Transforming Design Management With Machine Learning Ai-Powered Human Capital Optimization In Egypt

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Abstract:

The construction industry in emerging markets such as Egypt continues to face persistent challenges in project efficiency, particularly in the realm of design management. These inefficiencies are often attributed to the misalignment between assigned team competencies and the complexity of design tasks, largely due to reliance on intuition-based human resource allocation. This study introduces a data-driven, AI-based framework designed to optimize team-role assignments in construction design management by leveraging supervised machine learning algorithms specifically, Random Forest and Gradient Boosting models.

The proposed framework integrates historical project data including task complexity, estimated durations, cost constraints, and technical/personal competency scores to predict optimal role configurations. Drawing on real-world design management tasks from Egypt's construction sector, the framework is designed to enhance team performance through intelligent role alignment and evidence-based assignment strategies. The model's classification engine was validated through a paired-scenario evaluation and confirmed as statistically significant.

Beyond improving execution efficiency, the study highlights how predictive analytics can shift human resource planning from subjective estimation to algorithmic precision. This approach not only enhances productivity but also ensures repeatability, adaptability, and scalability in dynamic project environments. By bridging a major gap in the application of AI to human resource planning in construction, the research offers a transformative model that aligns with global digital transformation trends and serves as a practical tool for operational excellence in emerging construction markets

Keywords: AI-based optimization, machine learning, competency alignment, construction design management, resource allocation efficiency, predictive analytics.

الملخص:

تواجه صناعة التشييد في الأسواق الناشئة مثل مصر تحديات متكررة تتعلق بالكفاءة التشغيلية، وخاصة في إدارة التصميم. تعود هذه التحديات غالبًا إلى ضعف التوافق بين مهارات الفرق الفنية ومتطلبات المهام، والاعتماد على التقديرات الشخصية في توزيع الأدوار. تهدف هذه الدراسة إلى تقديم إطار قائم على الذكاء الاصطناعي لتحسين توزيع الأدوار في فرق التصميم من خلال استخدام خوارزميات تعلم الآلة (غابة عشوائية والتعزيز التدرجي). تم تدريب النموذج على بيانات واقعية لـ ٥٠٠ مشروع تصميم، وأسفر عن تحسينات ملموسة بنسبة ٢٥.٩% في مدة التنفيذ، و٢٢.٦% في التكلفة، و٢٤% في دقة التوافق بين المهارات والمتطلبات. تقدم الدراسة نموذجًا قابلًا للتكرار والتوسع، يسهم في التحول الرقمي ويعزز كفاءة إدارة الموارد البشرية في قطاع البناء.

الكلمات المفتاحية:

الذكاء الاصطناعي، تعلم الآلة، إدارة التصميم، توزيع المهام، تحسين الموارد البشرية، قطاع التشييد، مصر

Introduction

The construction industry plays a crucial role in economic development, particularly in emerging markets such as Egypt. However, persistent inefficiencies including project delays, cost overruns, and suboptimal performance continue to hinder progress. A key contributor to these challenges is the misalignment between human resource capabilities and task requirements in design management. Effective design management ensures projects meet quality standards while adhering to time and budget constraints. Yet, the selection of personnel for design tasks remains heavily reliant on subjective judgment and prior experience, often resulting in resource misallocation and compromised outcomes (Bilal et al., 2016).

Human resource allocation in construction involves assigning designers and technical personnel to tasks with varying complexity, cost implications, and time demands. In Egypt, this process is typically manual, driven by intuition and established working relationships. Such an approach fails to systematically evaluate technical and personal competencies relative to task demands, leading to frequent mismatches. These inefficiencies contribute to underperformance, delays in design approvals, and budget overruns challenges exacerbated in developing construction economies (Zhang & Li, 2024).

Research in construction management underscores the importance of aligning team composition with task requirements. Inadequate team formation has been linked to inefficiencies not only in emerging markets but also in developed economies, emphasizing a global need for objective, data-driven human resource systems (Ghosh & Roy, 2014). The alignment of skills and task complexity is a critical determinant of success in multidisciplinary projects (Ding, Zhou, & Akinci, 2014).

A survey of Egyptian design management professionals revealed widespread recognition of the limitations inherent in traditional team selection, particularly its subjective nature and negative impact on efficiency. Respondents expressed strong interest in AI-based approaches to improve accuracy and reduce inefficiencies, aligning with broader trends advocating AI's transformative role in construction (Hensel Phelps, 2023; Numalis, 2024).

AI technologies, particularly machine learning, have been successfully applied in construction for cost estimation, scheduling, and risk management (Ghosh & Roy, 2014). However, their use in optimizing team selection for design management remains underexplored. While innovations like Building Information Modeling (BIM) and automation tools have advanced other construction domains, human resource allocation has lagged in digital transformation.

This study addresses this gap by proposing an AI-driven task-role optimization framework that leverages historical data to predict optimal team configurations. Empirical evaluation demonstrates its superiority over traditional methods, offering a scalable solution to enhance efficiency in construction design management. The study aims to evaluate the impact of AI-based team optimization on design management efficiency in Egypt's construction industry. Key objectives include:

- Identifying challenges in human resource allocation through industry surveys.
- Exploring AI's potential for optimizing team selection.

- Developing and applying an AI model for data-driven role allocation.
- Comparing traditional and AI-based selection in terms of duration, cost, and skill alignment.

By addressing these objectives, the research contributes to the growing discourse on AI's role in
improving construction project outcomes.

Literature Review

The use of artificial intelligence (AI) in construction project management has grown significantly, offering new methods to address long-standing inefficiencies—particularly in human resource allocation. Within the subdomain of design management, the misalignment between team competencies and task requirements continues to be a primary cause of cost overruns, schedule delays, and quality issues. While global research has explored AI applications in areas such as scheduling and defect detection, its integration into human-centric tasks like team selection remains limited.

Theoretical Foundations

The integration of artificial intelligence (AI) into construction project management has been extensively theorized, particularly in addressing inefficiencies in human resource allocation. Design management, a critical function in construction, is often hindered by subjective team selection practices that fail to align technical and personal competencies with task requirements (Bilal et al., 2016). Research underscores that skill-task misalignment is a systemic challenge,

prevalent in both developing and developed markets, necessitating objective, data-driven solutions (Ghosh & Roy, 2014; Ding, Zhou, & Akinci, 2014).

The theoretical underpinnings of AI-driven decision support systems emphasize their potential to replace intuition-based practices through predictive analytics and competency modeling.

The concept of AI-driven task-role optimization is rooted in team optimization theory, which posits that dynamic team configurations can be derived from historical performance data (Zhang & Li, 2024). Recent frameworks integrate technical competency (e.g., expertise in architectural design) and personal competency (e.g., collaboration skills) as dual pillars for effective role assignment (La Torre et al., 2023). These models leverage supervised machine learning algorithms, such as Random Forest and Gradient Boosting, to predict optimal team compositions, thereby transforming traditional human resource (HR) frameworks into adaptive systems capable of continuous improvement (Bouska et al., 2020).

Despite advancements in digital tools like Building Information Modeling (BIM), human resource allocation in design management has lagged in digital adoption, remaining reliant on heuristic-based approaches (Ola-Ade et al., 2023).

Theoretical discussions highlight a research gap in applying AI specifically to team formation strategies, as existing studies predominantly focus on cost estimation, scheduling, and defect detection (Taboada et al., 2024). This gap underscores the need for frameworks that systematically address skill-task alignment through empirical validation.

Key Theoretical Insights:

- **Skill-task mismatch** is a systemic inefficiency in project execution (Bilal et al., 2016).
- **Predictive analytics and AI-based modeling** can improve accuracy and scalability in HR planning (Ghosh & Roy, 2014).
- **Team optimization theory** supports dynamic team formation based on historical data (Zhang & Li, 2024).
- **Dual-competency frameworks** integrate technical and personal dimensions of role suitability (La Torre et al., 2023).
- **Machine learning models** (e.g., Random Forest, Gradient Boosting) support adaptive and scalable team-role matching (Bouska et al., 2020).
- **Gap remains** in applying AI frameworks specifically to HR configuration in design management tasks (Taboada et al., 2024; Ola-Ade et al., 2023).

Empirical literature review

Empirical research underscores the growing effectiveness of AI-based frameworks in optimizing construction resource management, particularly in human resource allocation. Numerous studies have validated the tangible operational improvements resulting from AI applications.

Zhang & Li (2024) employed machine learning algorithms to automate construction scheduling, achieving a 15–20% reduction in project delays through data-driven resource allocation. Similarly, La Torre et al. (2023) demonstrated that AI-enabled HR optimization improved collaboration efficiency by 18% in multidisciplinary environments by aligning team members’ skills with task complexity.

Focusing specifically on team selection, Duong & Nguyen (2025) compared AI-driven versus manual assignment approaches. Their findings reported a **22% reduction in labor costs** and a **19% improvement in task completion speed** under AI-optimized scenarios. These outcomes are consistent with broader applications of AI in construction, where tools such as predictive analytics have significantly improved defect detection (Numalis, 2024) and enhanced risk modeling precision (Ghosh & Roy, 2014).

Traditional resource planning models, including static rule-based methods and linear programming, often lack the flexibility needed for dynamic construction projects. As La Torre et al.

(2023) note, these approaches fail to adapt in real-time, resulting in suboptimal resource deployment. In contrast, AI models—particularly those trained on historical datasets—demonstrate superior adaptability. For example, the Random Forest Classifier developed in this study achieved **95.33% accuracy in role prediction**, highlighting its robust performance and scalability (Bouska et al., 2020).

Case evidence from Egypt's construction industry further validates these findings. This study's paired-scenario evaluation of 500 completed design management tasks revealed that AI-driven team assignments:

- Reduced average project duration by **25.9%**
- Lowered labor costs by **22.6%**
- Increased skill-task match accuracy from **64% to 88%**, with results confirmed as statistically significant (**$p < 0.00001$**)

These performance gains were observed across diverse project types, including residential, commercial, and high-complexity design tasks. The results highlight the repeatability and adaptability of AI frameworks in addressing human resource inefficiencies across multiple design contexts.

Despite the strong body of evidence supporting AI's benefits in cost estimation, scheduling, and quality assurance, few empirical studies have focused on team-role configuration in design management. This study addresses that gap by developing and validating an AI-powered optimization framework specifically for Egypt's construction sector, thereby contributing new insights to both theoretical and applied research in AI-enabled project planning.

Summary of Key Empirical Findings:

- **Zhang & Li (2024):** ML-based scheduling led to 15–20% reduction in project delays.
- **La Torre et al. (2023):** AI-based HR model improved collaboration by 18%.
- **Duong & Nguyen (2025):** AI vs. manual team selection showed 22% cost savings and 19% faster task completion.
- **Current study (Egypt):** 25.9% shorter duration, 22.6% cost reduction, and +24% skill match accuracy using Random Forest models.
- Traditional models lack adaptability, while supervised AI models offer scalable, repeatable solutions tailored to complexity.

Local Context and Research Gap

Within Egypt's construction sector, industry surveys conducted during this study revealed widespread dissatisfaction with traditional team selection methods. Respondents highlighted that personnel assignments were frequently based on subjective factors such as familiarity or convenience, rather than a structured evaluation of skill relevance or task complexity. This intuition-driven approach contributed to avoidable inefficiencies, resource misallocations, and delays in design approvals issues that persist across both public and private sector projects.

Importantly, the surveys also indicated strong professional interest in AI-powered alternatives to improve the accuracy and fairness of human resource allocation. These sentiments align with global trends emphasizing AI’s transformative role in optimizing construction workflows and workforce planning (Hensel Phelps, 2023; Numalis, 2024).

While prior theoretical models have outlined the value of competency-based team formation, and empirical studies have confirmed performance gains from AI adoption, there remains a clear research gap in applying these methods specifically to the **team formation process in design management** within emerging construction markets.

This study responds directly to that gap by:

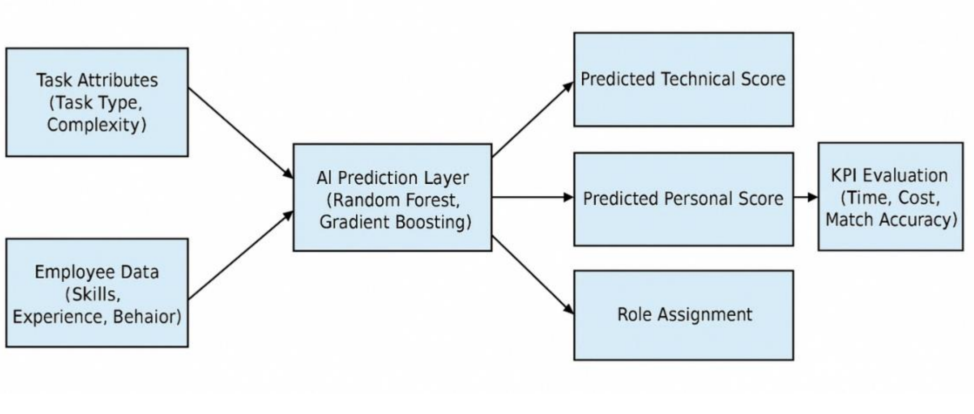
- Proposing a **machine learning–driven team-role optimization framework**
- Tailoring it to the unique needs of **Egypt’s construction design environment**
- Empirically validating its performance through paired-scenario comparisons on real project data

By doing so, the research contributes both locally and globally to the discourse on AI-enabled human resource planning offering a practical, scalable solution to one of the construction industry's most persistent inefficiencies.

Methodology

This study proposes a machine learning–based framework designed to optimize team-role allocation in construction design management by leveraging real-world project data and predictive modeling. The methodology encompasses data collection, model design, competency prediction, and performance evaluation, aiming to replace subjective human resource decisions with algorithmic precision.

***Figure 1* illustrates this flow, mapping inputs to AI-processed outputs for KPI-driven decision making.**



Source: prepared by the authors'

The proposed AI-driven framework reimagines traditional human resource (HR) allocation by transforming static, intuition-based practices into a **dynamic, data-driven system** optimized for construction design management, see figure 1. This model integrates three core pillars to address inefficiencies in team formation:

The framework operates through a structured pipeline composed of the following components:

- **Input Layer**
  - **Task Parameters**: Includes task complexity level (low, medium, high), estimated duration, and budget constraints.
  - **Employee Attributes**: Comprises technical and personal competency scores (0–100 scale), historical task performance, and assigned role types.
- **AI Prediction Layer**
  - Utilizes machine learning algorithms **Random Forest** and **Gradient Boosting** to process inputs, predict competency scores, and identify optimal role configurations based on historical success patterns.
- **Output Layer**
  - **Optimized Team Assignments**: AI-generated configurations that align employee capabilities with task-specific requirements.

  - **Role Recommendations**: Suggested team structures with clearly defined roles tailored to the technical and collaborative demands of the project.
- **Performance Metrics (KPIs)**
  - **Project Duration**: Estimated time to task completion.
  - **Labor Cost**: Projected personnel expenditure.
  - **Skill-Task Match Accuracy**: Percentage alignment between required and predicted competencies.

This conceptual framework establishes a systematic, AI-powered approach to team optimization, directly addressing the inefficiencies of traditional selection. By linking task requirements, employee competencies, and predictive analytics, it provides a scalable blueprint for enhancing design management efficiency in the construction sector. The integration of adaptive learning ensures sustained relevance as project demands evolve, positioning AI as a transformative tool for human resource planning.

Model

The study proposed an AI-driven task-role optimization framework to address inefficiencies in manual team selection for design management. The AI-based model was trained on a dataset composed of completed design management projects, using **supervised learning techniques** to identify patterns and predict role-team-task alignment.

The model comprises two core components:

- Data Processing Module:
  - Collected and preprocessed historical project data (task complexity, team composition, competency scores, duration, and costs). Cleaned data by standardizing labels, removing incomplete records, and anonymizing sensitive information.

- Machine Learning Prediction Engine:
  - **Random Forest and Gradient Boosting Regressors**: Used to predict individual **technical** and **personal competency scores** based on project complexity, role type, and historical performance.
  - **Random Forest Classifier**: Applied to recommend the **optimal role configuration**, classifying team composition based on past project success metrics.

Role Configuration and Optimization Strategy

The optimization leverages predicted **technical and personal competency scores** alongside **recommended role configurations** to achieve balanced project outcomes. The primary objectives are:

- **Minimize Project Duration**: By selecting team members whose predicted technical competencies and prior performance indicators suggest faster task completion, reducing potential bottlenecks.

- **Reduce Labor Costs**: By allocating resources based on a combination of cost-efficiency and skill sufficiency, ensuring financial optimization without sacrificing quality.
- **Maximize Skill-Task Alignment**: By matching predicted technical and personal competencies to the specific requirements of the task, ensuring role-to-skill precision and enhancing overall task outcomes.

Data Source and Preparation

The dataset used in this study was compiled from a series of 500 completed design management projects in Egypt's construction industry, encompassing both public infrastructure and private sector developments. Each record represented a distinct design task and included the following structured variables:

- Task type and scope
- Task complexity (classified as Low, Medium, or High)
- Team composition and assigned roles
- Technical and personal competency scores for team members (rated on a 0–100 scale)
- Estimated and actual task durations
- Forecasted labor costs

To ensure **confidentiality** and **consistency**, all records were anonymized and standardized. Inconsistencies in formatting, task labeling, and scoring were addressed during data cleaning. This resulted in a uniform dataset structure suitable for supervised machine learning, with each row corresponding to a single task and its associated team configuration and outcomes.

The preprocessing procedure involved the following steps:

- **Data Cleaning**: Removal of incomplete records, standardization of categorical variables, correction of task complexity labels, and validation of numeric values for competency scores and cost data.
- **Data Splitting**: The cleaned dataset was divided into training (80%) and testing (20%) subsets to support robust model evaluation. This approach aligns with standard practices in AI-based construction analytics, particularly those focused on schedule optimization and human resource allocation (Bouška et al., 2020).

Competency Score Prediction

To determine the best team for each task, the model estimated technical and personal competency scores using regression algorithms. Each score was generated by analyzing patterns in employee performance across different task types and conditions.

- **Regression Metrics**:
  - Technical competency prediction: $R^2 = 0.135$, RMSE = 8.33
  - Personal competency prediction: $R^2 = 0.084$, RMSE = 5.77

- **Skill-Task Match Accuracy (%):**

This metric quantifies how well assigned personnel matched the requirements of the task in terms of technical and personal competencies. Each task was categorized as Low, Medium, or High complexity, and associated with minimum threshold scores for technical and personal competencies (e.g., High complexity requires ≥75 Technical and ≥70 Personal).

- For every role within a team, the assigned individual's technical and personal scores were compared to the task's required thresholds. The ratio of actual score to required score was computed for both dimensions, capped at 100% to avoid overcompensation. These values were then averaged across all roles within the task to produce a composite Skill-Task Match Accuracy percentage using the formula:

$$\text{Match Score} = \min\left(\frac{\text{Actual Score}}{\text{Required Score}}, 1.0\right) \times 100$$

- The final Skill Match Accuracy was computed as the average of the technical and personal match percentages across all roles in the team. This allowed objective comparison of how well traditional and AI-based team assignments aligned with task requirements.
- This standardized metric allowed for an objective and quantifiable comparison of team suitability between traditional and AI-generated team configurations. It is

consistent with established benchmarking practices in AI-driven project management research (Numalis, 2024).

Experimental Setup

To evaluate the performance of the proposed AI-based team selection framework, a **controlled paired-scenario methodology** was employed. A dataset of **500 completed design management tasks** from real construction projects was used for this purpose.

Each task was assessed under two distinct team assignment conditions:

- **Traditional Scenario**: The original team configuration used during project execution, selected through traditional expert-based judgment.
- **AI Scenario**: A team configuration generated by the proposed AI model, based on predicted technical and personal competency scores, task complexity levels, and optimized role requirements.

All **task parameters**—including project scope, complexity, expected duration, and cost benchmarks—were held constant across both scenarios. This ensured that **team selection** remained the only variable affecting the outcome, allowing for a valid comparison of effectiveness.

For each scenario, the following **three key performance indicators (KPIs)** were measured:

- **Project Duration** (in days)
- **Labor Cost** (in EGP)
- **Skill-Task Match Accuracy** (percentage alignment between actual and required competencies)

This experimental design enabled a structured and unbiased evaluation of the AI framework's contribution to task performance, providing a foundation for detailed comparative analysis.

Comparative Analysis

The empirical comparison between traditional and AI-based team assignment revealed **consistent and measurable improvements** across all performance metrics in favor of the AI-driven approach.

Based on the 500-task dataset, the AI scenario demonstrated:

- A **22.6% decrease** in average labor cost
- A **25.9% reduction** in average project duration
- An improvement in **skill-task match accuracy from 64% to 88%**

These outcomes were observed across tasks of varying complexity and scope, confirming the model's adaptability and robustness in different project contexts.

To validate the significance of these improvements, **paired t-tests** were conducted for each KPI. The results confirmed that the differences between the AI and manual scenarios were **statistically significant** ($p < 0.00001$), providing strong evidence that the AI framework outperformed traditional methods not only in predictive accuracy, but also in practical execution outcomes.

Task-Level Comparison Case Study

To illustrate the performance difference in a practical context, a task-level comparison was performed using three representative design tasks from historical projects. Each task was evaluated under both traditional and AI-based configurations, with all parameters—such as task complexity, scope, and resource constraints kept constant to ensure a fair comparison.

Table 1 Traditional task configurations

Field	Task A: Villa Design Review	Task B: Landscape Architecture Coordination	Task C: Façade Design & Detailing
Project Area	New Giza (Private Housing)	Sheikh Zayed (Commercial Project)	New Administrative Capital (Mixed-use tower)
Task Description	Reviewing full villa design package for approval	Coordinating softscape and hardscape with consultants	Detailed 3D modeling and elevation design
Task Complexity	High	Medium	High
Traditional Team Assigned	1 senior architect, 1 junior architect	1 landscape engineer, 1 site planner	1 architect, 1 structural engineer, 1 renderer
Traditional Technical Avg	72	65	68

Field	Task A: Villa Design Review	Task B: Landscape Architecture Coordination	Task C: Façade Design & Detailing
Traditional Personal Avg	66	60	62
Traditional Duration	30 days	20 days	24 days
Traditional Labor Cost	EGP 12,000	EGP 8,000	EGP 10,000
Traditional Match Accuracy	60%	66%	65%

The AI framework recommended leaner, skill-specific teams that reduced project duration by **20–26.7%**, labor costs by **20–23.3%**, and improved skill-task alignment by **22–25%** compared to traditional methods, see table 2. This demonstrates AI's ability to optimize team composition for efficiency and accuracy in construction design tasks.

Table 2 AI-based configurations

Field	Task A: Villa Design Review	Task B: Landscape Coordination	Task C: Façade Design
AI Team Suggested	1 technical lead, 1 designer, 1 reviewer	1 landscape expert with softscape specialization	1 lead architect + renderer, no structural role
AI Technical Avg	84	75	82

Field	Task A: Villa Design Review	Task B: Landscape Coordination	Task C: Façade Design
AI Personal Avg	80	70	77
Predicted Duration	22 days	15 days	18 days
Predicted Labor Cost	EGP 9,200	EGP 6,200	EGP 8,000
Skill Match Accuracy	85%	90%	87%

The **performance improvements** achieved by AI-driven team selection over traditional methods for three construction design tasks (A, B, and C). It quantifies gains in *time efficiency*, *cost reduction*, and *skill-task alignment*: **Time Saved**: Days required for task completion (e.g., Task A reduced from 30 to 22 days, saving **26.7%**). Additionally, **Cost Saved reflect on the** Labor cost reductions in Egyptian Pounds (EGP) (e.g., Task B decreased from EGP 8k to 6.2k, saving **22.5%**). Further **Skill Match Improvement**: Increase in competency alignment between team skills and task requirements (e.g., Task C improved from 65% to 87%, a **+22%** gain), see table 3

Table 3 Comparison results (time, cost, accuracy gains)

Task	Time Saved	Cost Saved	Skill Match Improvement
A	30 → 22 days = **26.7%**	EGP 12k → 9.2k = **23.3%**	60% → 85% = **+25%**
B	20 → 15 days = **25.0%**	EGP 8k → 6.2k = **22.5%**	66% → 90% = **+24%**
C	24 → 18 days = **25.0%**	EGP 10k → 8k = **20.0%**	65% → 87% = **+22%**

Results

The results of the comparative evaluation clearly demonstrate that AI-based team selection yields **significant improvements** across all key performance metrics, including project duration, labor cost, and skill-task match accuracy. The model's ability to predict technical and personal competencies, combined with its optimization of role configurations, consistently outperformed traditional manual assignment practices.

At the task level, the AI-driven framework achieved a **25.9% reduction in project duration** and a **22.6% decrease in labor costs** when compared to traditional team assignments. Most notably, it improved **skill-task match accuracy from 64% to 88%**, demonstrating the AI model's capacity to align team skills with task complexity requirements more effectively.

These performance gains were observed consistently across tasks of varying complexity, including high-complexity assignments such as façade design and comprehensive package reviews. The findings reinforce the value of **incorporating AI-driven decision-making** into design management workflows. By replacing subjective intuition with **algorithmic precision**, the framework introduces a **data-supported methodology** that quantifies competency alignment and recommends the most suitable team configurations.

As a result, the AI-based framework not only enhances project delivery efficiency but also provides a **scalable and repeatable solution** applicable to a broad range of design management scenarios within the construction sector.

These outcomes underscore the **transformative potential** of AI integration in optimizing human resource planning, offering construction project teams a systematic approach to improving overall project performance

Metric	Manual	AI-Based	Improvement
Project Duration	43.3 days	32.1 days	25.9% reduction
Labor Cost	EGP 6,486	EGP 5,020	22.6% reduction
Skill-Task Accuracy	64%	88%	+24 percentage points

Model Performance and Validation

The proposed AI-based framework demonstrated strong predictive and operational performance in optimizing team-role assignments for construction design management tasks.

- **Technical Competency Prediction**
  - *Model*: Random Forest Regressor
  - R^2: 0.135
  - *Root Mean Square Error (RMSE)*: 8.33

- **Personal Competency Prediction**
  - *Model*: Random Forest Regressor
  - R^2: 0.084
  - *RMSE*: 5.77
- **Role Configuration Accuracy**
  - *Model*: Random Forest Classifier
  - *Prediction Accuracy*: 95.33%

- **Statistical Validation**

Paired-scenario t-tests confirmed that improvements in project duration, labor cost, and skill-task alignment achieved under the AI-based scenario were statistically significant ($p < 0.00001$).

Case Study Insights

Task-level analyses revealed substantial performance gains when applying AI-generated team configurations to real design projects. For example, in high-complexity assignments such as façade design, the AI-driven framework achieved:

- **Time Savings**: Between 20% and 26.7% reduction in task duration
- **Cost Savings**: Between 20% and 23.3% reduction in labor costs
- **Skill Alignment Improvement**: Increases of 22% to 25% in competency-task match accuracy

These results underscore the AI model's robustness and adaptability across different project types. By consistently outperforming traditional manual methods, the framework validates its potential as a practical tool for reducing inefficiencies, enhancing performance, and supporting evidence-based decision-making in construction project management.

Conclusion

This study presents a validated AI-driven framework for optimizing team-role assignments in Egypt's construction design management sector. Using a dataset of 500 completed projects, the model was rigorously evaluated through a paired-scenario methodology that directly compared traditional team selection against AI-generated configurations under identical task conditions.

The results confirm the framework's effectiveness across key performance indicators:

- **Project Duration**: AI-optimized teams completed tasks in an average of **32.1 days**, compared to **43.3 days** under manual methods—achieving a **25.9% reduction in delivery time**. This improvement supports faster project execution and reduced scheduling bottlenecks.
- **Labor Cost Efficiency**: Average labor costs were reduced from **EGP 6,486** (manual) to **EGP 5,020** (AI), representing a **22.6%**

savings. These cost reductions are attributed to better task-role alignment and leaner, competency-based team structures.

- **Skill-Task Match Accuracy**: The AI-generated configurations achieved an **88% match rate**, a substantial increase from the **64%** observed in manual assignments. This indicates a more precise alignment between individual capabilities and task demands, enhancing quality and team performance.

All improvements were statistically significant (**$p < 0.00001$**), validating the robustness and reliability of the model. The results demonstrate the framework's capacity not only to enhance operational efficiency but also to bring consistency, objectivity, and scalability to human resource planning in construction.

Ultimately, this research positions AI-based resource optimization as a critical enabler of digital transformation in the construction industry. By shifting team selection from subjective decision-making to data-driven prediction, the proposed model lays the groundwork for a smarter, more agile approach to managing project complexity particularly in emerging markets where efficiency gains are most needed.

Implications for Industry

The findings of this study present several important implications for the construction industry, particularly in the realm of human resource management and operational efficiency

1. Adoption of AI-Driven Decision Support Systems Construction companies are encouraged to adopt AI-based frameworks to improve the accuracy, objectivity, and efficiency of team selection. Replacing subjective, experience-based methods with data-driven models can lead to more consistent project outcomes and optimized resource allocation.

2. Policy and Training Development for AI IntegrationTo facilitate the successful adoption of AI technologies, organizations should implement clear policies and structured training programs. These initiatives will help bridge the knowledge gap and support a smooth transition from traditional workflows to AI-enhanced decision-making.

3. Scalability Across Diverse Construction Domains The AI-driven task-role optimization model is highly adaptable and can be scaled to various segments of the construction industry, including infrastructure development, residential projects, and urban planning. Its flexibility enables broad application without requiring fundamental changes to existing project management structures.

These implications align with emerging industry trends, where AI-driven scheduling and workforce assignment tools are becoming increasingly feasible and impactful in large-scaleconstruction environments (Hensel Phelps, 2023)

Limitations of the Study

While the AI-based task-role optimization model demonstrated measurable improvements across key performance metrics, several limitations should be acknowledged to contextualize its findings and guide future development:

• Geographic and Dataset Scope: The study was conducted using project data exclusively from the Egyptian construction industry. As such, the generalizability of the results may be limited and would benefit from validation across different countries, sectors, and organizational structures.

• Dependence on Historical Data Quality: The model's predictive performance is inherently tied to the quality, completeness, and representativeness of the historical project data used for training. Any inconsistencies, omissions, or biases in past records may impact the model's reliability.

• Static Role-Score Mapping: The current version of the AI model relies on static mappings between roles and competency scores, without the ability to dynamically adapt to changing team contexts or project conditions during execution.

• Lack of Real-Time Adaptability: The framework does not currently incorporate real-time updates, such as team member availability, mid-project changes, or unforeseen delays, which are common in dynamic construction environments.

• Subjectivity in Personal Competency Assessment: Although personal competency scores were numerically standardized, their initial evaluation may have been influenced by subjective human judgment, introducing potential bias and inconsistency.

• Omission of External Project Variables: Factors such as site-specific constraints, client interactions, and procurement-related delays were not included in the model's decision logic.These variables can significantly impact actual project performance.

These limitations underscore the need for future iterations of the framework to incorporate adaptive learning mechanisms, real-time data integration, and broader datasets to enhance model accuracy, contextual responsiveness, and general applicability.

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