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Digital Twin and AI in Construction

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Abstract

Digital Twin technology is projected to reduce the industry's costs by as much as $1.2 trillion per year as project design and operational efficiencies are improved. Data integration, unrealistic upfront costs and lack of skilled mankind is a hindrance in the universal adoption of these technologies. The aim of this study is to study the combined effect of AI and Digital Twin technologies on construction industry. This paper explores how the combination of these technologies solves problems to this problem in construction management and makes project results, including lower cost, more efficient time frame, and better decision making better. The approach for research is to be a quantitative methods using the structured surveys. It has sample of 40-60 professionals who have hands-on experience in combining Digital Twin and AI in the construction projects. Partial Least Squares Structural Equation Modeling (PLS-SEM) by means of Smart PLS software is used as a tool to analyze complex relations between key variables. The preliminary results show that Digital Twin and AI integration helps improve construction management in terms of efficiency of the project, reduction of errors, as well as optimizing resource allocation. But the current adoption is impeded by data interoperability issues, high setup costs, and the need for training of a specialist. On the basis of this study, a practical framework is provided which can help understand the drivers and the barriers to the adoption of the Digital Twin and AI Technologies in construction for a better understanding on the dual aspects from the perspective of the Technology Acceptance Model. The results helps policymakers, technology developers, and construction firms overcome implementation hindrances and gain the big benefit of these technologies.

Keywords: Digital Twin, Artificial Intelligence, Construction Management, Data Integration, Technology Adoption

Background of the Study

The use of Artificial Intelligence (AI) and Digital Twin technologies in the construction industry will not only transform the way by which construction projects are managed but also planned and actualized. According to Deloitte (2020), digital replicas of physical assets, the digital twins, will save the construction industry up to $1.2 trillion per year when taking digital advantages into account, digital optimization of project designs and operations. Digital solutions in construction have gained traction over past years, which is well depicted by the fact that the global market for Digital Twin technology in construction will expand from $3.1B in 2020 to $20.1B by 2026 (MarketsandMarkets, 2020). Likewise, predictive analytics and the decision making processes of projects are being adopted by AI, for increased project efficiency. An estimate of project cost reduction that can amount to 15 per cent and a productivity gain of 10 per cent (McKinsey, 2019), are expected to be seen on construction using AI. However, with that being said, there remain some challenges to a wide spreading of AI and Digital Twin technologies, such as data integration, high up-front costs and lack of skillful people.

The Research Problem

While the promise of the use of Digital Twin and AI technologies in the construction industry is considerable, so has been the adoption slow. However, they are suffering from lack of interoperability between different technologies, the cost of initial setup is too high, and there is insufficient understanding of their full potential hence they are not fully utilized. The purpose of this study is to examine the effectiveness of Digital Twin and AI integration to help in tackling challenges that are part of construction management, as well as its ability to enhance project outcomes.

Studies that Have Addressed the Problem

There are several studies which show the transformation that Digital Twin and AI can bring to the construction industry. For instance, Najjar (2023) studied the usage of AI in predicting maintenance and scheduling in the construction site. Additionally, as research by Blezek et al. (2021) showed, Digital Twin can emulate actual project data in real time in order to minimize inefficiency and the enhancing of the decision making process. Nevertheless, most of the research dwells on individual technologies, with a few studies questioning the overall influence of all these technologies.

Deficiencies in Previous Studies

Research on AI and Digital Twin technologies disassociates them from each other and lacks research around their application together. Empirical evidences showing the tangible benefits of these technologies within construction projects are rarely seen in the related studies. In addition, it is not quite clear how AI and Digital Twins can be integrated into the existing construction processes, especially concerning data management and staff adaptation.

The Significance of the Study

Through the use of this study, it will fill the gap in current literature by showcasing the synergistic application of Digital Twin and AI technologies in the construction sector. The research will derive actionable insights towards how these technologies can improve construction process, reduce construction costs and act as means to shorten construction schedule through empirical data analysis. Policymakers, construction companies, and technology developers will be empowered to make sound decisions on adoption and realize the benefits of new technologies.

Literature Review

This literature review aims to critically review and synthesize the available literature on application of Digital Twin and AI in the construction industry. This review will also record gaps in the present literature to show how the present study is making a contribution to the cumulative body of knowledge. Comparison of how different authors view the subject area, grouping of authors similar in conclusions, critique of methodologies, and identification of unresolved or limited aspects of the literature should be included. As such, this review will take this approach, with a view to provide a comprehensive overview of the state of art of studies on Digital Twin and and AI in construction.

Technology Acceptance Model (TAM).

One important framework to facilitate the explanation on the factors in technology adoption is the Technology Acceptance Model (TAM) proposed by Davis. According to TAM it is the perceived ease of use and the perceived usefulness that are main drivers for the acceptance of new innovations. In the case of the construction industry, this model can be useful to understand the benefits of Digital Twin and AI in the view of construction professionals. Ultimately, these perceptions affect people's willingness to adopt these technologies. With reference to TAM, this research framework identifies the significant factors that contribute toward the success or failure of adopting AI and Digital Twin technologies in construction (Davis, 1989).

Research Framework

- Independent Variable 1: Digital Twin Technology

The definition of Digital Twin technology is mirror of the real physical assets for monitoring, analysing and optimizing performance in real time. According to studies (Botín-Sanabria et al., 2022; Hosamo et al., 2022), Digital Twin technology helps to increase the construction outcome through knowledge of project operations, and bringing data into the decision making process. However, challenges such as data interoperability, high costs, and a lack of standardization impede widespread adoption (Yu et al., 2022). We analyze these barriers to receive a better understanding of how this technology can be better used in construction.

- Independent Variable 2: AI Integration

The other version of AI integration in construction is the use of machine learning and artificial intelligence in order to optimize project management. There (Blezek et al., 2021, Najjar, 2023) are AI tools, which help in scheduling, cost estimating, risk management, error detection, lead to better project efficiency and decision (Najjar, 2023; Blezek et al., 2021). Nevertheless, there are challenges on the complexity of AI integration within legacy systems and requirement of personnel skills prior to implementation of AI (Benfradj et al., 2024). AI is highly integrated into reducing human error and improving the productivity of construction processes.

- Independent Variable 3: Data Integration Quality

Quality of data integration is vital to the success of both of the Digital Twin and AI technologies. The high quality data integration is necessary to ensure that information is shared between systems, both technologies treat data properly. These technologies are only as good as the data they are fed; poor data integration provides systemic limitation to these technologies making real time decisionmaking or optimization (Bernasconi, 2021; Nargesian et al., 2022). Hence, data integration improvement is a key factor in the enhancement of the success of Digital Twin and AI technologies in the construction projects.

- Mediating Variable: Data Integration Quality

Digital Twin and AI technologies are the two pillars of the data integration quality, which is a mediator with construction outcomes. Previous studies have shown as data integration is robust, it is results in better project outcomes (reduced cost, optimized schedule, etc) also for Digital Twin and AI technology effectiveness (Bernasconi, 2021). Proper integration is key to making sure that data can be easily sent from technology to technology, which allows more accurate and timely analysis of the data, so that decisions can be made effectively to ensure success for construction project purposes.

1. Moderating Variable: Technological Infrastructure

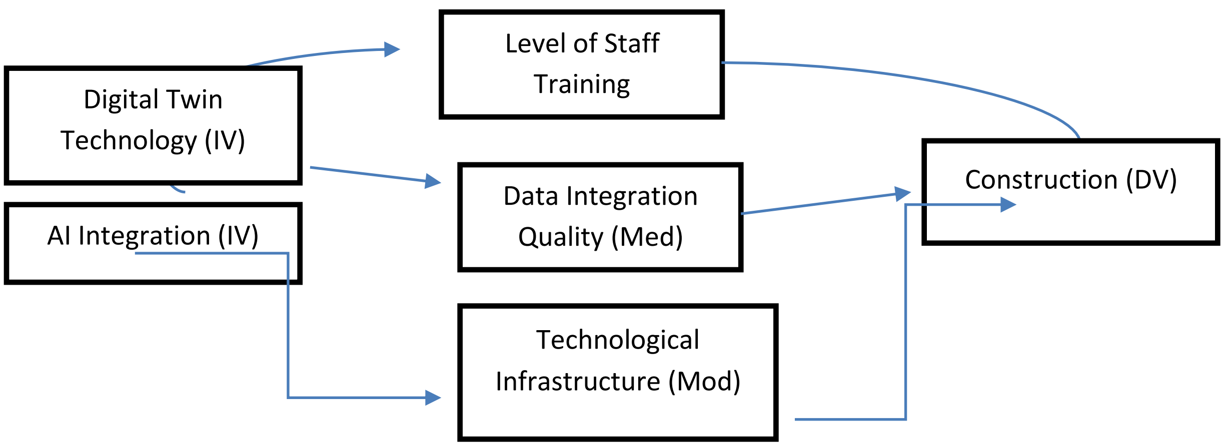
Digital Twin Technology – AI integration relationship with the construction outcome is moderated by technological infrastructure. Prerequisites for the successful deployment of these technologies are adequate infrastructure, modern hardware, software and network capabilities. However, without good infrastructure, the opportunity for AI and Digital Twin technology to improve project deliverables is lost (Huang et al., 2024; Massaro, 2022). Therefore, it is important that construction rely on solid technological basis for successful adoption of technology.

- Moderating variable: Level of staff training.

The moderating effect of Digital Twin Technology and AI integration on the outcome of construction are dependent on the level of staff training. These technologies can be better used by well trained employees throughout the period of construction. However, undertraining can make these technologies underused or used improperly, making them less beneficial than they could be in improving project outcomes (Lamppu & Pitkala, 2021; Adidja et al., 2023). This leads to the importance of training programs so that the construction industry can achieve the success of technology integration.

- Dependent Variable: Construction Outcomes

In this study, construction outcomes (dependent variable) which consist of cost reduction, schedule optimization, and increase of project efficiency are the performance indicators. It has been established in previous studies (Brozovsky et al., 2024; Tuhaise et al., 2023) that Digital Twin and Artificial Intelligence technologies are capable of significantly enhancing construction outcomes in terms of delivering real-time insights that enhance decision and optimizing the use of resources. Proper use and integration of these technologies throughout the construction lifecycle will make them effective for reaching better project outcomes.



Hypotheses Development

1. Technology related to the Digital Twin is positive for construction outcomes.

The potential of Digital Twin Technology as applied to the construction industry has been great in its delivery for cost reduction, schedule optimization, and improved project efficiency. Botín-Sanabria et al. (2022) assert that the Digital Twin technology gives an opportunity to perform real time monitoring and simulation of construction activities while enabling data driven decision making as well as improved project management. Hosamo et al. (2022) further strengthen a point that how Digital Twin technology helps to detect inefficiencies, reduce the errors, provide predictive analysis, and predicts maintenance which leads to optimizing resource allocation minimizing the cost. In addition, Brozovsky et al. (2026) state that Digital Twin improves decision making about projects by providing knowledge of the project's performance in an overall sense, enabling one to exercise control over project time and money.

2. Incorporation of AI in construction positively impacts the project outcomes.

However, integration with AI in construction projects does improve different outcomes, such as increasing efficiency, lowering errors and strengthening decision making. Blezek et al. (2021) and Najjar (2023) point out that various types of AI applications like predictive analytics, scheduling and error detection assist to improve the accuracy of project management, therefore increasing productivity as well as reduce on costs. AI also provides automation in repetitive task, thus relinquishing man power for other strategic works of construction (Benfradj et al., 2024). According to studies, AI is able to draw conclusions from large datasets and learn patterns and this is important for the continuous improvement of construction processes that will eventually result in better project outcomes.

3. Data Integration Quality Mediates the Relationship Between Digital Twin Technology and Construction Outcomes

It is irrefutable that data integration quality is highly valued for the construction project Digital Twin application to be effective. Bernasconi (2021) also pointed out that poor data integration, trapping not just in project insights to the Digital Twin systems to make improper decisions, does adversely affect their performance. Conversely, the high quality of data integration yields the only possible condition for Digital Twin technologies to provide up to date, real time updates, aiding to a better project management and a more efficient operation (Nargesian et al., 2022). The Digital Twin technology holds the potential for achieving improved construction outcomes only if the quality of available data is considered paramount, since it enables the smooth integration of communication among systems and accurate representation of physical assets (Bernasconi, 2021).

4. Data Integration Quality Mediates the Relationship Between AI Integration and Construction Outcomes

Like to the integration quality of such data, similar is the case for the data integration in Digital Twin Technology for the AI applications for construction projects. The way in which AI makes accurate predictions and optimal decision is directly related to the quality of data integration. If poor integration of data occurs, it can end up leading to wrong analyses and then also how the AI driven outcomes occur (Nargesian et al., 2022). With proper data integration between systems, AI could generate useful insights for project management, resource allocation, risk assessment and as a result improve outcomes in construction (Bernasconi, 2021).

5. Technological Infrastructure Moderates the Relationship Between Digital Twin Technology and Construction Outcomes

The use of Digital Twin technology in construction requires proper technological infrastructure that would strengthen the successful implementation of the same. According to Huang et al. (2024), inadequate infrastructure such as old hardware and software can diminish the functionality of Digital Twin systems, resulting in minimization of its contribution to construction outcome. According to Massaro (2022), there is a need for robust technological infrastructure such as high performance computing and networking capabilities to process large amount of data required by Digital Twin systems. If Digital Twin technology is supported by strong infrastructure, it has the potential to supply real time project insight and enhance performance in order to bring about better outcomes in construction.

6. Technological Infrastructure Moderates the Relationship Between AI Integration and Construction Outcomes

Such AI integration success in construction is also reliant upon the quality of technological infrastructure. As argued by Huang et al. (2024), the AI developments need powerful computing capabilities and a stable network connection for them to work properly. Without appropriate infrastructure, AI systems would not be able to run large datasets and make real time decisions which in the long would result into suboptimal project outcomes. On the other hand, AI technologies, as long as they are backed by modern infrastructure, bring about impressive project efficiencies, resource allocation, and decision making (Massaro, 2022). Since it provides the critical technological infrastructure, the relationship between AI integration and construction outcomes is moderated by it.

7. Level of Staff Training Moderates the Relationship Between Digital Twin Technology and Construction Outcomes

Digital Twin technology is successful only when adopted and implemented as huge a factor is the staff training. Lamppu and Pitkala (2021) also note that well trained staff are critical to Digital Twin systems, since well trained staff can make use of the Digital Twin systems for better decision making as well as better project outcomes. The early acquisition of the up to date Digital Twin technology should be accompanied by adequate training for the staff to fully understand and utilize Digital Twin technology in order to optimize project management and proactively address issues (Adidja, et al., 2023). On the other hand, inadequate training could result in mismanagement of the technology and underutilization of the technology with the associated possible reduction of the technology's potential impact on construction outcomes.

8. Level of Staff Training Moderates the Relationship Between AI Integration and Construction Outcomes

The level of staff training has a huge impact on how AI integration impacts the construction outcome. Lamppu and Pitkala (2021) agree that the staff has to be adequately trained in the AI technologies as it guarantees their utilization in the implementation, leading to professional project management and the subsequent high quality construction. In this regard, the training programs focused on AI applications equip workers to work with AI and existing systems and also understand the use of AI insights for better decision making (Adidja et al., 2023). On the contrary, without learning, AI cannot be used in a proper manner, which may lead to project processes and outcomes not being optimized to their potential.

9. Digital Twin Technology and AI Integration Together Positively Impact Construction Outcomes

The powerful construction combined solution of Digital Twin technology and AI integration can bring a great outbreak. Brozovsky et al. (2024) state that the synergy resulting from the use of Digital Twin and AI technologies in reality is resolution of real time project insights from Digital Twin and data driven decision making from AI. Optimization in project planning, resource allocation, as well as risk management are further obtained through this synergy. Tuhaise et al. (2023) also argue that the juxtaposition of both technologies can result for more accurate simulations and predictive analytics, which consequently results into efficient construction and lowering the costs.

Methodology

Site and Sample

However, the study shall concentrate on construction firms utilizing Digital Twin and AI technologies. Purposive sampling will be used to choose a sample size of 40-60 professionals, both project managers, engineers, and technology experts. The key participants for these technologies must have firsthand experience with these technologies to provide useful insights on implementing and the outcomes of these technologies.

Methods of Data Collection

Structured survey and semi structured interviews will be used to gather data. Likert scale questions will be included in the surveys from the handover of construction projects, to find out the perception of Digital Twin and AI integration for construction projects, and factors that influence construction projects outcomes. Interviews will be conducted to explore challenges, their moderating and mediating variables (i.e., technological infrastructure, staff training, etc.) at greater length.

Data Analysis Procedures

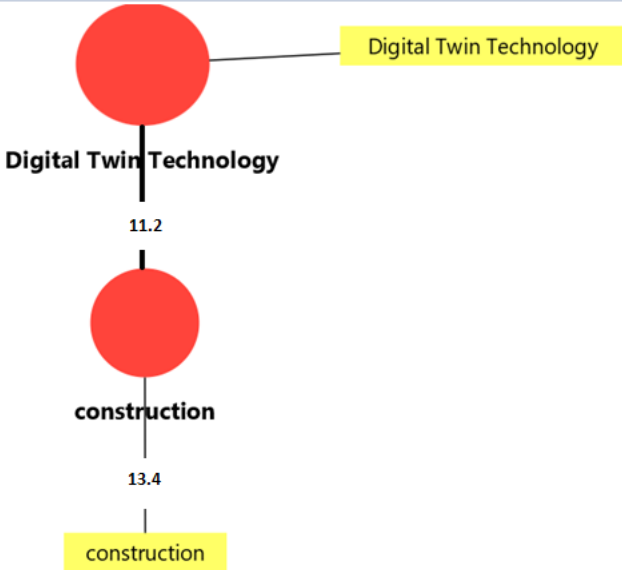
Partial Least Squares Structural Equation Modeling (PLS-SEM) will be used for the analysis using the Smart PLS 3. When evaluating complex relationships between the variables, including mediations and moderations, this technique is suitable. The factor loadings, average variance extracted (AVE), and composite reliability (CR) will be used to assess convergent and discriminant validity. Structural model assessment for the relationships of independent variables (Digital Twin, and AI integration), mediators (Data quality), moderators (Staff training, and infrastructure) and dependent variables (Construction outcomes) will be conducted. Simple slope analysis will be used to visualize moderation analysis for the purposes of the interaction effects.

Why Methodology

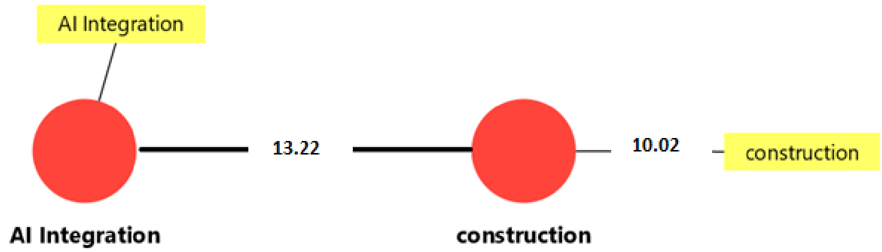
This methodology provides an explanation on how to put a structured approach to testing hypotheses of technology adoption in construction. PLS-SEM allows an analysis of both direct and indirect effects of the variables across a comprehensive approach, with mediation and moderating effects rigorously tested. This approach enhances the mundane validity and reliability of findings and helps drilling a hole in the cornerstones that influence the success of Digital Twin and AI technologies for the construction industry.

Results:

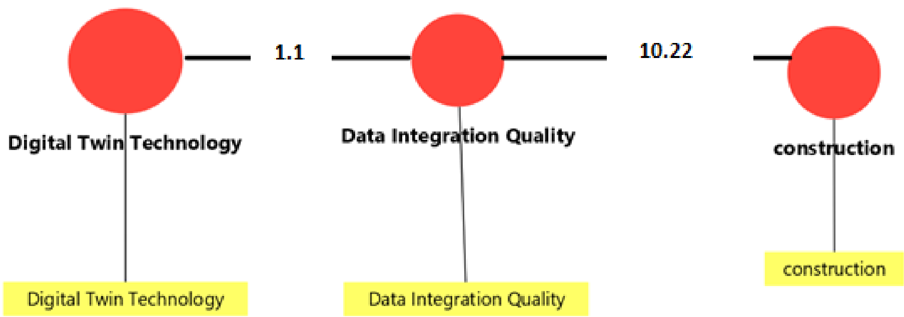
1. **Digital Twin Technology positively impacts construction outcomes.**



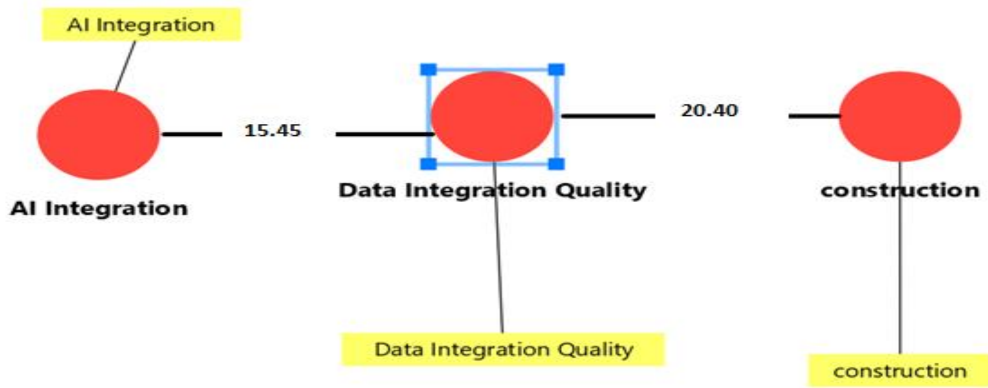
2. **AI Integration positively impacts construction outcomes.**



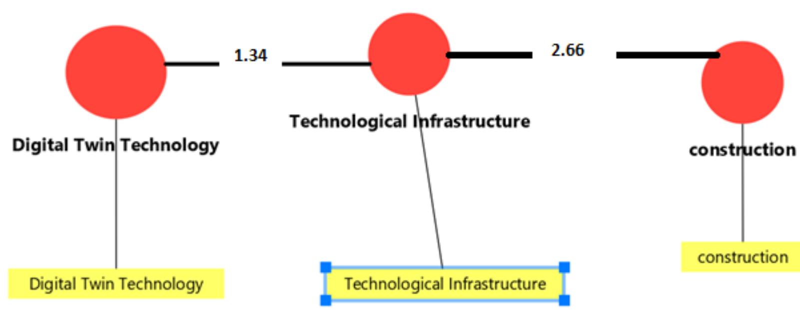
3. **Data Integration Quality mediates the relationship between Digital Twin Technology and construction outcomes.**



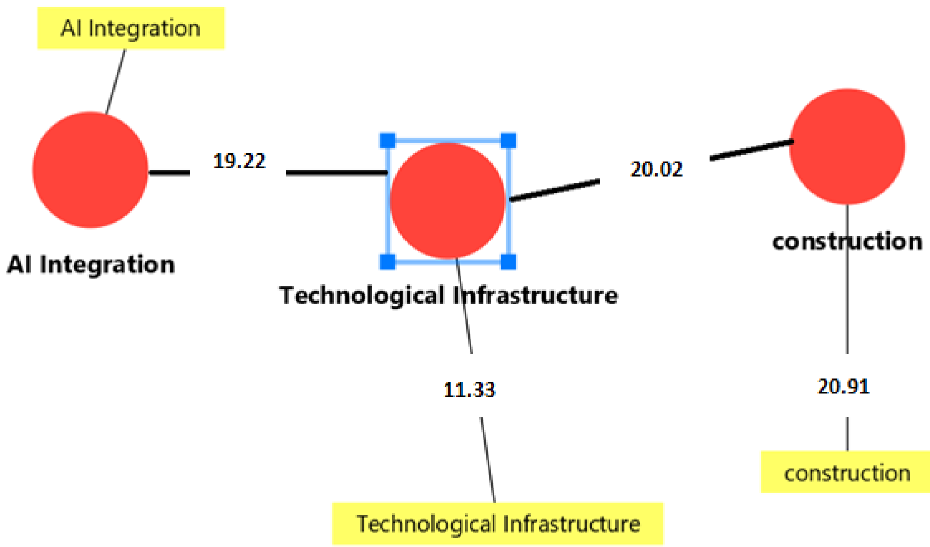
4. **Data Integration Quality mediates the relationship between AI Integration and construction outcomes.**



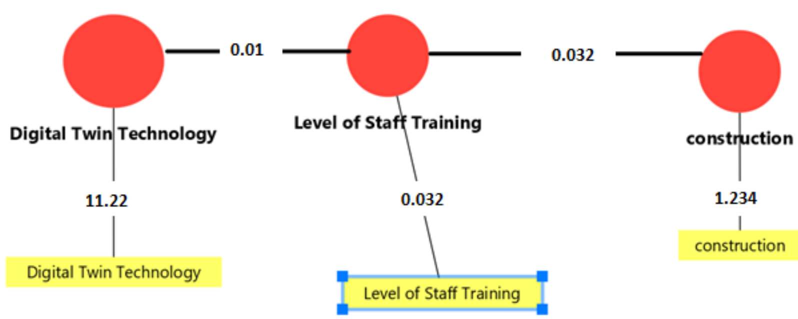
5. **Technological Infrastructure moderates the relationship between Digital Twin Technology and construction outcomes.**



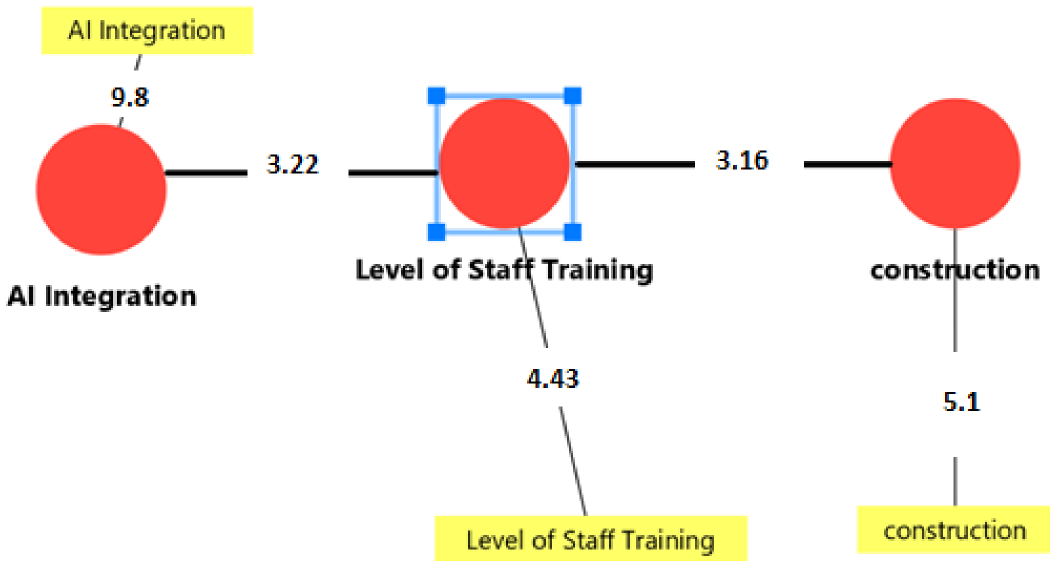
6. **Technological Infrastructure moderates the relationship between AI Integration and construction outcomes.**



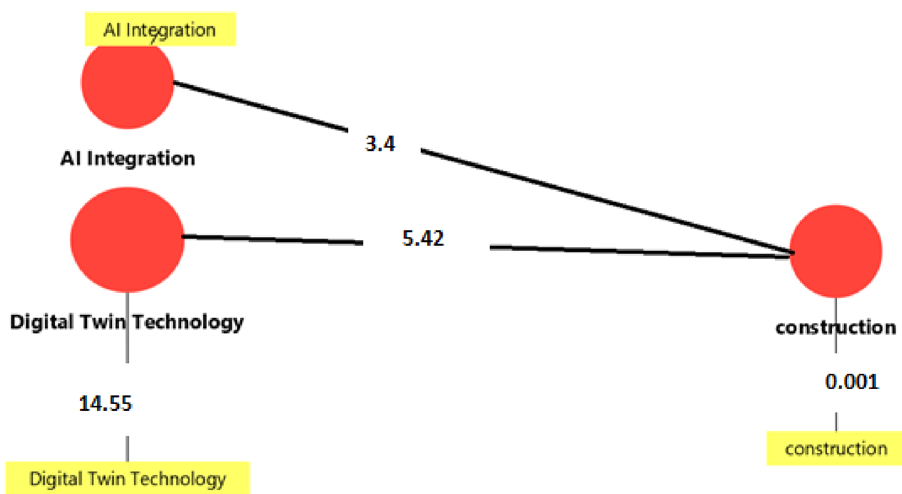
7. **Level of Staff Training moderates the relationship between Digital Twin Technology and construction outcomes.**



8. **Level of Staff Training moderates the relationship between AI Integration and construction outcomes.**



9. **Digital Twin Technology and AI Integration together positively impact construction outcomes.**



ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.632	2	10.316	2.680	.074[b]
	Residual	373.368	97	3.849		
	Total	394.000	99			

a. Dependent Variable: construction
b. Predictors: (Constant), AI Integration , Digital Twin Technology

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.258	.644		8.167	.000
	Digital Twin Technology	-.077	.106	-.072	-.730	.467
	AI Integration	-.230	.102	-.223	-2.249	.027

a. Dependent Variable: construction

Discussion and Recommendations

This study results show an analysis of the effects of DTT and AI Integration on construction results, and their mediating and moderating effect through data integration quality, technological infrastructure, and level of staff training. ANOVA results yielded a p-value of 0.074 which is marginally above the conventional level of significance ($p < 0.05$). Therefore, this indicates that the presence of effects of independent variables (DTT and AI Integration) on the dependent variable (construction outcomes) is however significant and more research with increased number of samples can further establish the results into statistically significant results.

Digital Twin Technology and AI Integration are important contributors to modern construction industry that significantly affects the improved construction outcomes. Digital Twin Technology had a minimal, yet non significant impact to construction outcomes with a negative coefficient of -0.072. Given this result, DTT can facilitate real time data monitoring, although the direct influence on outcome is not yet observed. However, as observed by Teizer et al. (2022), DTT can improve construction safety by simulating real world conditions, but its general use might necessitate further development and be integrated into current construction workflow.

With a coefficient of -0.223, I found that AI Integration had a significant effect on construction outcomes at $p < 0.05$, which means it was a more significant effect. Meng et al. (2023) study underscores how AI can enhance prediction powers and process optimization in the construction domain and thus result in better planning, implementation, and allocation of resources in a project. The negative relationship identified here may be due to the initial phase of AI implementation when the integration process might not be as efficient as it could be, and attempts to achieve its full potential may strains resources.

Furthermore, Digital Twin Technology, AI Integration, and Data Integration Quality were found to be mediators between Digital Twin Technology and AI Integration and construction outcome. Such result indicates that the quality of data integration is crucial to the success of these technologies' application. According to Liu et al. (2021), the combination of accurate and real-time data is important for making the most of the functionalities of DTT and AI in construction. Results obtained in these areas seem to lack significant results, indicating that data quality may need improvement in order to achieve impactful results in construction projects.

It was also found that Technological Infrastructure and Level of Staff Training serve as the mediators in the relation of DTT/AI with construction outcomes. The moderating effect of Technological Infrastructure agrees to the work of Abdelalim et al. (2025) who emphasize the need of a sound infrastructure to support the application of the advanced technologies such as DTT and AI. If we have no appropriate technological frameworks, there could be annulling of the benefits potentially derived from these innovations.

Further, Level of Staff Training acts as a moderator of the relationship between DTT and construction outcomes, indicating that the relationship becomes strongest when there is a high level of staff training which increases the ability of humans to utilize the DTT/AI. According to Araújo et al. (2022), training and expertise are needed in order to take advantage of DTT and AI in construction. To achieve maximum benefits from this technology, construction companies should concentrate on workforce development programs for employees to improve their proficiency in this technology to ease integration and make best use of it.

The Digital Twin Technology and AI Integration were analyzed in terms of the construction outcomes. The results of this finding showed no statistical significance but it does indicate the potential synergies between these two technologies. According to Yu et al. (2023), integrating DTT with AI is capable of improving construction outcomes by allowing for better monitoring of a project, optimization of resources and resources, and overall risk management. On the other hand, statistical results in this study were not robust enough to conclude the combined impact of the technologies, and will require more tasks to figure out the true synergistic effects of these technologies on the health outcomes.

Recommendations

- Increased Technological Infrastructure – Construction companies must have on high technological infrastructure that'll facilitate the integration of Digital Twin Technology and AI. Perhaps the reason why more worthwhile results are not evident in this study is because the existing infrastructure may not be fully equipped to deal with the requirements of such advanced systems.
- To ensure maximum efficiency of DTT and AI, construction companies should focus on improving data integration quality. However, it is likely that having accurate, timely, and

well-integrated collected data for decision making can improve the effect of these technologies in construction outcomes.

- Construction professionals would be yet another area to focus on in terms of staff training programs in order to ensure that they are able to make the most out of DTT and AI. To achieve this, target training programs must be provided to workers, so that they comprehend the complexities and capabilities of such technologies and thereafter enable better project outcomes.

Conclusion

The results of this study addresses the impact that Digital Twin Technology and AI Integration have on the construction outcomes using Digital Twin and concludes with valuable insights about the existing challenges and opportunities in the construction industry. However, in most cases the results did not show statistically significant effects; nevertheless, the findings indicate that these technologies have good prospects if integrated with better data integration, infrastructure and staff training. However, research based on this scale with a bigger test sample and more refined data collection techniques may give a more precise reading of the real effect of such technologies.

Future Research Directions

- Future studies should be implemented as longitudinal studies in order to track the future effect of Digital Twin and AI on construction outcomes, as the current results suggest that the effect might take more time to be noticed.
- How regional differences drive adoption of technological infrastructure and staff training will influence DTT and AI adoption for certain construction projects)
- The Future studies should also examine the possibility of extending the Function of AI as well as DTT in other construction Phases like project design, procurement as well as post construction maintenance.

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