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Research Article

The Effect of Performance Expectancy on BIM Learning Performance Throughout the Mediation Role of Learning Intention

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Abstract:

Building Information Modelling (BIM) is a new technology with transformative capabilities in the AEC industry. Increasing emphasis is being placed on integrating this technology into vocational education to enhance students' employment opportunities and industry readiness. Founded upon the Unified Theory of Acceptance and Use of Technology (UTAUT) and Technology Acceptance Model (TAM), this study has examined the effect of performance expectancy (PE) on vocational college students' BIM learning performance (BLP) through intention to learn BIM (ILB) as a mediating variable. A quantitative cross-sectional survey design collected data from 190 students enrolled in BIM-related courses across China. Upon employing exploratory factor analysis, correlation, and multiple regression analyses, the assumption of unidimensionality along with internal consistency of the Greater PE, ILB, and BLP constructs were corroborated. The findings revealed that PE has no direct relationship on BLP, but PE has a strong effect on ILB, which then positively impacts BLP, thus indicating the presence of full mediation. These results underscore the critical role of students' motivational and career-driven expectations in shaping their engagement with BIM technologies. The study contributes to the theoretical advancement of UTAUT and TAM in vocational learning contexts and offers practical recommendations for curriculum designers, educators, and policymakers to foster BIM proficiency through enhanced student motivation and goal alignment.

1. Introduction

A relatively new technology that has found use in the construction sector is building information modelling (BIM). Also, BIM technology and related research and education are common topics of conversation among construction industry educators and builders these days. According to the relevant study, BIM technology has gained significant traction in the AEC industries, making recent graduates in those fields more marketable to potential employers. In addition, if college students become experts in BIM, the whole construction sector may be able to reap its benefits and improve productivity.
Accelerating the industry's transition requires strengthening such a reinforcing loop. Understanding the current state of BIM technology learning behaviour among college students and studying the critical positive effect route of such activity is key for providing better education and stimulating the reinforcing loop. Researchers in building information modelling (BIM) for educational purposes often seek to establish links between business, projects, and classroom instruction. For instance, Ebrahimi et al. look for ways to enhance current buildings using sustainability and building information modelling.
According to a study by Eadie et al. on BIM use throughout a project's lifetime, educators who focus on the right areas of building information modelling (BIM) have a better chance of finding employment in the BIM business. Additionally, with the goal of enhancing the BIM teaching method, Tsai et al. created a new online BIM learning course. Jia suggested that Chinese BIM programs combine

modern technology with more conventional academic practices after comparing BIM programs in the US and China. Looking at the gap between BIM theory and practice from a competency-based education standpoint, Guo et al. investigated potential solutions. In contrast, Ding et al. investigate what practitioners consider to be the most important component in BIM adoption. The key elements impacting architects' BIM, according to their research, are BIM motivation, BIM technical obstacles, and BIM competence.

1.1 Embracing Technology

Applying the UTAUT paradigm, Howard et al. investigate individual viewpoints on building information modelling (BIM) work. The findings indicate that behaviour intention of personal involvement in building information modelling (BIM) is unaffected by performance expectation, indicating that BIM is seen as an uncompensated supplement to current work procedures.

There is a dearth of studies examining the learning behaviour of BIM technology from the viewpoint of individual students, according to a review of the present research corpus. It has recently been suggested to look at BIM education from the students' point of view. Students' enthusiasm for building information modelling (BIM) technologies, as pointed out by Agirbas, may boost their ability to absorb professional architectural knowledge. Two of them detail the social environment, incentives, and accomplishment required, as well as the school (college) culture, personal aptitude, and grasp of BIM industrial applications. In addition, taking into account the existing literature, this study incorporates the UTAUT theory to investigate, from the perspective of individual learners, the factors that impact college students' intentions and behaviours regarding building information modelling (BIM) learning, as well as the relationships between these variables, with the ultimate goal of advancing the field of BIM education.

Traditional construction methods rely on alterations to logistical plans that could lead to problems or disputes (Nelson & Sekarsari, 2019). The expenses are increased due to the need for long-term maintenance and the disruption of operations caused by these difficulties (Kia, 2014). Consequently, it seeks an idea or plan that makes it easier to organise things in order to lessen this problem (Kolosnichenko et al., 2021).

One technology technique that is intended to support current building projects is Building Information Modelling (BIM) (Ding, Niu, et al., 2020). Although it was initially intended for use as a MIS, one of the models This is supported by research published in 2020 by Li, J. et al., 2019 by Nelson and Sekarsari, and 2020 by Sacks and colleagues. Because it gives valuable information as feedback for correct system control, MIS (Abualdenien & Borrmann, 2020) is pretty crucial in firms and companies. Hardware, software, human resources, auxiliary tools, and networks are often all part of it. Models in US-generated MIS began to include BIM in early 2017 (Hunhevicz et al., 2021). In the fields of architecture, engineering, and construction, building information modelling (BIM) is a method that helps to recreate all project data into a three-dimensional model (Darko et al., 2020).

Several significant enterprises and State-Owned Enterprises (BUMN) adopt BIM, according to Nelson & Sekarsari (2019). Bim is defined as a system, management, process, or procedures for working on a project and is not limited to software such as Autodesk Revit, ArchiCAD, AECOSim, and others (Kia, 2014). Its usefulness in construction is constrained to solving the problem of making the most efficient use of limited resources (time, money, and people). All the data from the proposed three-dimensional model of the controlled construction goes into this process.

Nonetheless, according to Ganiyu et al. (2020), every middle-class worker is a BIM graduate. According to Permana et al. (2019), students at DPIB Vocational colleges for Design and Information Technology are expected to have exceptional abilities in areas such as spirituality, leadership, and critical thinking. Thus, vocational training equips individuals with the social and adaptive skills necessary to thrive in a team setting. Vocational colleges train students to work as intermediate-level workers by emphasising hands-on experience above classroom instruction. This has more of an impact on different internal or external factors than on graduates' preparedness for the workforce.

Students in vocational colleges are eligible for job readiness coaching because they are resilient, self-reliant, and have a positive attitude towards learning and change (Browne & Millington, 2015). Their ages range from 19 to 23. A large body of research indicates that TAM is considered as a comprehensive model for investigating eLearning adoption by students.

According toDavis (1986), The Technology Acceptance Model (TAM), has served as a pivotal framework for researchers to identify and interpret the determinants affecting users' behavioral intentions toward technology adoption. Until now, TAM has been widely used in information technology research. The Technology Acceptance Model (TAM) primarily comprises two key constructs: perceived ease of use (PEOU) and

perceived usefulness (PU). Within this model, PEOU and PU serve as the most frequently adopted constructs to account for the variance in users' behavioral intention (BI), which in turn influences their actual use (AU) of a technology.
Learners' intention in the usefulness of technology in accomplishing goals is highly connected to their performance expectation, which in turn determines their motivation and learning performance, which is particularly essential for vocational college students. This study aims to examine the relationship between students' performance expectations and their learning performance in Building Information Modelling (BIM), with a focus on vocational collegess. It highlights the role of students' intention to learn BIM as a mediator in this context. This project's overarching research questions are as follows: (1) What role does students' performance expectations have in shaping their intentions to study building information modelling (BIM) in vocational colleges?
(2) Given that students are supposed to study about building information modelling (BIM), how about their learning performance?
(3) Is there a buffer between students' performance expectations and their actual BIM learning performance among vocational colleges students who want to pursue the subject?

1.2 Performance Expectancy of Students

Performance expectancy is the expected impact of a technology's functional advantage even in uncertain conditions (Sewandono et al,2023)

Rumangkit et al（2023） employed a quantitative research approach, with questionnaire surveys serving as the primary data collection method. Questionnaires were distributed online via Google Forms, and purposive sampling was used to select 100 student respondents who had experience using learning support media such as Canva, Kahoot, Zoom, Google Meet, and others. Data were analyzed using SmartPLS software. The study confirmed that perceived usefulness of learning support media is a key driver of students' intention to use such tools, and this intention further promotes their long-term commitment to using the media. These findings provide empirical references for the promotion and application of educational technology tools.
Sarie (2024) found that nursing students' performance expectancy is positively associated with the intention to adopt ICT and social media, while effort expectancy positively moderates this relationship.
Chao (2019) analyzed the factors influencing students' behavioral intention to use mobile learning (m-learning), conducting a cross-sectional study using a research model based on multiple technology acceptance theories. Data were derived from an online survey of 1,562 respondents and analyzed via structural equation modeling. Partial least squares (PLS) regression was employed for model testing and hypothesis verification. The results showed that behavioral intention was significantly and positively influenced by performance expectancy, while perceived risk significantly and negatively moderated the relationship between performance expectancy and behavioral intention.

Bamigbola and Udomah（2025）Based on the UTAUT theory, a survey of 310 private senior high school students in Nigeria revealed that performance expectancy significantly influenced electronic device use, while facilitating conditions showed no significant association.
Drawing from existing literature, performance expectancy has emerged as a highly consistent predictor of technology acceptance and actual usage in learning contexts. This highlights the critical role of performance expectancy as a behavioral driver in the integration of educational technology, as it aligns with students' cognitive evaluations of how tools enhance learning efficiency, task performance, and academic outcomes.

1.3 Evaluation Using Self-Schemes

According to Marschall, G., and Watson (2019), self-schemes are mental representations that are constantly evolving and include information about the individual.
By managing and directing the processing of self-related information that is a part of people's social experiences, it connects perception with conduct. Future envisioning also makes use of it as a selection technique (Marschall, G. & Watson, 2021). According to Browne and Millington (2015), as one's self-awareness grows, it transforms into a cognitive architecture that allows them to take an unbiased approach to their job, rather than relying only on mechanical audits of their performance. These folks construct very extensible, self-contained systems based on rich semantic networks. Individuals' preconceived notions and biases also have a role in how they look for information, how they process and organise it, and how well it recalls from memory.
An individual's sense of self-efficacy undergoes a phenomenological transformation when they rely on sensory information to compute and rationalise their environment prior to integrating it with their actions and behaviours. This is in continual interaction with a smart, dynamic, and chaotic environment, even if

it is an abstraction of itself. Then, according to Watson and Marschall (2019), perfomance expectancy is defined as the way in which one's self-schemas react to real-life situations. People do this when they are trying to make sense of what they've experienced. Examining the significance and rationale behind students' self-schemata adaptation, this research uses students who learned BIM technology in Vocational colleges as an example.

1.4 Features, Categories, and Origin of Performance Expectancy

Performance Expectancy (PE) refers to the extent to which an individual believes that the use of an information technology or system will enhance individual performance or effectiveness (Venkatesh al., 2003). Since the predicted timeliness, output, and quality will also be improved due to increased effectiveness, PE is that significant benefits will be achieved by using a particular technology or system. Meanwhile, Venkatesh et al. (2003) argued that PE can be explained by the following five elements: Perceived Usefulness in TAM model, Relative Advantage, Extrinsic Motivation in, Job-fit and Outcome Expectations of the SCT model

Specifically, perceived usefulness primarily reflects the extent to which individuals believe that using information technology or systems can improve their job performance and productivity. It has considerable explanatory power for performance expectations, including beliefs that using the system can make work faster and easier, enhance productivity and efficiency, improve job performance, and be helpful for work (Davis, 1989; Davis et al., 1989).

External motivation refers to individuals' intention to perform a task because the technology or system is perceived to contribute to valuable work outcomes, such as improved job performance or advancement (Davis et al., 1992).

Job fit refers to the degree of alignment between information technology and one's work, and the extent to which the technology or system enhances individual job performance, such as improving work outcomes, productivity, and efficiency overall, indicating that using the technology or system is helpful for one's work (Thompson et al., 1991).

Relative advantage refers to the degree to which individuals feel that using information technology is better and more beneficial than using other resources, such as being able to work faster, easier, and with higher quality, and increasing productivity (Moore & Benbasat, 1991).

Outcome expectations are the subsequent performance expectations related to work and individual goals after individuals believe that the information technology can meet their task requirements, such as saving time, improving efficiency and quality, increasing output, enhancing work abilities, and increasing the chances of promotion and salary raise (Compeau & Higgins, 1995; Compeau et al., 1999).

1.5 Work Ready

When a person's mental, physical, and social capacities are all in sync, they are considered work ready. A person's level of maturity determines their ability to adapt to a given scenario and their level of engagement in a certain activity (Baharuddin et al., 2017).

Competence in certain areas is indicative of how well people are prepared for their jobs (Makki et al., 2016). There are four factors that influence how well someone is prepared for work: Symptoms indicate complete maturation on all levels (mental, emotional, and physical), include spirituality and physical health, positive job experiences, and expertise in any field. Indicators of industrial work readiness, as outlined by Browne & Millington (2015), include the following: (1) the ability to think logically and objectively; (2) the possession of adequate knowledge and skills; (3) the desire to work; (4) the capacity to adapt to one's surroundings; (5) the ability to work in tandem with others; (6) the sense of responsibility; (7) self-control; (8) the ability to stay abreast of technological advancements; and (9) critical thinking skills (Ganiyu et al., 2020; Haase et al., 2018).

1.6 BIM Education's Research Situation

Building information modelling (BIM) training is becoming more vital in the modern day. According to Chegu Badrinath et al., students who have been trained in building information modelling (BIM) can effectively combine and display project data, meeting the demands of modern businesses. Despite BIM's widespread use and academic interest, not all nations have made an effort to promote it. A research conducted by Kolari'c et al. revealed, for instance, that Slovakia and Croatia had subpar BIM implementations. In addition, the growth of BIM education is seen to be substantially influencing BIM adoption and awareness, and motivating those nations to incorporate BIM technology into the AEC sector even further. According to researchers from a variety of nations, contextualised learning might be impacted by a rise in BIM awareness and the subsequent growth of BIM technology, which could be achieved via the widespread use of digitalisation and the enhancement of BIM education.

The rapid growth of building information modelling (BIM) technology is compelling educational institutions to place a stronger emphasis on teaching students BIM technical skills. Virtual, augmented, and mixed reality have provided a great theoretical foundation for building a thorough BIM teaching system in university classrooms. Nevertheless, BIM education is unable to fully sustain the growth of the AEC sector, and the training scale of BIM technical capabilities is inadequate to satisfy the demands of industrial development. Some researchers believeds that present BIM education fails to adequately combine BIM with other architectural disciplines, despite the fact that many schools and institutions have included BIM-related courses into their curricula. Negative attitudes towards new technologies are a direct result of people's lack of knowledge about them; this may have far-reaching effects on the industry's growth and the adoption of new technology. Educational institutions should be aware that students' perceptions about BIM technology have a substantial impact on the level of proficiency their students achieve in using it.

2. Methodology

2.1 Research Design & Participants

With Intention to Learn BIM (ILB) as a mediator, this research used a quantitative, cross-sectional survey methodology to investigate how Performance Expectancy (PE) of vocational students affects their Bim Learning Performance (BLP). Drawn was a convenience sample of N = 235 vocational college students registered in China for courses linked to BIM. 190 total replies remained for study after data cleansing.

2.2 Objectives of the Study

1. To examine the influence of performance expectancy (PE) on vocational college students' intention to learn BIM (ILB).
2. To assess the impact of intention to learn BIM on actual BIM learning performance (BLP) among vocational college students.
3. To investigate whether intention to learn BIM mediates the relationship between performance expectancy and BIM learning performance.
4. To identify key cognitive and motivational indicators that influence students' perception and adoption of BIM in vocational education.

2.3 Instrument Development

A structured questionnaire was designed around three multi-item scales, measured on a 5-point Likert scale (1 = "Strongly Disagree" to 5 = "Strongly Agree"):

1. **Performance Expectancy (PE)** (6 items, e.g. "BIM technology increases my educational productivity.")
2. **Intention to Learn BIM (ILB)** (4 items, e.g. "I want to continue learning BIM technology deeply in the future.")
3. **BIM Learning Performance (BLP)** (4 items, e.g. "Through BIM learning, I have developed proficiency in BIM software operation, enhancing my skill level.")

2.4 Validity & Reliability

With the first component explaining 36.98% (PE), 58.39% (ILB), and 52.31% (BLP), respectively—all item loadings ≥.51—exploratory factor analysis (Principal Component Analysis with Kaiser-Guttman criteria) revealed one-dimensionality for each construct. For PE, Cronbach's α =.89; for ILB,90; and for BLP, internal consistency was superb.

2.5 Hypotheses of the Study

Based on the objectives and existing theoretical framework, the following hypotheses were formulated:

- **H1**: Performance Expectancy significantly influences Intention to Learn BIM among vocational college students.
- **H2**: Intention to Learn BIM significantly influences BIM Learning Performance.
- **H3**: Performance Expectancy has a significant direct effect on BIM Learning Performance.
- **H4**: Intention to Learn BIM mediates the relationship between Performance Expectancy and BIM Learning Performance.

2.6 Statistical Tools and Techniques

Using SPSS Version 25, a set of well-known statistical methods were used to guarantee the validity and strength of the study conclusions. These instruments were carefully chosen to verify the underlying measurement model and examine the expected correlations among the constructs—Performance Expectancy (PE), Intention to Learn Bim (ILB), and Bim Learning Performance (BLP). The following lists the specific statistical instruments used in the research:

2.7 Descriptive Statistics

The demographic traits of the respondents were compiled using descriptive statistical analysis, which also investigated the answer distribution across all the questionnaire questions. To reflect core trends and variability, one employed measures like mean, standard deviation, frequency, and percentage. This first study set the groundwork for further inferential studies and gave understanding of the participants' overall characteristics.

2.8 An EFA that makes use of PCA (Principal Component Analysis)

Principal Component Analysis with varimax rotation was used under exploratory factor analysis to evaluate concept validity. The purpose of this research was to identify the components that make up the instruments used to measure PE, ILB, and BLP. Items with factor loadings greater than 0.50 were retained, and constructs were considered legitimate if they explained more than 50% of the total variance. In particular, 36.08% of the variance was accounted for by performance expectations, 58.19% by intentions to learn bim, and 52.31% by bim learning performance.

2.9 Reliability Analysis

For every concept Cronbach's Alpha was computed to assess the internal consistency of the measurement scales. With alpha values over the reasonable 0.70, all three constructions showed great dependability. PE specifically produced a Cronbach's alpha of 0.89, ILB of 0.90, and BLP of 0.87, therefore verifying the consistency and dependability of the measuring devices.

2.10 Correlation Analysis

To investigate the direction and degree of the linear interactions among the fundamental variables, Pearson correlation coefficients were calculated. This study was just a first step in evaluating the relationships among PE, ILB, and BLP. The findings revealed statistically significant and positive associations, meaning that increased desire to learn BIM and better learning outcomes are connected with an increase in performance expectation.

2.11 Multiple Linear Regression Analysis

To examine the predictive power of the independent variables and test the proposed hypotheses, multiple regression analyses were conducted. The models tested included:

- Performance Expectancy predicting Intention to Learn BIM,
- Intention to Learn BIM predicting BIM Learning Performance, and
- Performance Expectancy directly predicting BIM Learning Performance.

Each model's fitness was evaluated using R^2, adjusted R^2, F-statistics, and p-values. Notably, the regression analysis revealed that Performance Expectancy significantly influenced ILB (Adjusted $R^2 = 0.254$, $p < 0.001$), and ILB significantly influenced BLP (Adjusted $R^2 = 0.462$, $p < 0.001$). These findings supported the hypothesized relationships.

2.12 Performance Expectancy (PE)

The factor analysis for Performance Expectancy extracted one dominant factor with an eigenvalue of 2.218, explaining approximately **36.98%** of the total variance. This indicates that the construct is **moderately unidimensional**, capturing just over one-third of the shared variance among its six items. The **communalities** after extraction range from **0.260 to 0.464**, which suggests that while some items contributed strongly to the factor (e.g., "BIM will help me stand out in job applications" at 0.464), others—such as "I find BIM easy to use for my academic tasks"—contributed less (0.260). Nonetheless, all items exceeded the minimum acceptable communality threshold of 0.2, justifying their inclusion.

We can see moderate to high connections with the underlying PE construct from the component loadings, which varied from 0.510 to 0.681. Notably, the items related to future career utility and job competitiveness loaded most strongly (0.659 and 0.681 respectively), reinforcing that students' performance expectations from BIM are strongly aligned with perceived career benefits. This aligns well with the theoretical underpinnings of the Technology Acceptance Model (TAM), where perceived usefulness is a key antecedent of intention and behavior.

2.13 Intention to Learn BIM (ILB)

The factor analysis for ILB turned up a strong unidimensional structure. With an eigenvalue of 2.336, a single factor was identified that accounted for 58.39% of the total variance—an outstanding result in social science research demonstrating that the items are cohesively assessing the same latent construct.

Each piece much helps to describe the whole construct; the communalities after extraction varied from 0.510 to 0.798, all far over the criterion of 0.5. With 0.798, "I am likely to enrol in future courses or workshops related to BIM" had the highest communality, thus stressing this as the most typical item of students' learning intention.

Consistent high component loadings ranging from 0.719 to 0.802 confirmed a good internal coherence of the construct. These principles show that the participants' drive to interact with BIM goes beyond their present course into proactive upskilling aspirations. This result helps to justify the presumption that students' desire to study BIM is a unique and well-formed cognitive inclination among the target demographic.

3. BIM Learning Performance (BLP)

A single component with an eigenvalue of 2.616 was discovered by the principal component analysis (PCA) for BIM Learning Performance, which extensively accounted for 52.31% of the total variance. This outcome is good as the concept catches more than half of the variance in answers.
Communalities varied from 0.199 to 0.724. Although several objects showed strong communalities higher than 0.5, the overall BLP indicator item had a quite low communality (0.199). This implies that whereas particular performance-related variables are accurate markers of learning outcomes, the more general or more abstract view of performance might not load as strongly. Still, everything added favourably to the factor.
Ranging from 0.716 to 0.851 for certain parts, the component loadings show even more the strength of the design. Affirming the pedagogical relevance of BIM integration, "I perform better academically when Bim is integrated into the curriculum" (0.851) had the greatest loading. With a lowest value of 0.446, the item reflects a broad view of BLP rather than a particular behavioural consequence, nevertheless meeting the reasonable threshold for exploratory study.

3.1 Overall Interpretation

For use in further structural equation modelling, the factor analyses verify that all three constructs—Performance Expectancy, Intention to Learn BIM, and BIM Learning Performance—are unidimensional and statistically sound. A consistent mediator variable in the investigation, intention to learn BIM turned up as the strongest construct in terms of variance explained and loading consistency. These findings also complement the conceptual framework of the research and help to validate the measuring tools. That is to say, real BIM learning performance is much driven by students' desire to study BIM, which is a relevant predictor of them. Moreover, the construct reliability and variance explained show a cohesive structure, thereby enhancing the empirical basis for mediation and regression analysis in next phases of the research.

With an especially focus on the mediating function of intention to learn BIM, the regression analyses performed across the three models provide a thorough knowledge of how performance expectation impacts vocational students's BIM learning performance. Examining predictors of Performance Expectancy (PE), the first regression model produced a R^2 value of 0.288, meaning that the chosen indicators—including those pertaining to students' intention and motivation—allow one to roughly explain 28.8% of the variation in PE. The biggest predictors of performance expectation were notably students's view that "BIM will help me stand out in job applications" ($\beta = 0.324$, $p < 0.001$) and that "BIM can help me complete tasks more quickly" ($\beta = 0.271$, p These results support the fundamental ideas of the Technology Acceptance Model (TAM), according to which expectations towards technology adoption are greatly shaped by perceived usefulness—especially in terms of career value and productivity. On the other hand, general intention indicators, like "I am likely to enrol in future courses or workshops," showed a negative and significant influence on PE ($\beta = -0.195$, $p = 0.021$), thus suggesting a possible conceptual overlap or redundancy deserving of further scale improvement.
Under the second model, the emphasis moved to knowing how BIM Learning Performance (BLP) affects students' Intention to Learn BIM (ILB). With a R^2 of 0.484 this model showed great explanatory power, indicating that the predictors explain about 48.4% of the variation in ILB. Motivating elements were clearly the most important component of this paradigm. Students' intentions were much impacted by statements like "I am motivated to explore new BIM tools and techniques" ($\beta = 0.261$, $p < 0.001$) and "I am likely to enrol in future courses" ($\beta = 0.273$, p Moreover, the confidence to implement BIM in practical projects ($\beta = 0.373$, $p < 0.001$) underlined even more the need of self-efficacy and forward-looking involvement.
The final regression model sought to ascertain how much real BIM Learning Performance could be predicted by PE and its indicators. Though the direct impact of overall Performance Expectancy on BLP was not statistically significant ($\beta = -0.063$, $p = 0.405$), the model indicated that 26.1% of the variation in BLP was explained ($R^2 = 0.261$). Rather, personal PE indicators—such as "BIM will help me stand out in job applications" ($\beta = 0.252$, $p = 0.001$), and "BIM can help me complete tasks more quickly" had a greater influence on the ability to learn ($\beta = 0.363$, $p = 0.001$).
This result suggests that whereas general expectation may not directly affect performance, particular utility judgements do have demonstrable academic effects. On the other hand, several negative

correlations surfaced, including "receiving good feedback on coursework" (β = -0.244, p = 0.006), perhaps because of differences between perceived feedback and real learning effectiveness, or depending on external validation over inner knowledge.

The three regression models taken together support the theory that Intention to Learn BIM is a fundamental mediator between Performance Expectancy and BIM Learning Performance. While PE by itself does not particularly forecast BLP, its impact is clearly shown by ILB, therefore verifying a complete mediation route. These revelations support the structural model underlying the research and fit accepted theories of technology adoption, implying that instead of concentrating just on technical knowledge or performance feedback, teachers and legislators should concentrate on improving students's motivation, confidence, and perceived career relevance of BIM tools. In the framework of vocational BIM education, this strategy is more likely to stimulate ongoing participation and better learning results.

Hypothesis Code	Statement	Result	Significance
H1	Performance Expectancy → Intention to Learn BIM	Supporte d	Significant ($p < 0.001$)
H2	Intention to Learn BIM → BIM Learning Performance	Supporte d	Significant ($p < 0.001$)
H3	Performance Expectancy → BIM Learning Performance (Direct)	Not Supporte d	Not Significant ($p > 0.05$)
H4	Intention to Learn BIM mediates PE → BLP relationship	Supporte d (Full edition)	Confirmed via regression path pattern

4. Conclusion

With an especially emphasis on the mediating function of intention to learn BIM, this paper investigated the impact of performance expectation on vocational students' learning performance in Building Information Modelling (BIM). The results showed that while not directly influencing learning achievement, performance expectation greatly influences students' desire and intention to interact with BIM. The study revealed that intention to learn serves as a complete mediator—that is, students' assessed value and potential career rewards of BIM transfer into enhanced performance essentially via greater intention and self-driven learning behaviour. Stronger predictors of learning outcomes than general academic feedback or ease-of-use characteristics were also practical judgements like BIM's value in job applications and its capacity to improve work efficiency. Furthermore very important in determining purpose were internal drive, readiness to upskill, and confidence in practical application, which in turn greatly affected learning performance.

Underlining that behavioural intention remains a fundamental construct in the successful adoption and performance outcomes of educational technologies, these results coincide with build upon, and broaden the scope of, the TAM and the Universal Theory of Acceptance and Use of Technology (UTAUT).

5. Recommendations

Based on the findings of this research, several recommendations can be proposed to vocational educators, curriculum designers, and policymakers:

1. **Integrate Career-Oriented BIM Curriculum:**
Educational institutions should design BIM modules that emphasize real-world applications, employability benefits, and industry relevance. Career-aligned learning outcomes can enhance students' performance expectancy.
2. **Foster Student Motivation and Engagement:**
Institutions should implement learning strategies that build intrinsic motivation, such as gamified BIM tools, project-based learning, and exposure to cutting-edge digital construction techniques.
3. **Enhance Awareness and Intentional Learning:**
Organizing workshops, certifications, and future-skilling bootcamps can reinforce students' intention to pursue BIM competencies beyond the classroom context.
4. **Emphasize Feedback for Development, Not Validation:**
Feedback mechanisms should focus on formative and constructive development, guiding students toward actionable improvement rather than merely evaluative scores.
5. **Teacher Training and Pedagogical Alignment:**
Faculty should be trained not only in BIM software but also in motivational pedagogy, enabling them to effectively link performance expectancy to students' learning intentions.
6. **Policy Support for Digital Construction Tools:**
National and state education policies must support the inclusion of BIM as a key technical competency for vocational college students, given its growing significance in industry practice.

6. Limitations of the Study

Although there are several important takeaways from the research, it does have certain limitations:

1. **Geographic and Sample Limitation:**

The results may not apply to a larger or more varied student population since the research only included vocational colleges students from a particular area.

2. **Cross-Sectional Design:**

Because the data was only recorded once, it is impossible to determine whether there was a cause and effect relationship or to monitor how learning performance, intention, and performance expectations changed over time.

3. **Self-Reported Measures:**

Because they relied on self-reported surveys, all of the variables might have been impacted by social desirability bias or exaggerated self-perceptions.

4. **Exclusion of External Variables:**

The study focused primarily on performance expectancy and intention. Other factors such as social influence, system accessibility, prior experience, and institutional support were not included but may also affect BIM learning performance.

5. **Limited Use of Advanced Structural Modelling:**

Although regression analysis was used effectively, the absence of structural equation modeling (SEM) with path analysis limited the comprehensive evaluation of the mediation effects in a single integrated model.

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