

Midocean University

Faculty of Management

Project Management

The Impact of AI-Powered Tools Training on Managerial Efficiency in Majan Construction Company

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1. Chapter 1: Introduction

1.1. Research Background

Over the past decade, state-of-the-art technologies such as artificial intelligence (AI), data analytics, and machine learning have significantly reshaped how organizations operate. From decision-making and resource planning to performance monitoring and strategic execution, these tools have elevated efficiency and productivity across industries (Hwang & Kim, 2021). Their widespread adoption is not only transforming business models but also redefining the roles and expectations of managers. In sectors like construction, where operations are complex and high-stakes, the potential for AI-powered tools to streamline workflows and enhance decision accuracy is especially critical (Czarnitzki et al., 2023; Damioli et al., 2021).

Despite this momentum, a persistent gap remains between technological availability and practical application. Although AI systems are increasingly available to construction firms, many managers struggle to integrate them into their day-to-day responsibilities. This issue is often rooted not in the limitations of the technology itself, but in the users' readiness and confidence to adopt these tools effectively. Gounde and Olusegun (2024) argue that the effectiveness of AI adoption is closely tied to digital preparedness, which is frequently constrained by inadequate training. This raises important questions about how structured training can empower managers to leverage AI technologies more effectively in real-world settings.

In particular, there is a lack of empirical research that examines how AI-powered tools training affects specific aspects of managerial efficiency, such as decision-making speed, task automation, and strategic planning in the construction industry. While several studies have highlighted the advantages of AI adoption in terms of overall productivity (Scott & Bommu, 2024; Li et al., 2025), few have focused on the individual capabilities of managers and how training directly influences their performance. Moreover, much of the existing literature focuses on the technology itself, rather than the human factors—skills, confidence, and behavioral change—that determine its success in the workplace.

To address this gap, the current study draws on well-established theories of learning and technology adoption. The Technology Acceptance Model (TAM) (Davis, 1989) suggests that users are more likely to engage with a new system if they perceive it as both useful and easy to use—both of which are heavily influenced by quality training. Similarly, Baldwin and Ford's (1988) Transfer of Training Theory emphasizes the role of training design and work environment in enabling learners to apply newly acquired skills on the job. Kirkpatrick's Four-Level Model (1996) also reinforces the idea that meaningful training leads to not only learning and behavior change, but also measurable organizational results. These theoretical foundations provide a robust framework for investigating the role of training in translating technological capabilities into practical managerial performance.

This research focuses on Majan Construction Company as a case study to explore this relationship. The company, like many in the region, is undergoing digital transformation and seeking to integrate AI into its managerial and operational processes. The study employs a mixed-methods approach, combining quantitative performance metrics with qualitative feedback from participating managers. Pre- and post-training assessments will measure changes in decision-making efficiency, automation use, and planning accuracy. In parallel, surveys and interviews will capture how managers perceive the training and its relevance to their roles.

By investigating both the outcomes and perceptions of AI-powered tools training, this research aims to contribute to the growing body of literature on digital readiness, managerial development, and technology integration in construction. It also provides practical insights for firms aiming to align their training strategies with emerging technologies to improve organizational effectiveness.

1.2. Research Problem

AI tools offer real benefits in construction management, but many managers aren't trained to use them effectively. At Majan Construction Company, this gap means valuable tools may be underused. This study looks at whether training can help managers use AI tools more confidently and improve their overall efficiency.

1.2.1. Theoretical Gaps

Most research on AI in construction tends to focus on what the technology can do, rather than how managers actually learn to use it. There's not much theory linking AI adoption to real-world issues like training, behavior change, or decision-making. This study looks to fill that gap by examining how training affects managers' ability to use AI tools effectively.

1.2.2. Practical Gaps

AI tools are available, but many managers aren't trained to use them effectively. At Majan Construction Company, this limits their impact. There's a need for practical training to bridge the gap between having the tools and using them well.

How does training in AI-powered tools affect managerial efficiency at Majan Construction Company?

1.3. Research Significance

AI tools can make a big difference in how construction projects are managed—but only if people know how to use them. This research matters because it looks beyond the technology and focuses on the people using it. By exploring how training helps managers at Majan Construction Company work more efficiently with AI, the study offers practical insights for other companies facing the same challenge. It shows that investing in people is just as important as investing in tools.

1.3.1. At the theoretical level

At the heart of this research is a simple idea: even the smartest technology needs people who know how to use it. While a lot of theory talks about what AI can do, not enough attention is given to how managers actually learn to use it and apply it in their daily work. This study brings a human-centered view to the conversation by showing that training plays a key role in turning potential into real impact. It adds to the theory by connecting AI tools not just to systems and outcomes but to people.

1.3.2. At the practical level

On a practical level, this research helps companies like Majan Construction Company get more out of the AI tools they already have. It focuses on the real-world challenge many organizations face: giving managers the training they need to confidently use new technology. By showing how the right training can improve decision-making and efficiency, this study offers clear, useful guidance for companies that want to make their digital investments pay off.

1.4. Research Questions

- How does AI-powered tool training impact the time managers take to make project-related decisions at Majan Construction Company?
- What is the change in the percentage of routine tasks automated by managers after receiving AI training?
- To what extent do managers apply AI tools in their daily tasks within three months of completing the training?

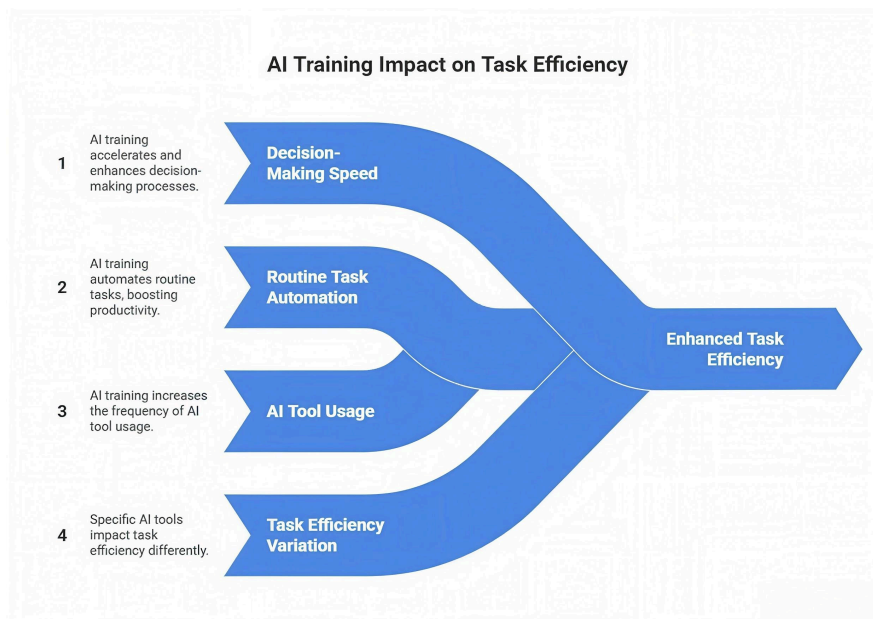
1.5. Research Objectives

- To determine the impact of AI-powered tool training on the speed and accuracy of managerial decision-making at Majan Construction Company.
- To analyze changes in the percentage of routine tasks automated by managers following AI training.
- To assess the frequency and consistency with which managers apply AI tools in their daily work after completing the training.
- To identify which AI-powered tools introduced during training are most frequently used by managers and how they contribute to task efficiency.

1.6. Research Hypotheses

- There is a statistically significant **positive relationship** between AI-powered tools training and managerial decision-making speed and accuracy at Majan Construction Company.
- There is a statistically significant **positive relationship** between AI-powered tools training and the percentage of routine tasks automated by managers.
- There is a statistically significant **positive relationship** between AI-powered tools training and the frequency of AI tool usage by managers within three months of training.
- There is a statistically significant relationship between the type of AI-powered tools introduced during training and the level of task efficiency achieved by managers.

1.7. Research Model



1.8. Empirical Study

This research will be conducted at **Majan Construction Company**, a mid-sized firm operating in the construction sector. The setting is highly relevant to the research topic, as the company is in the process of integrating AI-powered tools into its management practices but has not yet implemented formal training programs for its managers. This makes it a practical environment for studying the effects of AI training on managerial efficiency.

The researcher has direct access to the organization's managers, with support from HR and executive leadership, enabling smooth implementation of surveys, performance tracking, and post-training interviews. All ethical considerations will be observed, including obtaining informed consent, ensuring confidentiality, and respecting participants' right to withdraw at any time.

Majan Construction Company is also representative of many similar-sized construction firms in the region, facing the same digital transformation challenges. Thus, findings from this study can offer insights that are generalizable to other companies in the industry that are also navigating the integration of AI into management.

1.9. Research Methodology

1. Research Philosophy: Positivism

This study adopts a positivist philosophy, as it seeks to test hypotheses through measurable data and statistically analyze the effects of AI-powered tools training on managerial efficiency. Positivism aligns with the goal of objectively assessing training outcomes using pre-defined metrics.

2. Research Approach: Deductive

The research follows a deductive approach. It starts with established theories about the relationship between training and managerial performance, and then tests specific hypotheses about how AI tool training affects decision-making, automation, and tool usage at Majan Construction Company.

3. Research Strategy: Case Study

A case study strategy is employed, focusing on a single organization—Majan Construction Company. This allows for a detailed, contextual investigation of training impacts in a real-world managerial setting.

4. Research Choice: Mixed Methods

A mixed methods approach will be used. Quantitative data (e.g., pre- and post-training performance metrics, frequency of AI tool usage) will be collected through structured surveys. Qualitative data (e.g., manager feedback on training experiences and challenges) will be gathered through semi-structured interviews.

5. Time Horizon: Cross-Sectional

The study uses a cross-sectional design, collecting data at two points in time (before and after training) to compare changes in managerial efficiency.

6. Data Collection and Analysis Techniques

a. Data Collection

- Quantitative: Online or paper-based surveys measuring KPIs such as decision-making time, task automation rate, and AI tool usage frequency.
- Qualitative: Semi-structured interviews to explore perceptions, barriers, and adoption experiences.

b. Data Analysis

- Quantitative analysis: Descriptive statistics, paired t-tests, and regression analysis to test hypotheses.
- Qualitative analysis: Thematic analysis of interview responses to identify recurring patterns and insights related to tool adoption and efficiency.

1.10. The Suggested Project Structure

The study is organized into five main chapters, each contributing to a systematic and comprehensive exploration of the research topic :

- **Chapter 1: Introduction**

This chapter presents the research background, problem statement, theoretical and practical gaps, research significance, questions, objectives, hypotheses, research model, and methodology overview.

- **Chapter 2: Literature Review**

A review of relevant academic literature on the independent variable (AI-powered tools training), the dependent variable (managerial efficiency), and the relationship between them. It helps position the research within existing academic debates.

- **Chapter 3: Research Methodology**

This chapter outlines the research philosophy, approach, strategy, time horizon, and the methods used for data collection and analysis. It explains how the research was designed and conducted.

- **Chapter 4: Statistical Analysis**

This chapter presents the results of the quantitative analysis, including descriptive and inferential statistics used to test the research hypotheses.

- **Chapter 5: Findings, Discussion & Conclusion**

This final chapter discusses the key findings in relation to the research questions and objectives, provides practical and theoretical implications, and concludes with recommendations and suggestions for future research.

2.Chapter 2: Literature Review

2.1. Introduction

Artificial intelligence (AI) is changing how companies operate, especially in industries like construction where time, accuracy, and smart decision-making are critical. While AI tools can do a lot, such as automating tasks, analyzing data, and supporting fast decisions, the real challenge lies in getting people, especially managers, to use them effectively. Having the tools is one thing, but knowing how to use them well is another. That is why training plays such an important role in whether AI delivers real results or just remains unused potential.

This chapter reviews what researchers have already said about these topics and why they matter. A literature review helps us understand what has been discovered so far, what theories have been developed, and where the gaps are. It also ensures this project builds on solid ground, not just repeating what is already known, but contributing something new.

In the sections that follow, the focus will be on three key areas. First, we will explore the independent variable, which is AI-powered tools training, and what it actually involves for managers. Second, we will look at the dependent variable, managerial efficiency, including what it means and how it can be measured in practical terms. Finally, we will explore what past research has found about the link between the two, specifically how training might influence how managers perform once they start using AI tools. This review sets the stage for the rest of the research and shows why this study is both timely and relevant.

2.2. The independent variable : AI-Powered Tools Training

Training in AI-powered tools has become a vital component of digital transformation in the construction industry. These tools, such as intelligent scheduling platforms, predictive analytics systems, and automated reporting dashboards, are designed to improve managerial performance by enabling faster decisions, reducing manual workloads, and increasing accuracy. However, these benefits can only be achieved when managers are properly trained to use the tools effectively.

AI tool training goes beyond simple software tutorials. It includes practical, task-focused learning that helps managers integrate AI into real project workflows. Gounde and Olusegun (2024) emphasize that AI technologies can significantly reduce delays and improve quality control in construction, but only when users are equipped with the right knowledge to apply them. Their study shows that AI enables smarter, data-driven decision-making by analyzing large datasets, something that untrained managers may not fully leverage.

Classic theories of training and technology adoption also support the importance of well-designed AI training. The Technology Acceptance Model (TAM) developed by Davis (1989) argues that users are more likely to adopt a technology if they perceive it as useful and easy to use. Training directly enhances both of these perceptions, making it more likely that managers will incorporate AI tools into their daily routines. Similarly, Baldwin and Ford's (1988) Transfer of Training Theory highlights that successful skill transfer depends on the design of training, the motivation of the learner, and the alignment of training with job tasks. In the context of this study, effective training ensures that AI tools are not only understood but also applied in ways that improve performance. Finally, Kirkpatrick's Four-Level Model (1996) suggests that real organizational outcomes, such as improved efficiency, are achieved when training leads to both learning and behavior change on the job.

Similarly, Nithyakarpagam and Mathiraj (2024) identify a lack of skilled personnel as one of the main barriers to AI adoption in construction. In their survey of over 400 construction professionals, 52% reported using AI tools in some capacity, and nearly half agreed that these tools improved scheduling and cost control. Yet the findings also highlighted that without adequate training, many organizations struggle to implement AI on a broader scale. This reinforces the idea that training is not just beneficial but essential.

Scott and Bommu (2024) further support this by showing that managers who receive structured AI training demonstrate improved performance, including higher task automation rates and fewer project errors. Their results suggest that training directly influences how efficiently managers use AI technologies in high-pressure environments like construction.

2.3. The dependent variable : Managerial Efficiency

Managerial efficiency refers to how effectively managers carry out their responsibilities, particularly in making timely decisions, coordinating resources, solving problems, and ensuring that operational tasks are completed with minimal waste of time and effort. In construction, where delays and mismanagement can lead to significant financial and reputational losses, the efficiency of managers plays a critical role in project success.

Traditionally, managerial efficiency was tied to experience and judgment. However, with the increasing integration of digital tools, efficiency now also depends on how well managers leverage technology to support their decision-making and operations. AI-powered tools have changed the way managers operate by providing real-time data, predictive insights, and automated task management systems that improve both speed and accuracy. Scott and Bommu (2024) observe that managers who are equipped with AI systems are more capable of handling large volumes of information, allowing them to make quicker and more informed decisions.

Li et al. (2025) reinforce this view, noting that AI-supported managers can better anticipate scheduling conflicts, resource shortages, or project risks before they escalate. Their findings suggest that the ability to respond proactively rather than reactively is a defining characteristic of high-efficiency managers in technologically advanced workplaces. In their systematic review, they found that managers who used AI tools regularly showed noticeable improvements in time management and forecasting accuracy.

Gounde and Olusegun (2024) also emphasize that managerial efficiency is not simply about completing tasks but doing so with consistency and strategic value. They highlight that frequency of AI use, ease of system adoption, and confidence in interpreting AI-generated outputs all contribute to whether a manager performs effectively. When AI tools are underused or misapplied, the potential gains in productivity are lost.

2.4. The relationship between the independent and the dependent variables

The relationship between AI-powered tools training and managerial efficiency has become increasingly relevant as organizations seek to modernize their operations. While advanced tools are readily available, the real value emerges only when managers are trained to use them effectively. This relationship is especially important in the construction industry, where delays, budget overruns, and poor communication can have significant impacts on project outcomes.

Multiple studies have shown that when managers receive structured, hands-on training in AI tools, their performance improves in tangible ways. For example, Scott and Bommu (2024) found that trained managers demonstrated a 30% increase in task automation and reported faster decision-making in project planning. Their work supports the idea that training strengthens the connection between available tools and actual outcomes.

Gounde and Olusegun (2024) also highlight this connection, noting that AI's benefits—such as smarter forecasting, improved quality control, and reduced project risk—are only fully realized when managers feel confident using the technology. This confidence typically stems from focused training that goes beyond technical instruction and builds real-world application skills.

Li et al. (2025) further argue that managerial efficiency improves when training helps bridge the gap between data insights and strategic action. In their review, managers who regularly used AI after training showed better planning accuracy and time efficiency than those who did not receive the same support. This suggests that the relationship between training and performance is not just theoretical—it's measurable.

In summary, the literature consistently supports a positive relationship between AI-powered tools training and managerial efficiency. The training acts as an enabler, allowing managers to convert AI potential into real improvements in how they plan, decide, and manage daily tasks. This study builds on these findings by examining how that relationship plays out specifically within Majan Construction Company.

2.5. Conclusion

This chapter reviewed the key literature related to AI-powered tools training and managerial efficiency, offering both theoretical insights and practical evidence. The findings consistently show that while AI tools hold great promise for improving decision-making, automating tasks, and optimizing performance, their true value depends on how well managers are trained to use them. Effective training plays a critical role in bridging the gap between technology availability and its meaningful application in the workplace.

The review highlighted that AI training improves not only technical skills but also confidence, adoption rates, and the overall impact of AI systems on managerial workflows. Studies by Scott and Bomm (2024), Gounde and Olusegun (2024), and Li et al. (2025) confirm that well-trained managers make faster and more accurate decisions, and are more likely to integrate AI into their daily routines. In contrast, lack of training often leads to underutilized tools and missed opportunities for efficiency gains.

These findings have important implications for future research. As AI continues to evolve, more studies are needed to explore how different types of training—whether online, in-person, or task-specific—affect performance across various industries. There is also room to investigate long-term outcomes, such as how sustained use of AI tools changes leadership roles and decision-making approaches.

By focusing on the relationship between AI training and managerial efficiency in a construction context, this study contributes to a growing body of research on digital transformation in management. It offers practical insights for companies looking to improve how their teams work with technology, and it highlights the importance of investing in people, not just platforms, to drive innovation.

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