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Artificial Intelligence-Driven Project Management in Construction: A Catalyst for Economic Growth and Sustainability

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ABSTRACT

The AI improves risk mitigation and optimizes resource allocation which also contributes to more successful project outcomes. The study aims to review Artificial Intelligence-Driven Plans in Project Management in Construction to review the Economic Growth and Sustainability under catalyst impact AI. Study has used a sample of 100 people to execute the results based on 6 hypothesis by survey of Google form. It reviews the effectiveness of AI technologies in construction management, risk management resource allocation rescheduling and predictive capabilities in the context of its impacts using primary quantitative data. Data has been executed with the smart PLS software to understand the statistical operations and the statistical support for the reliability and viability context. The results justify that there is positive effect of AI technologies in the construction sector for dealing the risk management in addition to resource allocation and rescheduling with the support of predictive capabilities. The study has positive implications for future prospects because it is offering recommendations for the project managers and decision makers in handling the construction sector challenges with the help of AI technological applications.

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1. Introduction

Artificial Intelligence (AI) has increased in use for project management in most areas including the construction industry with time. It plays an essential role in economic growth and the enhancement of productivity because automation is helpful in global economic growth and contributes to GDP (Regona et al., 2022). The study has reviewed how artificial intelligence is a true catalyst in the enhancement of the construction industry and is offering solutions for risk management and sustainability in addition to the promotion of the concept of green sustainability in construction (Davahli, 2020). The study is an investigation and essential topic to understand the need for various AI technologies including BIM building information modelling and budgeting schedules to enhance the idea of accelerated project timeline rules in cash flows and construction output boosting. The objectives are also emphasizing resource allocation and risk management to explore the algorithms in the optimization of resource allocation.

1.1. Problem Statement

Artificial intelligence is important in the automation of industry processes and decision-making (Pan & Zhang, 2021). This is why it is essential to investigate the topic to understand the enhancement of the overall project with the exploration of AI tools. The popular AI tools include predictive analysis, robotics and machine learning that are promoting the idea to revolutionize construction and project management. Keeping in view the importance of the topic and understanding the idea of how AI can enhance efficiency and reduce the risk of fostering sustainable solutions, Regona et al. (2022) it is important to review the topic for the transformation of construction activities from traditional methods to risk handling. The topic has been analyzed from the lens of existing risks and accidents in construction activities where traditional project management has not been successful in struggling and addressing comprehensive issues. The comprehensive issues that need to be handled with the help of struggling tools and the advent of AI. There is a need to understand how AI can be a true catalyst in sustainable growth and promotion of development.

1.2. Research Aim and Objectives

The study aims to review Artificial Intelligence-Driven Plans in Project Management in Construction to review the Economic Growth and Sustainability under catalyst impact AI. The main objectives are:

- To identify the AI tools currently being used in construction project management and assess their impact on efficiency and productivity.
- To evaluate how AI improves risk mitigation and optimizes resource allocation, contributing to more successful project outcomes.
- To analyze how AI enhances project scheduling through predictive analytics, reducing delays and increasing the reliability of project timelines.
- To examine the relationship between AI adoption in construction and its broader economic benefits, including reduced project costs, increased productivity, and contributions to GDP growth.

1.3. Research Questions

1. Which AI tools are currently being used in construction project management and assess their impact on efficiency and productivity?
2. How does AI improve risk mitigation and optimize resource allocation, contributing to more successful project outcomes?
3. How does AI enhance project scheduling through predictive analytics, reducing delays and increasing the reliability of project timelines?
4. What is the relationship between AI adoption in construction and its broader economic benefits, including reduced project costs, increased productivity, and contributions to GDP growth?

1.4. Hypothesis

- H1: AI tools currently being used in construction project management have a positive impact on efficiency and productivity.
- H2: AI has a positive impact on risk mitigation and optimizes resource allocation, contributing to more successful project outcomes.
- H3: AI has a positive impact on project scheduling through predictive analytics, reducing delays and increasing the reliability of project timelines.
- H4: AI adoption in construction and its broader economic benefits have a positive impact on reducing project costs, increasing productivity, and contributing to GDP growth.
- H5: AI's role has a positive impact in promoting sustainability within the construction industry, particularly by minimizing waste, improving energy efficiency, and supporting sustainable urbanization.
- H6: AI has a positive impact on meeting the technological, organizational, and regulatory barriers

1.5. Significance of Study

The study is significant because it narrates the idea of how AI adoption can be productive in the construction industry. It is executing the positive impacts of faster infrastructure development and lowering the costs to increase the possibility of profitability in the construction sector. It also promotes the idea that how the skilled workforce can be a driving agent for innovation and application offer creating jobs in the construction industry under the privilege of safety and security (Abioye et al., 2021; Davahli, 2020). Keeping in view the literature gap that has been left by the previous authors for the catalyst impact of AI in risk management and acceleration of innovation, the current study has an essential role and significance in reviewing the hypothesis already mentioned to support the idea of how cost reduction and risk security has been possible in the construction industry under the privilege of AI tools.

1.6. Organization of Study

The study has been divided into six chapters. The first chapter is introduction, second literature review and third methods. The fourth chapter is results, fifth discussion and last one is conclusion.

2. Literature Review

2.1. AI Technologies in Construction Management

It is essential to review the AI tools that are used in construction project management. They support the idea of assessing the impact on efficiency and productivity in the sector. Technologies are applicable in the construction sector starting from machine learning ML technologies and computer vision to the NLP natural language processes and robotic automation. Pimenow, Pimenowa and Prus (2024) review that climate change has been demanding the acceleration of ML as a crucial tool in energy efficiency applications because it encourages the idea of how sustainable solutions and energy optimization can be applicable in renewable integration and carbon reduction processes. It has been found that all have some essential and professional role in meeting the challenges of the construction industry however ML focuses on predictive analysis to facilitate the timeline with better cost application and risk management models. It also encourages the idea of how resource optimization can allocate labour material and enhance decision-making by reducing project risks with accurate forecasting and planning activities (Davahli, 2020). The other technologies include computer versions that impact safety compliance and reduce errors. NLP has a professional role in exploring the chat boards that reduce the chances of accidents and increase their communication with stakeholders by enhancing the administrative overhead and project data accessibility. Robotics are replacing human beings at various places and also offering excavation and demolition processes that increase productivity and reduce the chances of accidents in manual labour.

2.2. Risk Management and Resource Allocation

The AI improves risk mitigation and optimizes resource allocation which also contributes to more successful project outcomes. Risk management is an essential concern in the construction industry because predictive analytics can help in identifying seasonal weather patterns and this decreases the chances of accidents due to the external factors of weather and environment (Khalid et al., 2024). Another example of risk handling is scenario planning and simulation with the help of risk exposure models and creating budgets and resource availability timelines with automated operations. Risk control is essential because risk scoring can also help in dealing with high-risk task pathways and inspecting hazardous areas. Olowa et al. (2022) review that the transformative effect of AI-driven plans into sustainable goals is helpful in the application of promotion of inclusivity and innovation cultivation projects by AI-driven applications. Resource allocation is another area that has been supported by AI-driven applications with the reduction of cost and encouraging the inefficiencies facilitation by adjusting labour schedules and making sure that how the equipment can be allocated to high-priority tasks. Resource allocation also includes dynamic scheduling for automatic task delay control and parallel task maximization with resource exploration. It narrates how the assigned skilled workers can be critically supported in task completion and optimize the shift patterns to decrease fatigue and help in dealing with the AI systems (Davahli, 2020). The two processes can work in collaboration to improve efficiency and enhance safety in addition to improving efficiency and making sure that sustainability and eco-friendly activities have been executed.

2.3. Scheduling and Predictive Capabilities

The AI enhances project scheduling through predictive analytics with the help of reducing delays and increasing the reliability of project timelines in the construction sector. It has been found that AI plays a professional role in scheduling by reducing manual errors and saving time for automated repetition. The predictive capabilities encourage the user to understand the multiple dimensions of projects they are the building information modeling can provide the schedule details by synchronizing the 3D models with the visual construction activities. The role of the predictive capabilities is positive where weather forecasts help to identify the bottlenecks to meet the errors. The weather forecast helps to avoid errors and identify the bottlenecks to meet the equipment availability gaps. Khalid et al. (2024) also recommend that risk management is possible with the predictive insights and modelling application capabilities that help in the achievement of sustainability goals with optimization of resource allocation and also taking advantage of AI management systems for decision-making processes.

2.4. Economic Growth Impact and Addressing Sustainability

There is a positive relationship between AI adoption in construction and its broader economic benefits. It has been found that it includes reduced project costs in addition to increased productivity (Haleem et al., 2023). This is positively contributing to GDP growth with the facilitation. It helps meet the time-lapse and gaps that are encouraging the use of machine-driven technology in cost saving by reducing delays and overruns. The approachable role of facilitation has been supportive in decision-making and enhancing efficiency in addition to sustainability in minimizing risk. It also helps to assess the AI's role in promoting sustainability within the construction industry. The role has been there in minimizing waste, improving energy efficiency, and supporting sustainable urbanization. Sustainability is a true aim that needs to be addressed with the help of scheduling and predictive capabilities where real-world applications can support the idea of understanding the need for a balanced approach application between the environment and society to achieve economic targets. Sustainability cannot be ignored on any account as analysed by Tao et al. (2024) that the endogenous economic growth model can be successful in meeting the need of low carbon energy transformation where sustainability has not been compromised in triggering the negativity in AI-based applications in the industries. The professional approaches are ideally implementing the economic growth model where AI has facilitated innovation to surpass the threshold of monitoring issues and risk assessment processes.

2.5. Barriers to AI Adoption

There are technological, organizational, and regulatory barriers that exist to hinder the widespread adoption of AI in construction. The positive role of AI systems can help to deal with the barriers and make sure that they can keep the balance between society and the environment to achieve the economic targets of any industry, especially the construction sector. Haleem et al. (2023) claim that predictive modelling can be helpful in this regard because RPA robotic process automation and machine learning can work in collaboration to decrease the risk of failure and make sure that successful applications have been encouraged to understand the needs of any system.

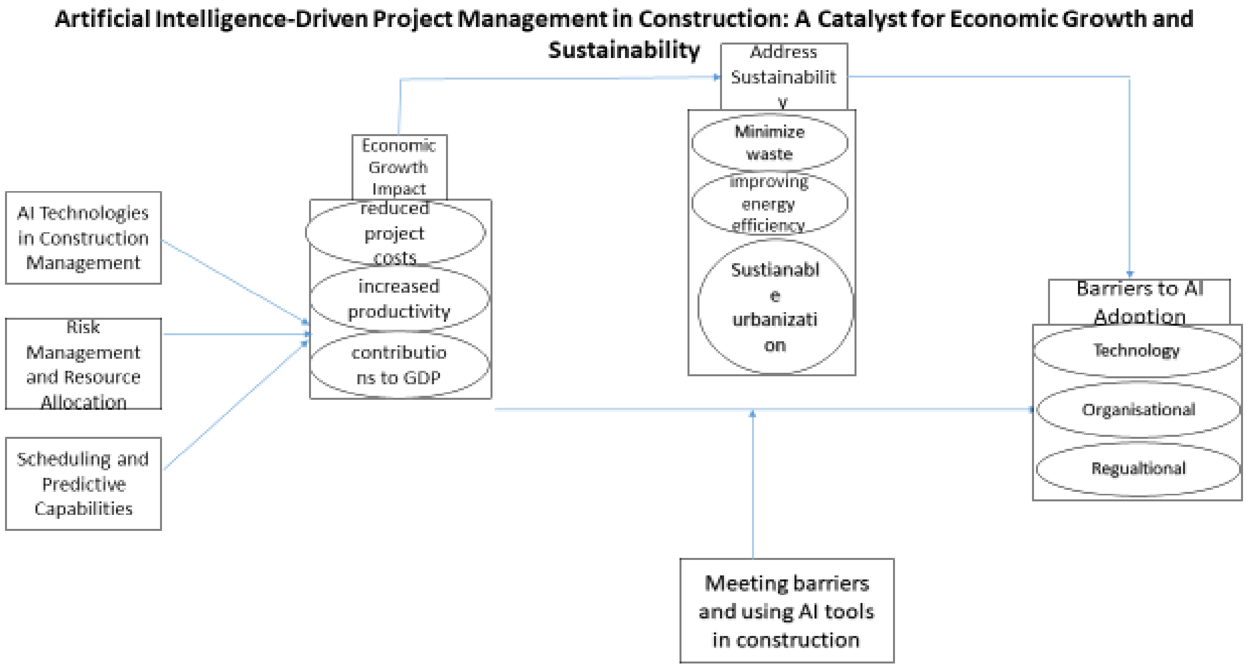
3. Theoretical Framework

Key theories are helpful in the context of construction support in dealing with economic stability and keeping the concept of sustainability at the same time. BIM theory of building information modelling, TBL theory of a triple bottom line and lean construction through as they are helpful in this context. BIM theory applies the phenomena of AI integration as a priority choice in the optimization of design-oriented solutions and understanding the need for predictive maintenance (Olowa et al., 2022). The role of sustainability has been encouraged in this theory where optimization and longer building lifespans have been executed with the help of collaborative management principles in construction with the sharing of digital model applications. It emphasizes the role of safety and security as a priority to make sure that the construction has been under the privilege of better approaches to safety and security. The other theory is the triple bottom line theory which focuses on the principle of sustainability's 3 main pillars. Economic, environmental and social pillars play an essential role in the integration of AI with smart efficiency solutions in building design under the privilege of TBL theory (An et al., 2021). The 2D emphasis on the automated reporting tools for complaints and environmental regulations by executing AI-driven simulation solutions not only enhances economic growth by reducing operational costs but also meets the supporting solution responsibility to ensure environmental goals achievement. The theory is applicable in the current analysis because it seems to be productive in meeting the economic as well as environmental goals by ensuring the construction timeline with support of social safety and security to the working teams and managers. A third theory is lean construction theory which minimizes waste and focuses on increasing the value of construction processes that have a truly sustainable application. The theory emphasises the use of AI integration with the execution of automated scheduling and predictive analysis that reduces resource waste and also forecasts material optimization, respectively (Albalkhy & Sweis, 2021). Keeping in view the role of the theory, it has been found that economic growth is possible by reducing costs and improving profitability by optimization of resource allocation. Further, it also plays a professional role in sustainability maintenance by minimising energy wastage and aligning sustainable construction practices to reduce material wastage under the privilege of construction activities.

3.1. Conceptual Framework

The conceptual framework has been derived based on the hypothesis and its impacts. It reviews the effectiveness of AI technologies in construction management, risk management resource allocation rescheduling and predictive capabilities in the context of its impacts. The impacts are reviewed for economic growth and addressing sustainability in addition to making the barriers to AI adoption with the specific variables mentioned in their subheadings.

Figure 1: Conceptual Framework



3.2. Literature Gap

The literature gap has been identified in reviewing the topic of artificial intelligence in the context of understanding how the idea has been explored by some other authors in the construction sector. It has been revealed that some studies have investigated risk management and dealing under the privilege of construction support projects and management however there is a need to review the topic from the lens of AI context to emphasise the application of predictive analysis and robotic and automation in the context of construction industry. The current study has met the literature gap because AI has been a dominant perspective in handling the risk dealing concepts in the construction industry to meet the challenges for the security and safety of human resources and the implication of robotics to utilize cost-effective and safe plans.

4. Methodology

The methodology provides an outline for the researcher to emphasise the application of relevant methodological tools to collect and analyse the data.

4.1. Theoretical Review

The literature review shows that three theories are identified to reveal the data and extract how it can help understand the need for AI as a catalyst in the construction industry. The theories will be tested under the context of a primary quantitative research project plan to understand how it is implemented in the present scenario and what can be forecasted for the future to support risk management under the privilege of AI tools and robotic applications in the construction industry. BIM theory has been reviewed for the phenomena of AI integration as a priority choice in the optimization of design-oriented solutions and understanding the need for predictive maintenance (Olowa et al., 2022). Economic, environmental and social pillars play an essential role in the integration of AI with smart efficiency solutions in building design under the privilege of TBL theory to support the opinion of the authors (An et al., 2021). The lean construction theory emphasises the use of AI integration with the execution of automated scheduling and predictive analysis, it has been reviewed to understand how it reduces resource waste and also forecasts material optimization, respectively (Albalkhy & Sweis, 2021). Theory testing is an important context in understanding the application of a deductive approach to justify the theoretical foundations of a specific study.

4.2. Research Design

The study has chosen a primary quantitative design which claims the evidence-based analysis to test the hypothesis for developing the connection between various variables. It has been applied in the current study where primary data has been supported for validation scales and supporting the evidence for understanding the primary context in interpretation and reporting based on the data collected from the respondents (Verma, Verma, & Abhishek, 2024). The quantitative design has been supported with the application of a survey form online with the help of the Google platform. The survey has been facilitated by the closed-ended questionnaire so the respondents will be able to provide the relevant data without any confusion.

4.3. Research Philosophy

The research has chosen positivist philosophy to interpret the data from the respondents based on the closed-ended questionnaire survey project. The philosophy is helpful in the interpretation of data because it supports the evidence of how the researcher is capable of outlining the relevant opinions based on the experiences of the respondents in the context of the construction industry for AI usage. The philosophy is also helpful while extracting the data and manipulating it with the help of specific theory testing under the context of a relevant research outline.

4.4. Research Approach

The research has chosen the deductive approach because three theories have to be tested in the current plan. The approach helps test the theory because the application of hypothesis and theory testing has been privileged under the context of a deductive approach. The deductive approach also helps to reveal the empirical findings based on the theoretical framework to test the recommended theories and avoid generic interpretations only based on the hypothesis. The hypothesis has been tested to understand the technical assistance with the theoretical evidence and justifications where concluding remarks and authenticity has been based on the facilitation of statistical output. The statistical output has been supported by the smart PLS software where data has been reviewed under the specific software to come up with the main opinions and sum up the results of the study.

4.5. Data Collection

The primary quantitative research design has been supported with the help of relevant research instruments. The research instrument is comprised of a survey tool to collect the primary quantitative data from the relevant respondents operating in the specific field (Pandey & Pandey, 2021). The purposive sampling technique has been adopted because it is a productive tool in choosing the exact respondents and making sure that how the non-probability sampling supports selecting the relevant respondents under the context of the deductive approach. The sample size has been 100 respondents because it is an ideal size to avoid irrelevant people and get meaningful results under an aligned sample size. A consent form has been sent to the respondents for the approval of the data collection plan and its aim is to be used only for a present study plan. The link has been sent to the respondents for filling out the Google survey form and the data has been collected back in the specific Excel file to maintain the statistical record for analysis further.

4.6. Data Analysis

The data has been analyzed with the help of a statistical technique of smart PLS which is found to be a good option to handle a small size of sample as mentioned in the current study. It is also helpful in offering a diagrammatic outlook of the variables and discussing the relationship based on the accuracy and suitability of variables (Verma, Verma, & Abhishek, 2024). The analytical tool helps provide the Cronbach alpha and HTM ratio where P and beta values help deal with the variables and guide the researcher about the comparison of the variables and their impact on one another. It has supported the evidence to justify the theory and literature as well as find the approval or disapproval of the hypothesis already identified in the earlier stages of the research.

5. Results

5.1. Statistical Results

The statistical data is analysed to support the data from the respondents. The data has been converted into an Excel file and then the Smart PLS software has been applied to it. The review of the variables and their comparative analysis has been shared here in the form of various results and statistical applications.

Table 1: Path Coefficient

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AS -> BAA	0.538	0.541	0.041	13.004	0.000
ATCM -> EGI	0.087	0.112	0.111	0.787	0.432
EGI -> AS	0.737	0.735	0.045	16.252	0.000
MBAC -> BAA	0.409	0.407	0.052	7.791	0.000
MBAC -> EGI	0.468	0.521	0.149	3.142	0.002
RMRA -> EGI	-0.199	-0.267	0.184	1.082	0.279
SPC -> EGI	0.653	0.651	0.071	9.258	0.000

Notes: *AS: address sustainability, EGI: economic growth impact, MBAC: meeting barriers in AI in construction, SPC: ATCM: AI tech in construction management, BAA: barrier to AI adoption, RMRA: risk management and resource allocation*

It has been found that most of the variables are not significant however a single variable has reached above 0.7. The data is showing 0.737 for EGI -> AS only. This shows the significant value for ECI in collaboration as we are addressing sustainability has been found prominent in collaboration economic growth with a positive impact.

Table 2: Outer loading

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AS 1 <- AS	0.853	0.851	0.031	27.480	0.000
AS 2 <- AS	0.805	0.804	0.055	14.595	0.000
AS 3 <- AS	0.932	0.933	0.010	97.993	0.000
AS 4 <- AS	0.702	0.702	0.071	9.912	0.000
AS 5 <- AS	0.950	0.951	0.005	188.531	0.000
ATCM 1 <- ATCM	0.798	0.720	0.254	3.136	0.002
ATCM 2 <- ATCM	0.668	0.597	0.208	3.210	0.001
ATCM 3 <- ATCM	0.503	0.447	0.306	1.646	0.100
ATCM 4 <- ATCM	0.813	0.705	0.324	2.512	0.012
ATCM 5 <- ATCM	0.877	0.782	0.268	3.274	0.001
BAA 1 <- BAA	0.791	0.790	0.043	18.540	0.000
BAA 2 <- BAA	0.732	0.730	0.068	10.764	0.000
BAA 3 <- BAA	0.903	0.902	0.016	55.695	0.000
BAA 4 <- BAA	0.870	0.871	0.020	43.380	0.000
BAA 5 <- BAA	0.680	0.678	0.077	8.858	0.000
EGI 1 <- EGI	0.896	0.891	0.024	37.882	0.000
EGI 2 <- EGI	0.778	0.781	0.026	29.681	0.000
EGI 3 <- EGI	0.779	0.774	0.034	23.052	0.000
EGI 4 <- EGI	0.665	0.673	0.064	10.341	0.000
EGI 5 <- EGI	0.423	0.429	0.128	3.304	0.001
MBAC 1 <- MBAC	0.764	0.765	0.067	11.419	0.000
MBAC 2 <- MBAC	0.943	0.941	0.014	69.345	0.000
MBAC 3 <- MBAC	0.894	0.894	0.028	32.484	0.000
RMRA 1 <- RMRA	0.464	0.464	0.120	3.880	0.000
RMRA 2 <- RMRA	0.880	0.876	0.034	25.626	0.000
RMRA 3 <- RMRA	0.796	0.785	0.058	13.653	0.000
RMRA 4 <- RMRA	0.955	0.957	0.008	120.329	0.000
RMRA 5 <- RMRA	0.900	0.899	0.023	39.576	0.000
SPC 1 <- SPC	0.858	0.853	0.042	20.647	0.000
SPC 2 <- SPC	0.855	0.846	0.052	16.293	0.000
SPC 3 <- SPC	0.811	0.807	0.055	14.712	0.000
SPC 4 <- SPC	0.965	0.964	0.010	97.431	0.000
SPC 5 <- SPC	0.879	0.877	0.028	30.909	0.000

The value has been recorded for most of the variable 0.9. This shows that significant variables probably existed because once SPC has shown high value and in collaboration, RMRA has also shown a value above 0.9 in one aspect. AS 3 <- AS has mentioned a value above 0.9, BBA and ATCM have also shown this kind of value at 0.9. This has been agreed to the significance of most of the variables in the collaborative review.

Table 3: R square

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AS	0.544	0.542	0.066	8.272	0.000
BAA	0.819	0.821	0.040	20.460	0.000
EGI	0.794	0.799	0.025	31.298	0.000

R square has been found about 0.8 for only one variable which is BAA.

Table 4: R Square Adjustment

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AS	0.539	0.538	0.066	8.125	0.000
BAA	0.816	0.818	0.041	19.980	0.000
EGI	0.786	0.791	0.026	29.782	0.000

BAA has shown again high value for the R square adjustment compared to the previous results.

Table 5: Average Variance

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AS	0.728	0.730	0.036	20.430	0.000
ATCM	0.553	0.512	0.087	6.376	0.000
BAA	0.640	0.640	0.034	18.661	0.000
AGE	0.527	0.532	0.034	15.321	0.000
MBAC	0.757	0.759	0.031	24.418	0.000
RMRA	0.669	0.668	0.041	16.432	0.000
SPC	0.766	0.760	0.056	13.769	0.000

The average wedding shows a high value for some variables above 0.7 including AS, NBAC and SPC. This shows their significant collaboration. Windows 10

Table 6: RHO c

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AS	0.930	0.930	0.012	75.286	0.000
ATCM	0.857	0.800	0.147	5.848	0.000
BAA	0.898	0.897	0.015	61.451	0.000
EGI	0.841	0.842	0.023	36.602	0.000
MBAC	0.903	0.903	0.015	58.815	0.000
RMRA	0.906	0.904	0.018	50.760	0.000
SPC	0.942	0.939	0.018	51.357	0.000

It has shown a high value for most of the variables because all the variables have been found about 0.8 however the peaking value has been found only for SPC as 0.9482 preceded by AS for 0.930.

Table 7: RHO a

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AS	0.922	0.923	0.012	80.012	0.000
ATCM	0.853	0.763	0.328	2.603	0.009
BAA	0.880	0.882	0.015	59.763	0.000
EGI	0.850	0.848	0.024	34.907	0.000
MBAC	0.867	0.869	0.020	43.228	0.000
RMRA	0.950	0.950	0.013	72.797	0.000
SPC	0.931	0.929	0.022	42.531	0.000

The significance has been found for most of the variables because all the variables are above 0.8 however the maximum value has again been recorded for this PC as 0.931. it is ensuring its significance and dominance as compared to other variables.

Table 8: Cronbach Alpha

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AS	0.904	0.904	0.018	49.089	0.000
ATCM	0.800	0.799	0.029	27.255	0.000
BAA	0.859	0.858	0.021	41.196	0.000
EGI	0.794	0.793	0.028	28.067	0.000
MBAC	0.837	0.837	0.029	29.102	0.000
RMRA	0.874	0.872	0.022	38.964	0.000
SPC	0.923	0.918	0.027	33.730	0.000

Cronbach alpha value has been raised for high for most variables however it has been found that the maximum value is recorded for this SPC and AS like the previous. It is empowering their potential as compared to other variables which seem less significant.

Table 9: HTMT

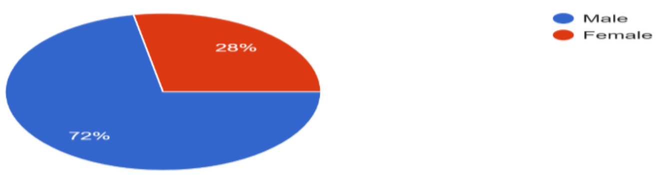
	Original sample (O)	Sample mean (M)	2.5%	97.5%
ATCM <-> AS	0.410	0.444	0.290	0.694
BAA <-> AS	0.981	0.980	0.923	1.025
BAA <-> ATCM	0.474	0.498	0.367	0.694
EGI <-> AS	0.735	0.744	0.632	0.859
EGI <-> ATCM	0.370	0.409	0.310	0.582
EGI <-> BAA	0.858	0.862	0.772	0.965
MBAC <-> AS	0.925	0.922	0.832	0.993
MBAC <-> ATCM	0.460	0.483	0.347	0.634
MBAC <-> BAA	0.984	0.983	0.900	1.066
MBAC <-> EGI	0.884	0.883	0.775	0.992
RMRA <-> AS	0.871	0.871	0.790	0.937
RMRA <-> ATCM	0.708	0.712	0.618	0.813
RMRA <-> BAA	0.815	0.820	0.714	0.913
RMRA <-> EGI	0.785	0.794	0.709	0.886
RMRA <-> MBAC	0.923	0.928	0.820	1.035
SPC <-> AS	0.799	0.803	0.719	0.904
SPC <-> ATCM	0.216	0.247	0.191	0.362
SPC <-> BAA	0.808	0.815	0.736	0.901
SPC <-> EGI	0.860	0.870	0.813	0.940
SPC <-> MBAC	0.788	0.790	0.703	0.883
SPC <-> RMRA	0.797	0.799	0.693	0.891

The value has been reviewed for comparative analysis where maximum values have been recorded and dominance justifying the importance of most of the variables. MBAC <-> BAA has shown dominant value here.

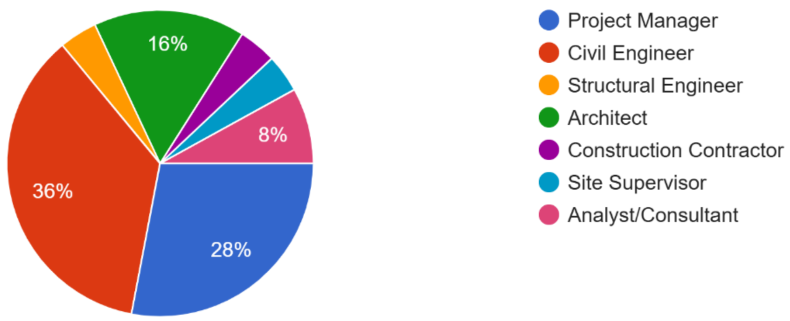
5.2. Demographic Results

The demographic results show that the maximum number of respondents will be logging the male gender comprising 72%. While only 28% of the respondents covered the female section.

Figure 2: Gender Data

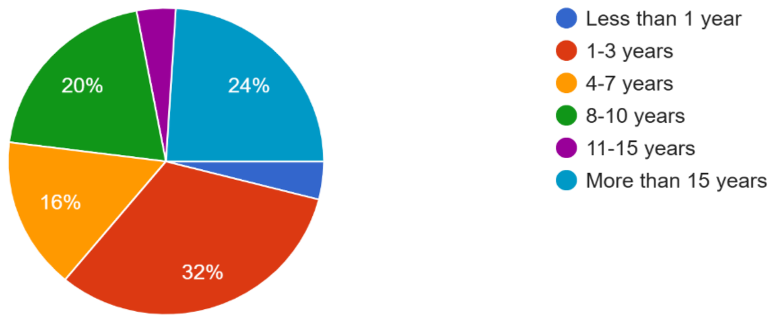


The competitive analysis of various professional reviews of the people has been reviewed which shows that the maximum number of respondents is 36% followed by project managers at about 28%. The other group is comprised of 16% in making architects however 8% are showing analysts and consultants while other people.



It has been found that your experience is different for the respondents. This shows that a maximum experience group is comprised of 1 to 3 years of experience for 32% which is preceded by more than 15 years of experience for about 24%. 20% are covering 8 to 10 years of experience however 16% are showing 4 to seven years of experience professionally.

Figure 3: Experience Data



5.3. Validity and Reliability

It has been found that the validity is high in the results because data has been taken from the variables in contrast and the impact has been traced accordingly. Various variables are checked for individuality and comparative analysis which justifies its influence and positive approaches to reveal how the data has been aligned with the help of a relevant comparison for instance different approaches are used to understand the role of expertise. The reliability is also high because the comparison of two or more variables in collaboration has helped the researcher to compare things and make sure that relevant components have been added.

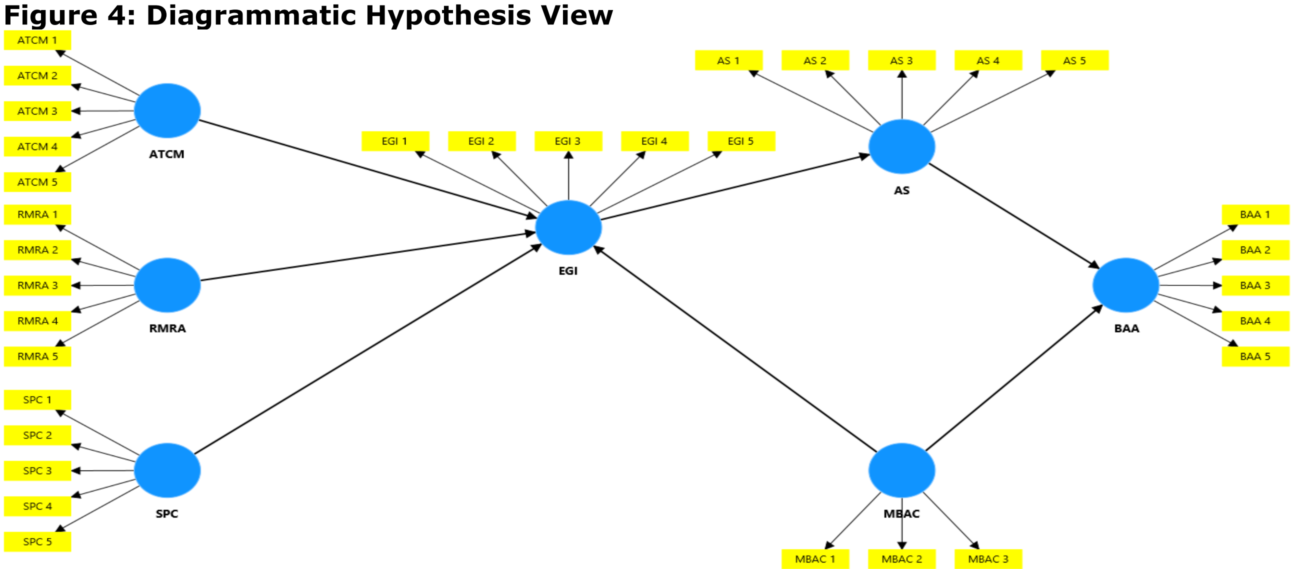
6. Discussion

6.1. Hypotheses Justifications

The hypothetical review shows that only 6 hypotheses have been outlined as per the conceptual framework. It has been reviewed that the first hypothesis is narrating H1: AI tools currently being used in construction project management have a positive impact on efficiency and productivity. This has been justified with a dominance value of AI tool review. Haleem et al. (2023) claim that predictive modelling can be helpful in this regard because RPA robotic process automation and machine learning can work in collaboration to decrease the risk of failure and make sure that successful applications have been encouraged to understand the needs of any system. However, it has been found that relevant approaches can help the application of dominance of AI tools and make sure that the robotic process can be applied in collaboration. The other hypothesis reviewed H2: AI has a positive impact on risk mitigation and optimizes resource allocation, contributing to more successful project outcomes. It has been found that most of the variables are not significant however a single variable has reached above 0.7. The data is showing 0.737 for EGI -> AS only. This shows the significant value for ECI in collaboration as we are addressing sustainability has been found prominent in collaboration economic growth with a positive impact. This shows that the optimization of resource allocation can be supported with evidence-based content that has a positive impact on the success of project outcomes. The other hypothesis is H3: AI has a positive impact on project scheduling through predictive analytics, reducing delays and increasing the reliability of project timelines. This shows the link of project scheduling by justifications of various implications. The predictive capabilities encourage the user to understand the multiple dimensions of projects they are the building information modeling can provide the schedule details by synchronizing the 3D models with the visual construction activities. The role of the predictive capabilities is positive where weather forecasts help to identify the bottlenecks to meet the errors. The weather forecast helps to avoid errors and identify the bottlenecks to meet the equipment availability gaps. Khalid et al. (2024) also recommend that risk management is possible with predictive insights and modelling applications.

The other hypothesis is H4: AI adoption in construction and its broader economic benefits have a positive impact on reducing project costs, increasing productivity, and contributing to GDP growth. The value has been reviewed for comparative analysis where maximum values have been recorded and dominance justifying the importance of most of the variables. MBAC <-> BAA has shown dominant value here. This shows the positive inference and justifies the optimization. The capabilities that help in the achievement of sustainability goals with optimization of resource allocation and also taking advantage of AI management systems for decision-making processes. The significance has been found for most of the variables because all the variables are above 0.8 however the maximum value has again been recorded for this PC as 0.931. It ensures its significance and dominance as compared to other variables. The other hypothesis is H5: AI's role has a positive impact on promoting sustainability within the construction industry, particularly by minimizing waste, improving energy efficiency, and supporting sustainable urbanization. The real-world applications can support the idea of understanding the need for a balanced approach application between the environment and society to achieve economic targets. Sustainability cannot be ignored on any account as analysed by Tao et al. (2024) that the endogenous economic growth model can be successful in meeting the need of low carbon energy transformation where sustainability has not been compromised in triggering the negativity in AI-based applications in the industries. The last hypothesis is H6: AI has a positive impact on meeting the technological, organizational, and regulatory barriers. The role of the AI tools is essential as the main value has been recorded for most of the variable 0.9. This shows that significant variables probably existed because once SPC has shown high value and in collaboration, RMRA has also shown a value above 0.9 in one aspect. AS 3 <- AS has mentioned a value above 0.9, BBA and ATCM have also shown this kind of value at 0.9. This has been agreed to the significance of most of the variables in the collaborative review.

Figure 4: Diagrammatic Hypothesis View



6.2. Research Questions

6.2.1. Explore AI Technologies in Construction Management

It has been reviewed which AI tools are currently being used in construction project management and assessed their impact on efficiency and productivity. The valuable justifications have been resolved where maximum data has been recording the support for use of AI tools enhancing the working efficiency for robotics and predictive analysis. This has been justified by the evidence from the literature as well as feedback from the respondents.

6.2.2. Enhance Risk Management and Resource Allocation

The other question reviewed for AI improves risk mitigation and optimizes resource allocation, contributing to more successful project outcomes. It has been found that all have some essential and professional role in meeting the challenges of the construction industry however ML focuses on predictive analysis to facilitate the timeline with better cost application and risk management models.

6.2.3. Improve Scheduling and Predictive Capabilities

The review of the role of AI enhance project scheduling through predictive analytics, reducing delays and increasing the reliability of project timelines has been there. The role of the predictive capabilities is positive where weather forecasts help to identify the bottlenecks to meet the errors. The weather forecast helps to avoid errors and identify the bottlenecks to meet the equipment availability gaps. Khalid et al. (2024) also recommend that risk management is possible with the predictive insights and modelling application capabilities that help in the achievement of sustainability goals with optimization of resource allocation and also taking advantage of AI management systems for decision-making processes.

6.2.4. Evaluate Economic Growth Impact

It analysed the relationship between AI adoption in construction and its broader economic benefits, including reduced project costs, increased productivity, and contributions to GDP growth. It has been found positive for the results. Sustainability is a true aim that needs to be addressed with the help of scheduling and predictive capabilities where real-world applications can support the idea of understanding the need for a balanced approach application between the environment and society to achieve economic targets.

6.2.5. Address Sustainability

It reviewed the AI's role in promoting sustainability within the construction industry, particularly by minimizing waste, improving energy efficiency, and supporting sustainable urbanization. Risk control is essential because risk scoring can also help in dealing with high-risk task pathways and inspecting hazardous areas. It is agreed by Olowa et al. (2022) review that the transformative effect of AI-driven plans on sustainable goals is helpful in the application of promotion of inclusivity and innovation cultivation projects by AI-driven applications.

6.2.6. Identify Barriers to AI Adoption

The review of technological, organizational, and regulatory barriers that can hinder the widespread adoption of AI in construction has been analysed. This narrated that There are technological, organizational, and regulatory barriers that exist to hinder the widespread adoption of AI in construction. The positive role of AI systems can help to deal with the barriers and make sure that they can keep the balance between society and the environment to achieve the economic targets of any industry, especially the construction sector.

6.2.7. Theoretical Justifications

The major TBL theory of a triple bottom line and lean construction are helpful in this context. It has been proven positive that the role of sustainability has been encouraged in this theory where optimization and longer building lifespans have been executed with the help of collaborative management principles in construction with the sharing of digital model applications. Further, BIM theory applies the phenomena of AI integration as a priority choice in the optimization of design-oriented solutions and understanding the need for predictive maintenance (Olowa et al., 2022). It emphasizes the role of safety and security as a priority to make sure that the construction has been under the privilege of better approaches to safety and security as mentioned in the results. The theory is the triple bottom line theory which focuses on the principle of sustainability's 3 main pillars. Economic, environmental and social pillars play an essential role in the integration of AI with smart efficiency solutions in building design under the privilege of TBL theory (An et al., 2021). This is also proven for risk handling and sustainable growth.

7. Conclusion

7.1. Main Findings

It has been found that AI technologies are playing a professional role in the construction sector their enhancement of risk management and resource allocation has been applied. The hypothesis is positive and it has been justified that the role of economic growth has been positive. The pragmatic approaches can help to identify the barriers and solve them with the help of AI adoption in the technological implementation and creative application in addition to robotics.

7.2. Recommendations

AI use cannot be ignored this is why it is highly recommended that project managers need to schedule and apply the predictive capabilities under the privilege of outlines described by the various authors and the results of the current study. It is need to support the evidence and make sure that relevant content has been provided in the paradigm of economic growth where project managers are equipped for the use of relevant approaches.

7.3. Implications

Research has met the literature where this is where it has positive implications for the project managers. It can also facilitate the experts in the IT industry. This is also good for the relevant use in the AI implications for the industry.

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