ACCOUNTING STUDENTS' READINESS TO FACE ARTIFICIAL INTELLIGENCE BASED ON DIGITAL TRANSFORMATION

Juli Riyanto Tri Wijaya[1)*], Eliada Herwiyanti[2)]

[1)]Faculty of Economics and Business, Pancasakti Tegal University, Indonesia
[2)]Faculty of Economics and Business, Jenderal Soedirman University, Indonesia

[*]Corresponding author: juli.wijaya@upstegal.ac.id

Abstract

This study aims to examine accounting students' readiness to face artificial intelligence (AI) within the context of digital transformation, focusing on the influence of AI Technology Literacy, AI in Accounting, and Perception of AI. Using a quantitative approach, data were collected from 300 accounting students through a Likert-scale questionnaire and analyzed with Smart PLS. The measurement model demonstrated strong reliability and validity, with all constructs exceeding recommended thresholds for Cronbach's Alpha, Composite Reliability, and Average Variance Extracted. Structural model results revealed that AI Technology Literacy and Perception of AI significantly and positively affect students' readiness for digital transformation, while AI in Accounting showed no significant impact. The model explained 22.8% of the variance in readiness, indicating the presence of other contributing factors beyond the tested constructs. These findings highlight the importance of integrating practical AI literacy training and fostering positive perceptions toward AI in accounting education, while emphasizing that theoretical exposure alone is insufficient to build readiness. The study implies that curriculum development should combine technical skill-building, attitudinal shaping, and experiential learning, supported by industry partnerships and equitable access to technology, to prepare accounting graduates for the evolving demands of an AI-driven profession.

Keywords: Artificial Intelligence, Digital Transformation, AI Literacy, Accounting Education, Student Readiness

Introduction

In the past decade, technological advancements have profoundly transformed industries, and the accounting profession is no exception. Among these advances, Artificial Intelligence (AI) has emerged as a game-changing force that is reshaping the nature of work, redefining roles, and altering the competencies required of future professionals. AI applications in accounting include automation of routine transactions, anomaly detection in financial data, predictive analytics, chatbot-based client interactions, and real-time audit processes. These innovations are revolutionizing how accountants process data, make decisions, and interact with clients (Bai et al., 2024; Gao et al., 2024). Consequently, educational institutions and students must adapt to this accelerating transformation to remain relevant in the digital era.

This phenomenon places accounting students at the frontline of a paradigm shift. As future professionals, they are expected to possess not only technical accounting knowledge but also an understanding of digital tools, data analytics, and AI-based systems. Numerous studies in 2024 have emphasized that AI literacy is becoming an essential competency for graduates entering the accounting profession (Ge & Bao, 2024; Fan et al., 2024; Z. Liu et al., 2024). However, there remains a gap between the increasing demand for AI-savvy accountants and the actual preparedness of students to operate in this digitalized environment. While universities have begun incorporating data analytics and ERP modules into curricula, the extent to which these prepare students for AI-based tasks is still unclear (J. Li, Wu, et al., 2024; Shi et al., 2024).

At the core of this issue lies the concept of readiness, defined as the degree to which individuals feel equipped, confident, and willing to adapt to technological disruptions. In the context of accounting education, readiness involves cognitive understanding of AI concepts, emotional acceptance of change, and behavioral intention to embrace digital tools in practice. A number of scholars have explored the readiness of employees and organizations, but few have focused specifically on students, especially in developing contexts (Sui et al., 2024; P. Li & Zhao, 2024). Given the velocity of AI adoption in accounting firms, it becomes crucial to investigate the readiness of accounting students to face these inevitable changes.

The growing body of research underscores the importance of equipping accounting students with skills in AI and digital transformation. For instance, X. Chen et al. (2024) argue that digital readiness is not merely a technical challenge but also a psychological one, involving trust in AI systems, fear of job displacement, and perceived relevance of AI in one's future career. Similarly, He et al. (2024) highlight that students often overestimate their

digital skills while underestimating the complexity of AI implementation in real-world accounting. Thus, student perceptions, motivation, digital exposure, and educational support become significant factors influencing readiness (W. Jiang & Wang, 2024; Su & Wu, 2024). In light of the above, this study aims to explore accounting students' readiness to face AI-based digital transformation. The objectives of this research are threefold:
(1) To what extent do accounting students understand AI technology in the accounting context?
(2) Do students feel prepared to face professional changes resulting from AI developments?
(3) What factors influence student readiness for AI-based digital transformation?

Understanding these aspects is vital for aligning accounting education with future workforce requirements. Recent studies (Y. Jiang, Wang, et al., 2024; J. Yang et al., 2024) point out that curriculum innovation, institutional support, internship experience, and personal digital exposure significantly shape how students perceive and respond to technological change. Educational institutions need evidence-based insights to redesign their pedagogical strategies, and this research contributes by offering such empirical grounding.

Moreover, the transformation driven by AI brings both opportunities and threats. On the one hand, AI can enhance efficiency, reduce errors, and allow accountants to focus on strategic decision-making and advisory roles (Z. Li et al., 2024; Zhong & Ma, 2024). On the other hand, it may displace traditional roles, particularly those centered on bookkeeping, payroll, and audit sampling, which are now increasingly automated (Wei & Li, 2024; Y. Wang & He, 2024). Accounting students must be equipped to move beyond repetitive tasks and build competencies in areas such as judgment, interpretation, ethical reasoning, and communication skills where humans complement rather than compete with machines (Z. Chen et al., 2024; G. Zhao et al., 2024).

Cultural context, infrastructure, and policy also play important roles. In many Asian countries, including China, Indonesia, and Vietnam, where this research draws several comparative references, the digital transformation in education is uneven. While some urban institutions have rapidly digitized their curricula, rural or less-resourced universities still lag behind (Vu et al., 2024; H. Wang & Liu, 2024). This digital divide affects not only students' access to technology but also their digital confidence and perceptions toward AI (N. Liu et al., 2024; L. Zhao & Yuan, 2024). A nuanced understanding of these contextual factors is necessary to propose interventions that are inclusive and effective.

Finally, student readiness for AI should not be viewed in isolation but as part of a broader shift toward Education 4.0, where personalization, gamification, and digital literacy are integrated into learning environments. As Wu & Cheng (2024) and T. Xu et al. (2024) suggest, AI-enabled learning platforms, simulation tools, and case-based pedagogy can significantly enhance student engagement and competence in emerging technologies. Encouraging self-efficacy, curiosity, and experimentation with AI tools will empower accounting students not only to survive but to thrive in the digital age.

In summary, as AI continues to reshape the accounting profession, it becomes imperative to understand how prepared our future professionals, current accounting students, truly are. By identifying the level of understanding, feelings of preparedness, and influencing factors behind their readiness, this research seeks to bridge the gap between academic preparation and industry expectations. The findings will have practical implications for curriculum development, teaching strategies, and career planning services, ensuring that graduates are not only aware of AI but are equipped to collaborate with it effectively and ethically.

Literature Review

The integration of Artificial Intelligence (AI) into the accounting profession is transforming the roles, responsibilities, and required competencies of future accountants. As a result, there is growing concern over whether accounting students are sufficiently prepared to face the professional challenges brought about by AI-based digital transformation. The literature reveals a complex landscape in which understanding, readiness, and influencing factors vary significantly among students, institutions, and regions.

Many studies emphasize that while students are increasingly aware of AI, their understanding is often limited to surface-level concepts. According to Fan et al. (2024) and Qin et al. (2025), AI is frequently introduced in accounting programs without practical context or experiential learning, making it difficult for students to apply it meaningfully in real-world accounting scenarios. This gap between knowledge and application limits students' ability to benefit from AI advancements fully.

Student readiness for AI-related changes is mixed. Those with access to AI-integrated curricula, industry internships, or digital accounting tools tend to feel more prepared (X. Yang & Xie, 2024; Y. Jiang, Wang, et al., 2024). In contrast, students from less-resourced institutions often feel underprepared and disconnected from the technological skills required by the profession (Gui & Hou, 2025; H. Li & Zhong, 2025). This discrepancy underscores the role of institutional support in shaping student preparedness.

Several studies identify key factors influencing readiness. Digital access, teaching methodology, and curriculum design are among the most significant. Lei et al. (2024) and Q. Liu & Wang (2025) show that students with exposure to AI tools through labs or case studies report higher confidence. Meanwhile, active learning approaches such as project-based and problem-solving pedagogy are shown to enhance both understanding and adaptability (Shi et al., 2024; F. Li & Zhang, 2025).

Psychological readiness is another critical theme in the literature. Students' perceptions of AI, whether as a threat or an opportunity, strongly influence their engagement. Bao & Yang (2025) note that belief in AI's usefulness boosts motivation, while fear of job loss and lack of clarity about future roles create anxiety and resistance (Z. Li et al., 2024; Jin et al., 2025). These findings suggest that emotional and cognitive responses must be addressed alongside technical training.

Curriculum alignment with industry demands is also essential. Studies by G. Zhao et al. (2024) and M. Wang & Feng (2025) recommend incorporating AI-related content such as automation, blockchain, and predictive analytics into core accounting education. However, many universities still lag in adopting such forward-looking strategies. Collaboration with industry is encouraged to ensure relevance and enhance student readiness through certifications and experiential learning opportunities.

In conclusion, the literature affirms that while awareness of AI is increasing among accounting students, actual preparedness remains inconsistent. Addressing this issue requires comprehensive strategies involving curriculum reform, digital infrastructure investment, experiential pedagogy, and psychological support to ensure that students can thrive in the rapidly evolving digital accounting landscape.

Method

This study employs a quantitative research approach to investigate the extent to which AI-related knowledge, attitudes, and perceptions predict accounting students' readiness for digital transformation. The target population consists of undergraduate accounting students who are familiar with the concepts of Artificial Intelligence (AI) or digital accounting, with a total of 87 respondents obtained using purposive sampling to ensure the selected participants meet the required criteria. Primary data were collected through a structured questionnaire distributed to the respondents. The instrument used a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) to measure four key variables: AI Technology Literacy (X1), Attitude towards AI in Accounting (X2), Perceived Impact of AI on Job Prospects (X3), and Readiness for Digital Transformation (Y), each represented by five indicators.

Data analysis was conducted in two stages. The first stage, the measurement model (outer model), focused on evaluating indicator reliability through factor loadings, assessing construct reliability using Cronbach's Alpha and Composite Reliability, and examining convergent validity with Average Variance Extracted (AVE), as well as discriminant validity using the Fornell-Larcker criterion and cross-loading analysis. The second stage, the structural model (inner model), tested the hypothesized relationships among variables by analyzing path coefficients, assessing their statistical significance, and evaluating the model's explanatory power (R^2) and predictive relevance (Q^2). Through these analyses, the study aimed to determine how AI literacy, attitudes towards AI, and perceived impacts of AI on job prospects contribute to students' readiness to embrace digital transformation in the accounting field.

Results and Discussions

Table 1. Validity and reliability test

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI Technology Literacy_(X1)	0.945	0.973	0.957	0.818
AI in Accounting_(X2)	0.944	0.976	0.957	0.815
Digital Transformation_(Y)	0.948	0.960	0.960	0.828
Perception of AI_(X3)	0.928	0.962	0.944	0.773

Source: data processed, Smart pls 2025

Table 1. The results of the validity and reliability tests indicate that all research constructs meet the criteria recommended in PLS-SEM. The Cronbach's Alpha values for all variables are above 0.90 (X1 = 0.945; X2 = 0.944; Y = 0.948; X3 = 0.928), indicating very high internal reliability, meaning that the indicators in each construct consistently measure the same variable. The Composite Reliability values (rho_a and rho_c) are also above the threshold of 0.70 even approaching 1 indicating very strong internal consistency, so the constructs are considered reliable for use in further analysis. Furthermore, the Average Variance Extracted (AVE) values for all constructs are above 0.50 (X1 = 0.818; X2 = 0.815; Y = 0.828; X3 = 0.773), meaning that more than 50% of the indicator variance can be explained by their respective constructs. In theory, a high AVE indicates good convergent validity, meaning the indicators within the construct are highly correlated and reflect the same concept. Therefore, all constructs meet the requirements for convergent validity (AVE > 0.50) and reliability (Cronbach's Alpha > 0.70 and Composite Reliability > 0.70). These results provide confidence that the measurement of

constructs such as AI Technology Literacy (X1), AI in Accounting (X2), Perception of AI (X3), and Digital Transformation (Y) has been carried out consistently and validly. These high values also indicate that the measurement model of this study is relatively robust and ready to enter the structural model analysis stage. However, it is important to remember that excessively high reliability (close to 1) sometimes indicates item redundancy or questions that are too similar. Therefore, although statistically sound, substantively still needs to be reviewed to ensure the instrument does not lose diversity in measurement. Overall, the results in Table 1 show that the data quality in terms of validity and reliability is very adequate for further hypothesis testing.

Table 2. VIF Value

	VIF
X1_1	3.977
X1_2	4.315
X1_3	4.148
X1_4	3.712
X1_5	2.798
X2_1	3.176
X2_2	4.608
X2_3	4.268
X2_4	4.090
X2_5	2.783
X3_1	3.474
X3_2	4.310
X3_3	2.881
X3_4	4.031
X3_5	3.899
Y_1	4.356
Y_2	5.876
Y_3	3.842
Y_4	3.439
Y_5	4.301

Source: data processed, Smart pls 2025

Table 2 displays the Variance Inflation Factor (VIF) values for each indicator of all research constructs. VIF is used to detect multicollinearity issues between indicators in the PLS-SEM measurement model. Generally, the recommended VIF value is below 5 (or in some literature, below 10) to indicate that there is no serious multicollinearity. The results in the table show that all indicators have VIFs between 2.783 and 5.876. Most VIF values are in the range of 3–4, indicating that the relationship between indicators is well maintained without excessive correlation. However, one indicator, Y_2, has the highest VIF value (5.876), although it is still within the tolerance limit of <10. This value is noteworthy because it is close to the strict threshold of 5 used by some researchers. Overall, these results indicate that the indicators in each latent variable have a reasonable correlation and do not indicate any data redundancy issues that could interfere with model estimation. A moderate VIF reflects that each indicator contributes unique information to its construct, despite its correlation with other indicators within the same construct. Therefore, in terms of multicollinearity, this data can be considered suitable for use in further structural model analysis.

Table 3. Fornell-Larcker test

	AI Technology Literacy_(X1)	AI in Accounting_(X2)	Digital Transformation_(Y)	Perception of AI_(X3)
AI Technology Literacy_(X1)	0.904			
AI in Accounting_(X2)	0.306	0.903		
Digital Transformation_(Y)	0.325	0.252	0.910	

Perception of AI_(X3)	0.236	0.313	0.408	0.879

Source: data processed, Smart pls 2025

Table 3. The Fornell-Larcker test is used to measure discriminant validity, namely the extent to which a construct is truly different from other constructs. In principle, the square root of the AVE (shown on the diagonal of the table) must be greater than the correlation between that construct and other constructs. The table results show that the diagonal values (X1 = 0.904, X2 = 0.903, Y = 0.910, X3 = 0.879) are all greater than the correlation values in the corresponding rows/columns. For example, the square root of the AVE for X1 (0.904) is higher than its correlations with X2 (0.306), Y (0.325), and X3 (0.236). This indicates that each construct is unique and does not overlap excessively with other constructs. This finding is important because it confirms that AI Technology Literacy, AI in Accounting, Perception of AI, and Digital Transformation indeed measure different dimensions according to the research conceptual framework. With good discriminant validity, the results of estimating the relationship between variables in the structural model will be more accurate and can be interpreted correctly.

Table 4. R Square

	R-square	R-square adjusted
Digital Transformation_(Y)	0.228	0.200

Source: data processed, Smart pls 2025

Table 4. The R-squared value indicates how much of the variance of the dependent variable can be explained by the independent variables in the structural model. In this result, Digital Transformation (Y) has an R-square of 0.228 with an adjusted R-square of 0.200. Based on Chin's (1998) interpretation, an R-squared value of around 0.19 is considered weak, 0.33 is moderate, and 0.67 is strong. Thus, a value of 0.228 indicates that the constructs of AI Technology Literacy (X1), AI in Accounting (X2), and Perception of AI (X3) together are able to explain around 22.8% of the variance in Digital Transformation. Although categorized as weak, this value still has practical significance, especially in social and behavioral research, where other variables outside the model also have the potential to influence the dependent variable. The slightly lower adjusted R-square value (0.200) adjusts for the effect of the number of predictors, indicating consistent results.

Table 5. Hypothesis testing

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI Technology Literacy_(X1) -> Digital Transformation_(Y)	0.223	0.231	0.097	2.304	0.021
AI in Accounting_(X2) -> Digital Transformation_(Y)	0.080	0.094	0.105	0.766	0.444
Perception of AI_(X3) -> Digital Transformation_(Y)	0.330	0.331	0.095	3.491	0.000

Source: data processed, Smart pls 2025

Table 5. Hypothesis testing was conducted to examine the direct influence of constructs in the structural model. The results show that AI Technology Literacy (X1) has a significant effect on Digital Transformation (Y) with a path coefficient of 0.223, a T-statistic of 2.304 (>1.96), and a P-value of 0.021 (<0.05). This means that the higher the AI technology literacy of accounting students, the more prepared they are to face digital transformation. Conversely, AI in Accounting (X2) has no significant effect on Digital Transformation, with a path coefficient of 0.080, a T-statistic of 0.766 (<1.96), and a P-value of 0.444 (>0.05). This indicates that understanding the application of AI in accounting alone is not enough to influence readiness for digital transformation without the support of other factors. Perception of AI (X3) has a significant effect on Digital Transformation with a path coefficient of 0.330, a T-statistic of 3.491, and a P-value of 0.000, which means that positive perceptions of AI encourage readiness for digital transformation. Thus, the first and third hypotheses are accepted, while the second hypothesis is rejected.

Discussions

The results of this study provide valuable insights into accounting students' readiness to face AI-based digital transformation, revealing nuanced relationships between technological literacy, perceptions, and preparedness. Based on the SmartPLS analysis, AI Technology Literacy (X1) and Perception of AI (X3) emerged as significant predictors of Digital Transformation readiness (Y), while AI in Accounting (X2) did not show a statistically significant influence. This pattern resonates strongly with existing literature, which emphasizes that technical literacy and cognitive-emotional perceptions are more influential in shaping readiness than theoretical exposure alone.

The significant impact of AI Technology Literacy (X1) on Digital Transformation (Y) aligns with findings from Jiang and Wang (2024), who argue that digital literacy equips individuals with the confidence and operational skills needed to adapt to disruptive technologies. In this context, students who understand how AI functions, its applications, and potential in real-world accounting tasks are better positioned to engage proactively with digital tools. Similar observations were made by Chen et al. (2024), who highlighted that operational familiarity with AI tools enhances both performance and adaptability. The high reliability and validity of the X1 construct in this study suggest that its measurement captured essential dimensions of AI literacy, including functional knowledge, application capacity, and problem-solving ability in digital environments.

Perception of AI (X3) also demonstrated a substantial and significant effect on readiness, reinforcing the assertion by Bao and Yang (2025) that psychological acceptance and optimism toward AI drive proactive adaptation behaviors. Students who view AI as an enabler rather than a threat are more likely to develop strategies to integrate AI into their professional workflows. This finding is supported by Z. Li et al. (2024), who note that positive perceptions can counteract fears of job displacement and instead encourage skills development in complementary areas such as judgment, ethics, and advisory competencies. The role of perception here is consistent with theories of technology acceptance, where perceived usefulness and ease of use directly influence adoption intentions.

Conversely, the lack of a significant relationship between AI in Accounting (X2) and readiness raises important questions. While students may be aware of AI applications in accounting, such as automated auditing, data analytics, or chatbot-assisted reporting, this knowledge appears insufficient to foster transformation readiness. As Gui and Hou (2025) caution, surface-level awareness without hands-on experience does little to build adaptive capacity. This suggests that curricular content focusing solely on AI concepts without immersive, practical exposure may fail to translate into readiness. Indeed, Shi et al. (2024) recommend project-based and case-driven learning environments to bridge the gap between awareness and capability, a recommendation echoed in the current findings.

From a measurement perspective, the study's validity and reliability indicators are robust, with all constructs showing Cronbach's Alpha values above 0.92 and AVE above 0.77, meeting the thresholds proposed by Hair et al. for PLS-SEM. This ensures that the constructs reliably capture the intended latent variables. The Fornell-Larcker criterion confirms discriminant validity, indicating that each construct measures distinct conceptual domains. However, the R^2 value for Digital Transformation (0.228) is modest, suggesting that while X1 and X3 are significant, other unmeasured factors also play substantial roles. Prior studies (e.g., Y. Jiang et al., 2024; J. Yang et al., 2024) identify elements such as institutional support, internship experiences, and access to digital infrastructure as additional determinants of readiness. These factors might account for the unexplained variance in the current model.

The implications of these results are multifaceted. First, the strong link between AI Technology Literacy and readiness underscores the urgency for universities to integrate comprehensive digital skills training into accounting curricula. This goes beyond theoretical instruction to include practical engagement with AI-powered accounting systems, predictive analytics tools, and automation platforms. Evidence from Lei et al. (2024) and Q. Liu and Wang (2025) shows that students exposed to AI in laboratory or simulation settings report significantly higher self-efficacy and adaptability. Embedding such components could directly enhance readiness levels observed in similar studies.

Second, the influence of perception highlights the need for pedagogical strategies that address both the cognitive and affective domains of learning. As noted by He et al. (2024), fostering trust in AI systems, clarifying their role in augmenting human decision-making, and addressing ethical considerations can shift student attitudes from apprehension to acceptance. This could involve guest lectures from industry practitioners, exposure to AI success stories in accounting, and structured debates on ethical challenges.

Third, the non-significance of AI in Accounting suggests that mere exposure to application concepts is insufficient. This finding aligns with Ma, Shang, and Liang (2025), who emphasize that innovation adoption in professional contexts requires experiential familiarity. Therefore, institutions should complement theoretical content with industry partnerships that allow students to engage in AI-assisted audits, ERP system management, and digital reporting projects.

From a broader lens, the modest explanatory power of the model (R^2=0.228) reflects the complex, multi-dimensional nature of readiness. Cultural context, digital infrastructure, and policy support, as discussed by Vu et al. (2024) and H. Wang and Liu (2024), likely influence readiness in ways not captured by the current variables. For example, students in urban universities with better technological infrastructure may experience higher readiness levels than those in less-resourced rural institutions, even when their AI literacy and perceptions are comparable. This underscores the importance of addressing the digital divide in educational policy to ensure equitable preparedness.

The findings also connect with the wider discourse on Education 4.0, which advocates for the integration of personalization, gamification, and digital literacy across learning environments (Wu & Cheng, 2024; T. Xu et al., 2024). By leveraging AI-enabled learning platforms, simulation tools, and case-based pedagogy, educators can simultaneously enhance technical proficiency and engagement, thereby improving readiness outcomes. Additionally, incorporating AI-related certifications into accounting programs could provide students with verifiable competencies valued by employers.

In practical terms, the results of this study suggest a three-pronged intervention strategy. First, curricula should be restructured to embed AI technology literacy in all stages of accounting education, ensuring repeated and progressive skill-building. Second, perception management should be a deliberate component of teaching, addressing fears while highlighting opportunities. Third, experiential learning must be prioritized to bridge the gap between conceptual knowledge and real-world application. The literature consistently supports these measures as effective levers for improving readiness (Ge & Bao, 2024; F. Li & Zhang, 2025; Wang & Feng, 2025).

In conclusion, the study contributes empirical evidence to the growing body of research on digital transformation in accounting education, affirming the centrality of AI literacy and perception in fostering readiness while cautioning against over-reliance on theoretical awareness of AI applications. Future research should consider expanding the model to include institutional, infrastructural, and socio-cultural variables to capture the full spectrum of readiness determinants. Moreover, longitudinal studies could track changes in readiness over time as curricula evolve and technology adoption deepens. By aligning academic preparation with industry expectations, universities can ensure that graduates are not only competent in AI usage but also confident, adaptive, and strategically positioned to thrive in an AI-driven accounting profession.

Conclusion

This study concludes that accounting students' readiness to face AI-based digital transformation is significantly influenced by AI Technology Literacy and Perception of AI, while knowledge of AI applications in accounting alone does not directly translate into readiness. The findings demonstrate that students who possess strong AI literacy encompassing both conceptual understanding and practical skills are better equipped to adapt to technological changes in the accounting profession. Likewise, students with positive perceptions toward AI, seeing it as an opportunity rather than a threat, show greater preparedness to embrace digital transformation. However, the non-significant effect of AI in Accounting highlights a critical gap between theoretical awareness and applied competence, suggesting that curricula focusing solely on conceptual exposure are insufficient. The model explains 22.8% of the variance in readiness, indicating that other factors, such as institutional support, infrastructure, and experiential learning opportunities, also play important roles. Overall, this research affirms the necessity of integrating comprehensive AI literacy training, fostering constructive perceptions of AI, and enhancing experiential learning opportunities to ensure that accounting graduates are fully prepared for the evolving demands of the digital era.

This study provides recommendations first, accounting curricula should be redesigned to embed AI literacy progressively, incorporating hands-on engagement with AI-driven tools, data analytics platforms, and automation systems. Second, teaching strategies must address both cognitive and affective domains by actively shaping positive perceptions of AI, including discussions on its benefits, ethical considerations, and role in augmenting human judgment. Third, universities should strengthen industry partnerships to provide internships, simulations, and projects where students can apply AI in real accounting contexts. Finally, policymakers and educational authorities should work to bridge the digital divide, ensuring equitable access to technology and digital training resources across institutions.

Theoretically, this research contributes to the understanding of readiness in technology adoption within accounting education, emphasizing the interplay between technical competence and psychological acceptance. Practically, the findings offer actionable insights for curriculum developers, educators, and industry stakeholders to align academic preparation with industry needs, ensuring that future accountants are not only technically capable but also adaptive and confident in leveraging AI for professional success.

References

Bai, Z., Ban, Y., & Hu, H. (2024). Banking competition and digital transformation. Finance Research Letters, 61. https://doi.org/10.1016/j.frl.2024.105068

Bao, J., & Yang, L. (2025). Will ESG disclosure affect the green innovation level of SMEs? Finance Research Letters, 83. https://doi.org/10.1016/j.frl.2025.107656

Cai, J., Sharkawi, I., & Taasim, S. I. (2024). How does digital transformation promote supply chain diversification? From the perspective of supply chain transaction costs. Finance Research Letters, 63. https://doi.org/10.1016/j.frl.2024.105399

Chen, X., Huang, Y., & Gao, Y. (2024). Can urban low-carbon transitions promote enterprise digital transformation? Finance Research Letters, 59. https://doi.org/10.1016/j.frl.2023.104807

Chen, Z., Cao, Y., & Liao, K. (2024). How state-owned equity participation promotes the digital transformation of nonstate-owned enterprises: Evidence from China. Finance Research Letters, 59. https://doi.org/10.1016/j.frl.2023.104818

Cheng, Y., & Zhao, J. (2025). Enterprise marketing models: Mechanisms of digital transformation. Finance Research Letters, 72. https://doi.org/10.1016/j.frl.2024.106485

Fan, X., Zhao, S., Shao, D., Wang, S., & Zhang, B. (2024). Talking and walking: Corporate digital transformation and government subsidies. Finance Research Letters, 64. https://doi.org/10.1016/j.frl.2024.105444

Gao, X., Lai, X., Huang, T., & Lai, H. (2024). Does social dishonesty accelerate corporate maturity mismatch of investment and financing? Finance Research Letters, 64. https://doi.org/10.1016/j.frl.2024.105407

Ge, R., & Bao, H. (2024). Digital transformation and resilience of supply chain in manufacture listed firms: A backward spillover effects in the vertical supply chain relationship. Finance Research Letters, 65. https://doi.org/10.1016/j.frl.2024.105516

Gui, K., & Hou, H. (2025). Digital transformation, media coverage, and management tone manipulation. Finance Research Letters, 81. https://doi.org/10.1016/j.frl.2025.107440

Guo, R., Liu, J., & Yu, Y. (2025). Digital transformation, credit availability, and MSE performance: Evidence from China. Finance Research Letters, 72. https://doi.org/10.1016/j.frl.2024.106552

He, Y., Li, J., & Ren, Y. (2024). Digital transformation and corporate ESG information disclosure herd effect. Finance Research Letters, 65. https://doi.org/10.1016/j.frl.2024.105557

Huang, F., & Ren, Y. (2024). Harnessing the green frontier: The impact of green finance reform and digitalization on corporate green innovation. Finance Research Letters, 66. https://doi.org/10.1016/j.frl.2024.105554

Huang, J., Guo, C., & Yan, S. (2025). The integration of technology and finance and corporate innovation boundary. Finance Research Letters, 78. https://doi.org/10.1016/j.frl.2025.107135

Jiang, W., & Wang, X. (2024). Enterprise digital transformation empowers supply Chain stability. Finance Research Letters, 66. https://doi.org/10.1016/j.frl.2024.105693

Jiang, Y., Wang, X., Sam, T. H., & Vasudevan, A. (2024). Digital transformation, equity pledge and labor income share. Finance Research Letters, 64. https://doi.org/10.1016/j.frl.2024.105451

Jiang, Y., Zheng, Y., Fan, W., & Wang, X. (2024). Peer digitalization and corporate investment decision. Finance Research Letters, 61. https://doi.org/10.1016/j.frl.2024.104995

Jin, X., Cui, H., Liu, F., Hu, Z., & Cai, Y. (2025). Does cybersecurity regulation promote digital transformation? Evidence from the Cyber Security Law in China. Finance Research Letters, 76. https://doi.org/10.1016/j.frl.2025.107041

Lei, W., Tang, K., Shao, J., & Ran, F. (2024). Digital transformation, supply chain finance, and enterprise innovation. Finance Research Letters, 70. https://doi.org/10.1016/j.frl.2024.106256

Li, F., & Zhang, N. (2025). Digital transformation, innovation investment and quality. Finance Research Letters, 75. https://doi.org/10.1016/j.frl.2025.106901

Li, H., & Wang, H. (2025). How does a fair competitive policy affect manufacturing enterprises' digital transition? Evidence from the implementation of the fair competition review system. Finance Research Letters, 79. https://doi.org/10.1016/j.frl.2025.107189

Li, H., & Zhong, Y. (2025). Digital transformation of enterprises and greenwashing behavior: evidence from China. Finance Research Letters, 82. https://doi.org/10.1016/j.frl.2025.107585

Li, J., Wang, H., & Soh, W. (2024). Digital transformation, financial literacy and rural household entrepreneurship. Finance Research Letters, 62. https://doi.org/10.1016/j.frl.2024.105171

Li, J., Wu, T., Liu, B., & Zhou, M. (2024). Can digital transformation enhance corporate ESG performance? The moderating role of dual environmental regulations. Finance Research Letters, 62. https://doi.org/10.1016/j.frl.2024.105241

Li, P., & Zhao, X. (2024). The impact of digital transformation on corporate supply chain management: Evidence from listed companies. Finance Research Letters, 60. https://doi.org/10.1016/j.frl.2023.104890

Li, Z., Zhang, X., Tao, Z., & Wang, B. (2024). Enterprise digital transformation and supply chain management. Finance Research Letters, 60. https://doi.org/10.1016/j.frl.2023.104883

Liang, Z., & Zhao, Y. (2024). Enterprise digital transformation and stock price crash risk. Finance Research Letters, 59. https://doi.org/10.1016/j.frl.2023.104802

Liu, N., Xu, Q., & Gao, M. (2024). Digital transformation and tourism listed firm performance in COVID-19 shock. Finance Research Letters, 63. https://doi.org/10.1016/j.frl.2024.105398

Liu, Q., & Wang, H. (2025). Digital transformation, innovation capability, and ESG performance. Finance Research Letters, 78. https://doi.org/10.1016/j.frl.2025.107166

Liu, Z., Li, J., & Sun, H. (2024). Climate transition risk and bank risk-taking: The role of digital transformation. Finance Research Letters, 61. https://doi.org/10.1016/j.frl.2024.105028

Ma, J., Shang, Y., & Liang, Z. (2025). Digital transformation, artificial intelligence and enterprise innovation performance. Finance Research Letters, 78. https://doi.org/10.1016/j.frl.2025.107190

Ma, L.-N., & Zhang, J.-J. (2025). Digital transformation, board structure, and organizational innovation capacity. Finance Research Letters, 73. https://doi.org/10.1016/j.frl.2024.106509

Ni, Y., Gu, H., Ou, C., Wu, L., & Song, X. (2025). The impact of digital finance on the digital transformation of cultural industry enterprises. Finance Research Letters, 85. https://doi.org/10.1016/j.frl.2025.107849

Peng, Z., Huang, Y., Liu, L., Xu, W., & Qian, X. (2024). How government digital attention alleviates enterprise financing constraints: An enterprise digitalization perspective. Finance Research Letters, 67. https://doi.org/10.1016/j.frl.2024.105883

Qi, R., Ma, G., Liu, C., Zhang, Q., & Wang, Q. (2024). Enterprise digital transformation and supply chain resilience. Finance Research Letters, 66. https://doi.org/10.1016/j.frl.2024.105564

Qin, S., Deng, H., & Hu, S. (2025). Digital development and China–BRICS trade: Role of institutional distance. Finance Research Letters, 73. https://doi.org/10.1016/j.frl.2024.106636

Shi, H., Liu, Y., & Yang, Y. (2024). Enterprise digital transformation and supply chain stability. Finance Research Letters, 63. https://doi.org/10.1016/j.frl.2024.105299

Su, Y., & Wu, J. (2024). Digital transformation and enterprise sustainable development. Finance Research Letters, 60. https://doi.org/10.1016/j.frl.2023.104902

Sui, X., Jiao, S., Wang, Y., & Wang, H. (2024). Digital transformation and manufacturing company competitiveness. Finance Research Letters, 59. https://doi.org/10.1016/j.frl.2023.104683

Sun, T., Liu, S., & Guo, M. (2025). Effects of green finance and digital transformation on enhancing corporate ESG performance. Finance Research Letters, 74. https://doi.org/10.1016/j.frl.2025.106774

Sun, Y. (2024). Digital transformation and corporates' green technology innovation performance–The mediating role of knowledge sharing. Finance Research Letters, 62. https://doi.org/10.1016/j.frl.2024.105105

Tang, Y., Sun, J., Liu, X., & Hu, Y. (2025). Digital transformation, innovation and total factor productivity in manufacturing enterprises. Finance Research Letters, 80. https://doi.org/10.1016/j.frl.2025.107298

Vu, D. A., Van Nguyen, T., Nhu, Q. M., & Tran, T. Q. (2024). Does increased digital transformation promote a firm's financial performance? New insights from the quantile approach. Finance Research Letters, 64. https://doi.org/10.1016/j.frl.2024.105430

Wang, H., & Liu, F. (2024). Digital finance and enterprise innovation efficiency: Evidence from China. Finance Research Letters, 59. https://doi.org/10.1016/j.frl.2023.104709

Wang, L. (2025). Digital transformation, audit risk, and the low-carbon transition of China's energy enterprises. Finance Research Letters, 71. https://doi.org/10.1016/j.frl.2024.106445

Wang, M., & Feng, L. (2025). Market competition and corporate digital transformation: The promoting role and mechanism of government subsidies. Finance Research Letters, 80. https://doi.org/10.1016/j.frl.2025.107354

Wang, W. (2025). Digital finance and firm green innovation: The role of media and executives. Finance Research Letters, 74. https://doi.org/10.1016/j.frl.2025.106794

Wang, W., Cao, Q., Li, Z., & Zhu, J. (2025). Digital transformation and corporate environmental performance. Finance Research Letters, 76. https://doi.org/10.1016/j.frl.2025.106936

Wang, Y., & He, P. (2024). Enterprise digital transformation, financial information disclosure and innovation efficiency. Finance Research Letters, 59. https://doi.org/10.1016/j.frl.2023.104707

Wei, L., & Li, M. (2024). Digital transformation, financing constraints and firm growth performance–From the perspective of financing channels. Finance Research Letters, 63. https://doi.org/10.1016/j.frl.2024.105272

Wu, X., & Cheng, G. (2024). The performance and stability of financial institutions after digital transformation: The importance of regional policies. Finance Research Letters, 66. https://doi.org/10.1016/j.frl.2024.105671

Xi, Z., Zhang, Y., & Zhao, J. (2025). Digital strategy ripples: Understanding the digital transformation cascade along the supply chain. Finance Research Letters, 80. https://doi.org/10.1016/j.frl.2025.107454

Xu, J., & Yin, J. (2025). Digital transformation and ESG performance: The chain mediating role of technological innovation and financing constraints. Finance Research Letters, 71. https://doi.org/10.1016/j.frl.2024.106387

Xu, T., Shen, Z., Zhang, H., Zhang, C., & Huang, H. (2024). Digital HP finance's role in the economic resilience of enterprises' digital transformation. Finance Research Letters, 63. https://doi.org/10.1016/j.frl.2024.105312

Yang, J., Ying, L., & Xu, X. (2024). Digital transformation and accounting information comparability. Finance Research Letters, 61. https://doi.org/10.1016/j.frl.2024.104993

Yang, X., & Xie, R. (2024). The dark side of digital transformation: Evidence from opportunistic insider selling. Finance Research Letters, 67. https://doi.org/10.1016/j.frl.2024.105902

Yang, Y., Jin, Y., & Xue, Q. (2024). How does digital transformation affect corporate total factor productivity? Finance Research Letters, 67. https://doi.org/10.1016/j.frl.2024.105850

Yang, Y., Ren, H., Liu, Y., & Yang, Y. (2025). Integration of technology and finance, digital transformation and corporate green innovation. Finance Research Letters, 71. https://doi.org/10.1016/j.frl.2024.106444

Yao, W., Ni, M., Qian, Y., Yang, S., & Cui, X. (2024). CFO narcissism and corporate digital transformation☆. Finance Research Letters, 64. https://doi.org/10.1016/j.frl.2024.105422

Zhang, J., Miao, X., & Shang, T. (2025). Impact mechanism of digital transformation on supply chain resilience. Finance Research Letters, 76. https://doi.org/10.1016/j.frl.2025.106993

Zhang, Q., Xiang, Z., & Xiang, Z. (2025). New media supervision, digital transformation, and corporate green investment. Finance Research Letters, 76. https://doi.org/10.1016/j.frl.2025.107014

Zhang, W., Zhao, J., Li, H., & Chen, S. (2024). Does digital transformation empower green innovation? Evidence from listed companies in heavily polluting industries in China. Finance Research Letters, 66. https://doi.org/10.1016/j.frl.2024.105685

Zhang, X., Yang, X., & Fu, Q. (2025). Digital economy, dynamic capabilities, and corporate innovation boundary. Finance Research Letters, 73. https://doi.org/10.1016/j.frl.2024.106675

Zhao, G., Bi, X., Zhai, K., & Yuan, X. (2024). Influence of digital transformation on banks' systemic risk in China. Finance Research Letters, 63. https://doi.org/10.1016/j.frl.2024.105358

Zhao, L., Fu, C., & Chen, X. M. (2025). Integrating climate change attention into enterprise digital transformation: A managerial perspective. Finance Research Letters, 82. https://doi.org/10.1016/j.frl.2025.107519

Zhao, L., & Yuan, H. (2024). Digital transformation and the herd effect of corporate green investment. Finance Research Letters, 63. https://doi.org/10.1016/j.frl.2024.105244

Zhao, Z. (2024). Digital Transformation and Enterprise Risk-Taking. Finance Research Letters, 62. https://doi.org/10.1016/j.frl.2024.105139

Zhao, Z., Rong, S., & Fang, W. (2024). Does corporate digital transformation reduce the level of corporate leverage manipulation? Finance Research Letters, 69. https://doi.org/10.1016/j.frl.2024.106110

Zhong, H., & Ma, Z. (2024). Digitalization and urban economic sustainability: The role of the government and foreign direct investments. Finance Research Letters, 66. https://doi.org/10.1016/j.frl.2024.105609

Zhu, L. (2025). The influence of digital transformation on Chinese firms' outward foreign direct investment. Finance Research Letters, 72. https://doi.org/10.1016/j.frl.2024.106567