor (Van Deursen & Helsper, 2015). Earlier scholarship documenting the urban-rural digital divide in China has tended to focus on first-level (physical access) or second-level (usage pattern) disparities, particularly education settings (Lin et al., 2023). The present study extends this literature in two directions: first, by demonstrating that the divide persists and intensifies at the level of AI-specific competency formation, even as hardware access has been substantially equalized by national infrastructure investment; and second, by providing a quantified estimate of the asymmetry in its magnitude across the urban-rural boundary within the vocational track.

The second significant finding from the multi-group analysis concerns the path from performance expectancy to behavioral intention, which was strong and significant among urban students but effectively zero and non-significant among rural students. This divergence reveals that the motivational architecture underlying AI adoption intention is not universal but is instead contingent upon the interaction between cognitive evaluations and structural context (Yurt & Kasarci, 2024).

For urban students, behavioral intention was most clearly associated with performance expectancy, while effort expectancy showed only a modest effect and social influence did not reach significance. This pattern suggests that urban students’ willingness to use AI is shaped primarily by whether they perceive concrete gains in productivity or task performance. In contexts where exposure to AI may already be relatively high, students may treat access as given and evaluate AI more in terms of instrumental return than social pressure.

For rural students, the pattern differed. Effort expectancy was the only significant predictor of behavioral intention, whereas performance expectancy and social influence did not reach significance. This suggests that in rural settings, perceived ease of use and usability may remain more immediate determinants of intention than abstract expectations about performance improvement. Under conditions where exposure, support, and hands-on familiarity may be less stable, students may first need to feel that AI tools are manageable before broader instrumental benefits become motivationally salient.

This divergence has direct implications for intervention design. Programs targeting urban vocational students may be more effective when they emphasize concrete task gains, employability benefits, and demonstrable productivity enhancement. By contrast, programs for rural students may need to prioritize usability scaffolding, guided practice, and reductions in perceived complexity before performance-based appeals can be expected to translate into adoption intention. A uniform national intervention strategy is therefore unlikely to be equally effective across contexts.

The interaction between cognitive traits and structural environment also warrants a more cautious interpretation. Computational thinking and cognitive absorption showed descriptively larger path coefficients in the urban group than in the rural group, but the multi-group analysis did not indicate statistically significant between-group differences for these paths. Rather than supporting a strong compensatory-capital claim, the present results suggest that these cognitive traits are beneficial in both contexts, even though the structural penalty associated with the digital divide is markedly stronger in rural settings. This points to the need to strengthen both individual competencies and institutional conditions, rather than assuming that cognitive traits can compensate for structural disadvantage on their own.

Taken together, these findings suggest that the standard UTAUT model, applied uniformly across populations, may obscure context-specific differences in the salience of particular motivational pathways. In the present data, most paths from AI literacy to the three UTAUT constructs were relatively stable across groups, whereas the path from performance expectancy to behavioral intention varied significantly. This pattern supports a more context-sensitive reading of UTAUT in which some adoption mechanisms remain stable, but others are reshaped by structural inequality and socio-spatial context.

5. Conclusion

This study investigated the structural and psychological determinants of AI literacy and its downstream effects on behavioral intention to use AI among vocational students in urban and rural China. By integrating human capital theory with the UTAUT framework and employing a multi-group PLS-SEM design, the study reveals that AI literacy functions as a critical mediating asset that converts cognitive traits and structural conditions into adoption intention — and that this conversion process is fundamentally unequal across the urban-rural divide. The digital divide suppresses AI literacy formation at nearly twice the rate in rural settings as in urban ones, while the motivational drivers of adoption intention operate through qualitatively different logics across the two groups. Taken together, these

findings suggest that the path from technological access to labor market readiness is neither automatic nor uniform: it is mediated by competency, conditioned by institutional ecology, and governed by context-specific motivational structures. For vocational students these dynamics have consequential implications for whether technological change functions as an equalizer or as a stratifier. This study offers a diagnostic framework for understanding that distinction and a foundation for designing interventions sensitive to the conditions under which AI literacy can be meaningfully developed. Two policy implications follow directly from the findings. First, policymakers should prioritize differentiated resource allocation rather than uniform national rollouts: because each unit of digital disadvantage exerts approximately twice the suppressive effect on AI literacy in rural institutions as in urban ones, infrastructure investment in rural vocational colleges — including stable internet connectivity, AI-capable devices, and instructional technical support — is a necessary precondition before curriculum-level AI literacy interventions can be expected to achieve parity of outcomes. Second, intervention design should be motivationally calibrated to context: programs for urban vocational students may be most effective when they emphasize demonstrable productivity gains and employability benefits, whereas programs for rural students should prioritize usability scaffolding, guided hands-on practice, and reductions in perceived complexity, building a foundation of effort-based confidence before performance-based appeals are introduced.

6. Limitations

Several limitations of the present study warrant acknowledgment. First, the cross-sectional design precludes causal inference. Although the structural model identifies statistically significant associations among the constructs, the observed pathways cannot be interpreted as evidence of directional processes unfolding over time. The relationships between digital disadvantage, cognitive traits, AI literacy, and adoption intention are likely dynamic and mutually reinforcing in ways that cross-sectional data cannot capture. Second, the sample was drawn from two vocational institutions in Shanxi Province, selected to represent urban and rural contexts respectively. While purposive sampling served the comparative aims of the study, it limits generalizability beyond institutions with similar demographic and structural profiles. Shanxi Province represents one regional context within a highly heterogeneous national landscape, and the magnitude of urban-rural differences observed here may not hold in provinces with different levels of economic development, infrastructure investment, or educational policy implementation. Third, all measures relied on self-reported questionnaire data collected from a single source at a single time point, raising the possibility of common method bias.

7. Future Research Implications

The findings point toward several productive directions for future research. Most immediately, longitudinal designs are needed to examine how the relationships among digital disadvantage, cognitive traits, and AI literacy evolve over the course of vocational training, and whether early interventions targeting computational thinking or facilitating conditions produce detectable competency gains at later measurement points. Such designs would also permit stronger causal inference regarding the

suppressive mechanism of the digital divide identified here. Second, future research should expand the geographic and institutional scope of inquiry, examining urban-rural differences in AI literacy formation across multiple provinces with varying levels of development and policy environments, in order to determine which aspects of the present findings are generalizable and which are context-specific to Shanxi or similarly structured regions.

Declarations

Consent to Participate Declaration

Every human participant has provided their consent to participate in the study and consent for publication of this study.

Ethical Consideration

This study was approved by the Ethics Committee of Jiuquan Vocational Technical University (ID: JVTU-CSR-2025-001). All participants provided written informed consent before participating. The study was conducted in accordance with the Declaration of Helsinki.

Availability of data and materials

The raw data supporting the conclusions of this article were attached, please refer to the supplement documents.

Competing interests

The authors have no competing interests.

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Author Contribution

YC and RC wrote the main manuscript text. Majid and Arham edited and supervised the manuscript. RY prepared figures and table. All authors reviewed the manuscript.

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Figures

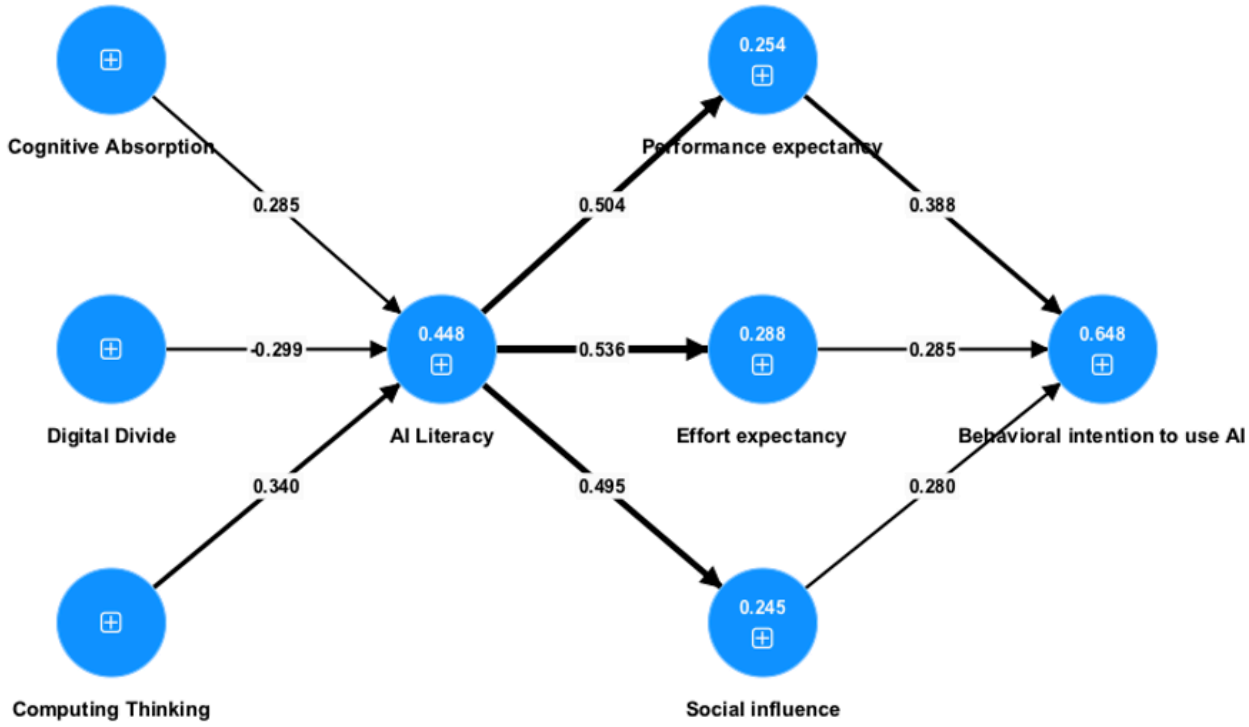


Figure 1

Results of the Structural Model: Urban Group

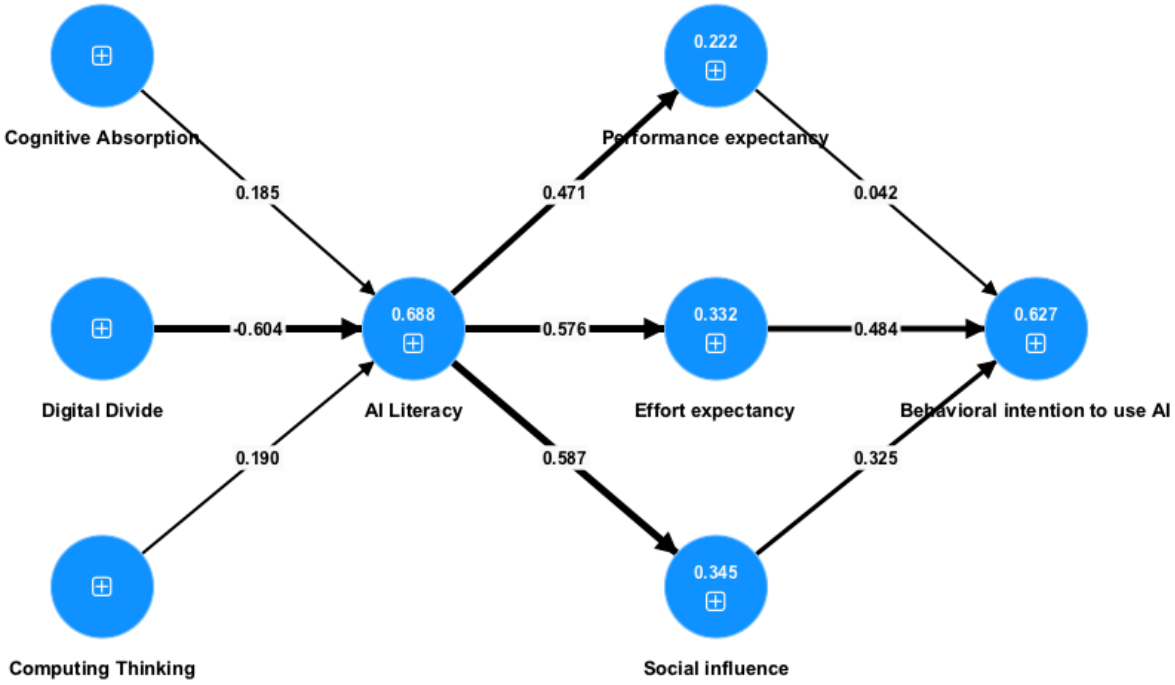


Figure 2

Results of the Structural Model: Rural Group

Supplementary Files

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- dataanalysis.xlsx