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The Effect of Performance Expectancy on Digital Technology Learning Performance of Students in Colleges of Construction

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Abstract: To address the imbalance between the supply and demand of "civil engineering + digital" interdisciplinary talents under the background of the digital transformation of the construction industry, and to reveal the internal connection between performance expectancy and digital technology learning performance of students in construction colleges, this study systematically explores the dimensional composition of performance expectancy and its influence path on digital technology learning performance based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and Digital Natives Theory, through methods such as literature research, in-depth interviews, questionnaire surveys, and structural equation modeling. The study identifies three core dimensions of performance expectancy: Perceived Usefulness for Career, Academic Perceived Enhancement, and Relative Advantage, and verifies the mediating effect of behavioral intention between performance expectancy and digital technology learning performance. The constructed theoretical model of "performance expectancy - learning intention - learning performance" explains the driving mechanism of digital technology learning performance of students in construction colleges, providing theoretical support and practical tools for the government to formulate talent incentive policies and for construction colleges to optimize talent training programs.

Keywords: Performance expectancy; Digital technology; Learning performance; Learning intention

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1. Introduction

The in-depth penetration of digital technologies (BIM, Internet of Things, AI, etc.) has promoted efficiency upgrading and model innovation throughout the whole life cycle of the construction industry. The Ministry of Housing and Urban-Rural Development of the People's Republic of China clearly identified intelligent construction and digital construction as the key paths for the high-quality development of the construction industry at the 2024 National On-Site Meeting on Intelligent Construction, requiring the accelerated large-scale implementation of emerging technologies. However, the "Digital Construction Talent Demand Forecast Report" released by the National Digital Construction Industry Industry-Education Integration Community in 2024 shows a significant imbalance between the speed of technological iteration and the quality of talent supply. The knowledge system of traditional construction practitioners is difficult to adapt to the transformation needs, and the market's demand for "civil engineering + digital" interdisciplinary talents is increasingly urgent.

As the core reserve force for the development of the construction industry, the digital technology learning performance of students from colleges of construction directly determines the effectiveness of talent supply [1]. Performance expectancy, as an individual's expectation of obtaining learning or work benefits through the use of digital technologies, has been proven by many studies to have an important impact on digital learning behavior [2–5]. However, existing studies mostly focus on general scenarios and fail to fully consider the particularity of the digital transformation of the construction industry and the digital native characteristics of students in construction colleges, resulting in incomplete dimensional decomposition of performance expectancy and insufficient in-depth analysis of the influence mechanism, which makes it difficult to effectively guide practice. Therefore, this study takes students in construction colleges as the research object to systematically explore the influence mechanism of performance expectancy on digital technology learning performance, which is of great significance for providing talent support for the transformation and development of the construction industry.

This study focuses on the following core questions: What is the dimensional composition and core elements of performance expectancy? How does performance expectancy influence digital technology learning performance?

2. Literature review

2.1. Performance Expectancy (PE)

Numerous scholars, such as Aronson & Carlsmith (1962), Dagevos (2021), and Nascimento, J., & Loureiro (2024), have confirmed that performance expectancy is closely related to individual behavior. Brock et al. verified the core driving role of performance expectancy on behavior through 7 experiments [6]. Venkatesh et al. clearly stated in the Unified Theory of Acceptance and Use of Technology (UTAUT) that performance expectancy is the strongest predictor of behavioral intention, and decomposed it into 5 dimensions: perceived usefulness, external motivation, task adaptation, relative technological advantage, and expected outcomes of technology use [7]. In China, studies primarily apply the concept of performance expectancy to scenarios, like digital healthcare, digital education and library information services, and they consistently confirm its significant impact on individual behavior. In the digital learning context of construction colleges, performance expectancy can be decomposed into three core dimensions: perceived usefulness for career (PUC), academic perceived enhancement (APC), and relative advantage (RA). Perceived usefulness for career is reflected in learners' recognition of the industry value and certification role of digital technology; academic perceived enhancement focuses on the gain effect on learning efficiency and academic scores; relative advantage emphasizes the efficiency advantage and practical attractiveness of new digital technology (such as BIM) compared with traditional tools (such as CAD).

2.2. Learning Intention (LI)

The Theory of Planned Behavior (TPB) points out that behavior is mainly determined by behavioral intention. The UTAUT model further verifies that performance expectancy significantly affects usage behavior through behavioral intention. This conclusion has been applied by many scholars in digital learning performance research [8]. In the context of digital education in construction colleges, the manifestations of learning intention are more specific, including both the internal motivation to continuously deepen the learning of digital skills such as BIM, and the external goals of engaging in BIM-related work, participating in skill competitions, and obtaining professional certifications in the future [8]; at the same time, it is also reflected in the behavioral tendency to continuously participate in online courses[9], learning plans for subsequent semesters, and recommending digital tools such as BIM to peers [10][11], ultimately pointing to the core demand of improving employment competitiveness through digital technology learning [12].

2.3. Learning Performance (LP)

As a tangible indicator of learning behavior outcomes, digital technology learning performance serves as a direct reflection of students' effectiveness in acquiring and applying professional technical skills in vocational education contexts. The digital technology learning performance of students in colleges of construction refers to the comprehensive performance of students in knowledge mastery, skill proficiency, practical application, and professional adaptation in the learning of digital technologies in the construction field, such as BIM and cloud computing [13], whose formation is driven by multi-dimensional factors and complex mechanisms. According to the current studies, performance expectancy is the core driving factor, which positively affects learning performance by stimulating learning intention.

2.4. Digital natives

The Digital Natives Theory illuminates the distinctive thinking patterns and behavioral habits developed by young people born after 1995 under the pervasive influence of digital technologies [14]. Existing studies hold varying views on the cognitive abilities, creativity, and learning styles of digital natives, yet they generally acknowledge the significant impact of these characteristics on their digital technology learning performance. Therefore, this study fully incorporates considerations regarding the thinking modes and behavioral habits of digital natives into the questionnaire design and combines their group characteristics when formulating digital skill training countermeasures in the subsequent stage, so as to enhance the practical guiding value of the research.

2.5. Model construction and hypotheses

Based on the UTAUT theory and relevant literature, the conceptual framework of the study is constructed as follows (**Figure 1**).

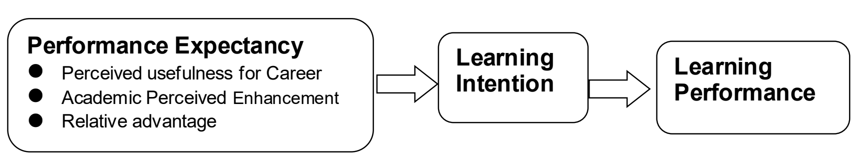

Figure 1. Conceptual framework of the study.

The following hypotheses are proposed:

(1) H1: Performance expectancy (including its dimensions: Perceived Usefulness for Career, Academic Perceived Enhancement, Relative Advantage) has a significant positive effect on learning intention;

(2) H2: Students' learning intention has a significant positive effect on learning performance;

(3) H3: Learning intention plays a significant positive mediating role between performance expectancy and learning performance.

3. Research methods

This study revised and designed research scales on the basis of well-established mature scales in the relevant field, adjusting the scale items in light of the specific context of this study, and finally collected data through questionnaire surveys.

3.1. Scale design

15 students with high participation in digital technology learning from construction colleges (BIM technology learning duration ≥ 6 months), 3 BIM teaching teachers, and 3 industry enterprise experts were selected for in-depth interviews. Among them, there are 3 undergraduate students and 12 vocational college students, covering majors such as Civil Engineering, Architecture, Building Equipment, Engineering Cost, and Water Supply and Drainage Technology, to ensure the representativeness of the interviewees. Drawing on existing mature scales such as Venkatesh et al. (2003) [7] and Qureshi et al. (2023) [12], combined with literature and in-depth interview results, a scale of performance expectancy and learning performance of students in construction colleges was constructed. The main content of the questionnaire consists of two parts: demographic information and influence factor indicators. All scales adopt a 5-point Likert scale (1 = completely disagree, 5 = completely agree). The pre-test results show that the Cronbach's α coefficient of each scale is ≥ 0.75.

3.2. Data collection

Under the background of the digital transformation of the construction industry, BIM technology has become the most widely used digital technology [15]. Therefore, in the questionnaire survey, students from construction colleges with BIM courses in China were selected as the research objects. Convenience sampling was used for the questionnaire survey from January to March 2025 and January 2026, and 528 valid questionnaires were collected. The gender distribution shows 323 males (61.2%) and 205 females (38.3%), which is consistent with the gender characteristics of the construction industry group. Majors cover core construction fields, with Engineering Cost (26.5%), Intelligent Construction Technology (24.1%), Civil Engineering (18%), Architecture (19.70%), construction equipment engineering technology (6.3%), Municipal engineering Technology (5.4%). Academic qualifications are mainly college diploma (84.1%), and undergraduates account for 15.9%, which is consistent with the positioning of the research objects. Regarding the learning duration of digital technologies, 333 people (63.1%) have studied for 1-2 years, and more than 80% of the respondents have studied for more than 1 year, with a solid learning foundation, so the survey data has high reference value.

4. Data analysis

SPSS 27.0 was used for descriptive statistics and reliability and validity tests, and AMOS 28.0 was used to construct a structural equation model to verify the path relationships and mediating effects between variables.

4.1. Descriptive statistical analysis

Descriptive statistics indicate that students in construction colleges generally hold a positive perception and attitude towards digital technology. Their perceived usefulness for career (3.95–3.97), academic enhancement effect (3.79–3.86), and relative advantage (3.94–4.02) are all in the high range. They generally recognize the value of digital technology, believing that it can enhance learning efficiency and facilitate career development and they demonstrate a strong learning intention (3.79 to 4.06). They plan to continue learning, participate in competitions, and obtain relevant certificates. Learning performance has initially emerged, and students' abilities in theoretical knowledge and software operation have been improved, with relevant scores reaching 4.04–4.16. At the same time, there are still relevant issues in digital technology learning: the learning intention score (3.79–4.06) indicate that some students still have insufficient learning intention toward digital technologies; the score of academic enhancement effect (3.79–3.86) is the lowest among all dimensions, revealing problems such as insufficient curriculum integration; practical teaching remains at the basic operation level, lacking in-depth scenarios, and the cultivation of high-order abilities is inadequate.

4.2. Reliability analysis

SPSS 27.0 software was used to test the reliability and validity of the data. This study uses Cronbach's alpha (α for short) as an important evaluation tool. A Cronbach's alpha value below 0.6 is considered poor, 0.7 is acceptable, and values above 0.8 are considered good. The results show that Performance Expectancy (9 items) is 0.867, Learning Intention (8 items) is 0.912, and Learning Performance (4 items) is 0.908. The consistency of each construct is very high, exceeding 0.8, indicating that the data has a high degree of stability and consistency.

4.3. Validity analysis

Validity analysis is an important method to test the accuracy and reliability of results. Since the content of this study is mainly derived from relatively mature models, the content validity is good. Before conducting structural validity analysis, Bartlett's test of sphericity and KMO test were performed in advance. The KMO value is between 0 and 1, and the larger the value, the more suitable it is for factor analysis. The KMO value is 0.934, and the significance level of Bartlett's test is 0, which is less than 0.05. The data indicate that each item meets the validity requirements.

4.4. Confirmatory factor analysis

The research model adopts the Maximum Likelihood (ML) method for confirmatory factor analysis. The results show that the Root Mean Square Error of Approximation (RMSEA) value is 0.019, which is within the acceptable threshold. The Comparative Fit Index (CFI) value is 0.988, also indicating a good fit. The Normed Chi-Square (χ^2/df) is 1.184, falling within the acceptable range. According to the test results, the standardized factor loadings of all observed items range from 0.71 to 0.89, all higher than the acceptable 0.6. The α values of all potential factors are between 0.814 and 0.912, all higher than the standard of 0.7. The Composite Reliability (CR) values of all factors are between 0.84 and 0.93, all higher than 0.7. The Average Variance Extracted (AVE) values are between 0.60 and 0.74, all higher than 0.5, indicating good reliability and convergence validity. The final results of the confirmatory factor analysis are shown in **Table 1**.

Table 1. The CFA results for all the constructs

			Estimate	S.E.	C.R.	P	SRW
PUC	<---	PE	1				0.745
APE	<---	PE	0.745	0.07	10.696	***	0.716
RA	<---	PE	0.671	0.066	10.14	***	0.608
PUC3	<---	PUC	1				0.898
PUC2	<---	PUC	0.913	0.037	24.702	***	0.865
PUC1	<---	PUC	0.831	0.04	20.731	***	0.76
APE3	<---	APE	1				0.779
APE2	<---	APE	1.172	0.066	17.621	***	0.845
APE1	<---	APE	1.021	0.066	15.586	***	0.708
RA3	<---	RA	1				0.831
RA2	<---	RA	1.11	0.047	23.568	***	0.872
RA1	<---	RA	1.106	0.046	23.967	***	0.888
LI3	<---	LI	0.917	0.057	16.056	***	0.69
LI4	<---	LI	1.003	0.056	17.888	***	0.76
LI5	<---	LI	0.947	0.057	16.585	***	0.712
LI6	<---	LI	1.2	0.065	18.555	***	0.783
LI2	<---	LI	1.142	0.065	17.684	***	0.753
LP1	<---	LP	1				0.835
LP2	<---	LP	0.941	0.045	20.913	***	0.78
LP3	<---	LP	1.049	0.041	25.527	***	0.89
LP4	<---	LP	1.04	0.042	24.847	***	0.874
LI8	<---	LI	1.115	0.065	17.062	***	0.73
LI1	<---	LI	1				0.764
LI7	<---	LI	1.096	0.061	18.043	***	0.764

The results of the confirmatory factor analysis show that the standardized factor loadings (SRW) of all observed variables are higher than the acceptable standard of 0.5, indicating that each observed variable can effectively reflect its corresponding potential factor. The Critical Ratio (C.R.) values of all non-reference observed variables are significantly greater than 1.96, and the P values are all less than 0.001 (***), proving that the correlation between observed variables and potential factors is highly statistically significant. In addition, each observed variable belongs to only one potential factor, and there is no cross-loading, indicating that the factor structure of the scale is consistent with the theoretical hypothesis, which can provide a reliable basis for subsequent model hypothesis testing.

4.5. Structural equation hypothesis testing

Table 2. The results of the hypothesis testing (Maximum likelihood estimates)

	Construct	Path	Construct	Estimate	S.E.	C.R	P	Result
H1	LI	←	PE	0.408	0.09	4.552	***	Significant
H2	LP	←	LI	0.767	0.053	14.478	***	Significant

The results of the structural equation model hypothesis testing show that the path coefficient of H1 (PE→LI) is 0.408 (C.R. = 4.552, $P < 0.001$), and the path coefficient of H2 (LI→LP) is 0.767 (C.R. = 14.478, $P < 0.001$). Both paths reach the statistically significant level, and the research hypotheses are supported.

Table 3. Mediated effect estimated using the bootstrap method

	PATH	Estimate	Lower	Upper	P	Result
H3	PE-->LI-->LP	0.231	0.75	0.394	0.007	Significant

The results of testing the mediating effect through the Bootstrap method show that in the path of "PE→LI→LP", the mediating effect value is 0.231 (95% confidence interval is [0.75, 0.394], $P = 0.007$). The confidence interval does not contain 0 and the P value is less than 0.05, indicating that IL plays a significant mediating role in the relationship between PE and LP, and the research hypothesis is supported.

5. Conclusions and recommendations

5.1. Research conclusions

Through theoretical construction and empirical testing, this study draws the following core conclusions: The performance expectancy of students in construction colleges is composed of three dimensions: "Perceived Usefulness for Career, Academic Perceived Enhancement, and Relative Advantage", among which Perceived Usefulness for Career is the core dimension; performance expectancy has a significant positive impact on digital technology learning performance, and learning intention plays a mediating role between them. The relevance to career development is the core driving force for students' digital technology learning in colleges of construction. This study also expands the application boundary of the UTAUT and constructs an analytical framework for digital learning performance suitable for students in construction colleges, providing a new perspective for related research and practice.

5.2. Recommendations

5.2.1. Suggestions for the government

As the foundational measure, establish a linkage mechanism of "skill certification - career development - policy incentives". Incorporate digital technology skill certifications, such as BIM and AI, into the professional qualification evaluation system of the construction industry, and provide policy incentives, such as employment subsidies and entrepreneurship support, for students who obtain advanced certifications to strengthen the perception of professional adaptability.

To increase investment in digital education in construction colleges. Support colleges to build digital technology training bases, develop industry-adapted digital textbooks and curriculum resources, and improve the exogenous teaching support environment.

To deepen industry-education integration and establish an industry-college docking platform, the government may introduce targeted policies to incentivize enterprises to actively participate in industry-education collaboration. Promote construction enterprises to participate in the formulation of talent training programs in colleges and universities, establish digital technology training bases, and enhance the alignment between digital technology learning content and industry demands.

5.2.2. Suggestions for colleges of construction

First, optimize the curriculum system and strengthen career orientation. Combining the characteristics of digital natives who have been exposed to digital tools since childhood and prefer fragmented, interactive learning scenarios, add core courses such as BIM digital integrated design and construction robot application, integrate digital technology into professional basic courses and specialized courses, and set up modular curriculum modules of "digital technology + major" that support fragmented learning; invite industry experts to participate in teaching, introduce real engineering project cases in the form of short digital videos and interactive 3D simulations, and improve the perception of technical usefulness.

Second, improve teaching resources and practice platforms. Because digital natives are proficient in using online resources for independent exploration and prefer immersive digital practice experiences, build a digital training center equipped with practical equipment such as BIM workstations and construction robots, and add virtual simulation modules that support personalized operation attempts; develop a mobile-friendly online learning platform to provide high-quality digital resources and real-time online Q&A services to meet students' independent learning needs.

Third, innovate teaching models and stimulate endogenous motivation. Digital natives favor social collaborative learning and have high acceptance of competitive incentives and personalized training. Therefore, teaching methods such as project-based learning and flipped classrooms should be adopted, and students should be encouraged to participate in digital innovation design competitions with social display channels.

Additionally, a personalized learning guidance mechanism should be established, and learning plans should be formulated based on students' interests and career plans to enhance their perception of learning empowerment.

6. Research limitations and future directions

This study has certain limitations: the sample only selects students from construction colleges through random sampling, with limited regional representativeness; other possible variables (such as family background and college background) are not explored. Future research can expand the sample scope to include students from construction colleges in multiple regions across the country; further analyze the moderating role of demographic variables such as major and academic background; and explore more influencing factors to improve the influence mechanism model.

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References

[1] Xiao F, Guo HJ, 2024, Digital Labor And Youth Development. China Youth Study, 35(04): 35–42.

[2] Jiang FJ, 2021, Research On The Influencing Factors Of College Students' Learning Behavioral Intention In Blended Teaching Environments. E-education Research, 42(06): 105–112 + 128.

[3] Wang CS, 2025, An Extended UTAUT Model Study On College Students' Willingness To Learn AI Painting Tools. Packaging Engineering, 46(08): 209–217.

[4] Zhao J, Ni MY, Zhang Q, et al., 2024, AIGC Reconstructs Graduate Academic Practice: A Study On The Influencing Factors Of Continuous Use Intention. Journal of Modern Information, 44(07): 34–46.

[5] Gao F, Lü J, 2025, Research On The Influencing Factors Of Students' Online Learning Satisfaction In Blended Teaching. Jiangsu Higher Education, (02): 78–85.

[6] Brock TC, Edelman SK, Edwards DC, et al., 1965, Seven Studies Of Performance Expectancy As A Determinant Of Actual Performance. Journal of Experimental Social Psychology, 1(4): 295–310.

[7] Venkatesh V, Morris MG, Davis GB, et al., 2003, User Acceptance Of Information Technology: Toward A Unified View. MIS Quarterly, 27(3): 425–478.

[8] Peng P, Ao Y, Li M, et al., 2022, Building Information Modeling Learning Performance Of AEC Undergraduate Students In China. Behavioral Sciences, 12(8): 269.

[9] Tung FC, Chang SC, 2008, Nursing Students' Behavioural Intention To Use Online Learning: A Questionnaire Survey. International Journal of Nursing Studies, 45(9): 1299–1309.

[10] Caldwell A, 2012, A Proposed Questionnaire to Measure Student Motivation and Intention Toward Learning Science. NCE-MSTL, Resource & Research Guides, 3(6): 12.

[11] Rajeh MT, Abduljabbar FH, Alqahtani SM, et al., 2021, Students' Satisfaction And Continued Intention Toward E-Learning: A Theory-Based Study. Medical Education Online, 26(1): 1961348.

[12] Fu S, Gu H, Yang B, 2020, The Affordances Of AI-Enabled Automatic Scoring Applications On Learners' Continuous Learning Intention: An Empirical Study In China. British Journal of Educational Technology, 51(5): 1674–1692.

[13] Qureshi MA, Khaskheli A, Qureshi JA, et al., 2023, Factors Affecting Students' Learning Performance Through Collaborative Learning And Engagement. Interactive Learning Environments, 31(4): 2371–2391.

[14] Prensky M, 2001, Digital Natives, Digital Immigrants. On the Horizon, 9(5): 1–6.

[15] Yang YN, Zhang ZC, Ma YD, et al., 2022, Analysis Of The Digital Transformation Path Of The Construction Industry From The Perspective Of Technology Logic. Science and Technology Management Research, 42(24): 137–142.