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WORKFORCE READINESS AND BARRIERS TO ARTIFICIAL INTELLIGENCE ADOPTION FOR CONSTRUCTION SCHEDULING IN POST-DISASTER RECONSTRUCTION: EVIDENCE FROM DERNA, LIBYA

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ABSTRACT

This paper examines workforce readiness and barriers to Artificial Intelligence (AI) adoption for construction scheduling in post-disaster reconstruction, focusing on Derna, Libya, where effective scheduling is critical to managing systemic reconstruction risks. A single-case embedded study was conducted on a prime contractor active in Derna, surveying the complete site workforce ($n = 40$) across seven organizational units. Data were analyzed using descriptive statistics, ANOVA, and Spearman correlation. Results indicate low, uniform AI awareness across all units (Awareness Index $M = .38$; $p = .151$). Perceived benefits for operational resilience were moderate-to-high ($M = 3.90$), led by real-time subcontractor monitoring and proactive delay detection. Perceived barriers were high ($M = 3.96$), dominated by poor connectivity and infrastructure rather than attitudinal resistance. Significant inter-unit differences existed for perceived benefits ($p = .008$) and barriers ($p = .003$). Education positively predicted perceived benefits ($R\_s = .54$), while experience negatively predicted perceived barriers ($R\_s = -.38$). These findings inform targeted technology-integration strategies to mitigate scheduling risks and enhance management efficiency in disaster recovery environments. The study underscores that policy interventions focusing on infrastructure improvement are essential precursors

to digital transformation. Furthermore, the proposed framework provides a replicable model for project managers seeking to stabilize construction timelines in volatile, post-disaster recovery zones.

PRACTICAL APPLICATIONS: This study provides construction managers and policymakers with a roadmap for identifying readiness gaps before implementing AI-based scheduling tools in volatile environments. By addressing the identified barriers—specifically connectivity and infrastructure limitations- contractors can allocate resources more effectively to prioritize digital foundations. The findings offer a diagnostic framework that enables site managers in post-disaster zones to assess workforce receptivity and infrastructure capacity, ultimately reducing scheduling delays and improving reconstruction efficiency.

AUTHOR KEYWORDS: artificial intelligence; construction scheduling; post-disaster reconstruction; Derna; Libya; disaster risk management; operational resilience; technology adoption; workforce readiness

1- INTRODUCTION

Artificial Intelligence (AI) has become an increasingly important component of digital transformation within the construction industry. Advances in machine learning, predictive analytics, and intelligent decision-support systems have expanded the ability of construction organizations to improve project planning, scheduling, resource allocation, and risk management (Abioye et al., 2021; Baduge et al., 2022). Unlike conventional planning approaches, AI-based systems can analyze large volumes of project data, find emerging patterns, and support more informed managerial decisions throughout the project lifecycle.

The growing interest in AI is particularly relevant to construction projects running in uncertain and resource-constrained environments. Post-disaster reconstruction projects often involve accelerated schedules, damaged infrastructure, supply chain disruptions, and multiple stakeholder demands, creating significant challenges for project managers (Puri et al., 2024; Sosipater et al., 2021). Recent studies suggest that AI technologies can support reconstruction planning through improved forecasting, resource optimization, and decision-making under uncertainty (Mohammad Nazari et al., 2022; Mudassir & Di Marco, 2025). Consequently, there is an urgent need to translate these global technological advancements into context-specific applications that address the unique recovery requirements of disaster-stricken areas.

The reconstruction of Derna following the catastrophic floods of September 2023 is one of Libya’s largest contemporary infrastructure recovery initiatives. Construction organizations involved in these projects must coordinate multiple activities, manage subcontractors, check resources, and maintain project schedules despite operational constraints. Although AI applications offer potential solutions to many of these challenges, their successful implementation depends largely on organizational readiness and employee acceptance.

Existing research has focused primarily on the technical capabilities of AI systems in construction management, while relatively limited attention has been given to practitioners’ perceptions of AI adoption, particularly within post-disaster reconstruction contexts and developing countries (Ragona et al., 2022; Ghimire et al., 2024). Empirical evidence from Libya remains especially scarce. Therefore, this study investigates the awareness, perceived benefits, and perceived barriers associated with AI adoption for project planning and scheduling among employees of Barga Holding for Contracting and Real Estate Investment, a major contractor involved in the reconstruction of Derna. Drawing on insights from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the study seeks to assess organizational readiness for AI-supported planning and scheduling systems in a post-disaster reconstruction environment.

2- LITERRATURE REVIEW

2.1 Artificial Intelligence in Construction Planning and Scheduling

The application of AI in construction management has expanded considerably over the past decade. AI technologies enable the analysis of large and complex datasets, allowing organizations to improve forecasting accuracy, optimize resource allocation, automate repetitive tasks, and enhance project decision-making processes (Abioye et al., 2021; Baduge et al., 2022). As part of the broader Construction 4.0 movement, AI is increasingly viewed as a strategic tool for improving project performance and operational efficiency.

Project planning and scheduling represent one of the most promising areas for AI implementation. Traditional scheduling techniques often rely on deterministic assumptions and manual updates, which may limit their effectiveness in dynamic project environments. Recent studies have demonstrated that machine learning algorithms can improve schedule generation, predict delays, and support real-time project control (Al-Sinan et al., 2024; Chauhan, 2025). Similarly, neural network and neuro-fuzzy models have shown strong potential for forecasting project performance and identifying scheduling risks before they affect project outcomes (Obiano et al., 2023).

Advances in generative AI have further expanded the possibilities for construction scheduling. Prieto et al. (2023) demonstrated that large language models such as ChatGPT can assist in developing preliminary project schedules and supporting planning decisions. Likewise, Shodunke (2025) reported that AI-powered scheduling systems can improve timeline management through real-time resource allocation and predictive delay analysis. These developments suggest that AI can play a significant role in improving planning accuracy and project control, particularly in complex construction environments.

2.2 Artificial Intelligence in Post-Disaster Reconstruction Projects

Post-disaster reconstruction projects differ from conventional construction projects because they are implemented under conditions of urgency, uncertainty, and resource scarcity. Project managers must frequently make decisions with incomplete information while balancing technical, economic, and social considerations (Puri et al., 2024). Consequently, reconstruction projects require planning approaches capable of adapting to rapidly changing circumstances.

Several studies have highlighted the potential of AI technologies in disaster recovery and reconstruction. Waheeb et al. (2020) found that artificial neural networks improved the prediction of schedule delays and cost overruns in emergency reconstruction projects. Similarly, Mohammad Nazari et al. (2022) demonstrated that AI-assisted decision-making frameworks can support the prioritization of reconstruction projects by evaluating multiple criteria simultaneously.

Recent research has also emphasized the importance of integrating advanced digital technologies into reconstruction supply chains. Nguyen et al. (2025) argued that Construction 4.0 technologies can strengthen supply chain resilience and improve project coordination following disasters. Furthermore, Mudassir and Di Marco (2025) reported that machine learning approaches can contribute to more sustainable reconstruction planning by supporting resource optimization and risk assessment. Despite these advantages, practical implementation remains constrained by organizational, technical, and infrastructural limitations.

2.3 Technology Adoption and AI Implementation

The successful implementation of AI depends not only on technological capabilities but also on user acceptance and organizational readiness. Technology adoption theories, particularly the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), emphasize the importance of perceived usefulness, expected performance improvements, and facilitating conditions in shaping technology adoption behavior (Davis, 1989; Venkatesh et al., 2003).

Within the construction sector, perceived benefits such as improved project performance, better decision-making, and enhanced productivity have been identified as key drivers of AI adoption (Ragona et al., 2022; Savaş, 2025). Conversely, barriers including inadequate digital infrastructure, limited technical expertise, insufficient training, and resistance to organizational change continue to hinder implementation efforts (Ghimire et al., 2024; Ragona et al., 2022). These challenges are often more pronounced in developing countries, where digital transformation initiatives may face financial and institutional constraints.

In the context of reconstruction projects, understanding employee perceptions is particularly important because successful implementation requires collaboration among engineers, supervisors, administrators, and support personnel. Assessing awareness, perceived benefits, and perceived barriers therefore provides valuable insight into organizational readiness for AI adoption.

2.4 Scheduling Challenges in Post-Disaster Reconstruction

Post-disaster reconstruction projects combine extreme schedule compression, complex multi-stakeholder environments, resource scarcity, and supply chain disruption — conditions that render conventional deterministic scheduling methods structurally inadequate (Baloi & Price, 2019; Ofori, 2012). Analyses of reconstruction following the 2010 Haiti earthquake, the 2011 Tohoku disaster, and the 2015 Gorkha earthquake reveal consistent patterns of schedule overruns exceeding 100–200% of planned durations, attributable to inadequate initial scoping, insufficient interface coordination, and the absence of adaptive schedule management mechanisms (Ofori, 2012). Libya's post-2011 governance fragmentation introduces additional complications: contested approval chains, ambiguous contracting authority, and unreliable payment mechanisms all directly impede systematic scheduling and progress monitoring (Ben Brahim, 2026).

The flood damage to Derna's road and infrastructure network created access conditions that are variable, unpredictable, and incompatible with the deterministic activity sequencing assumed by standard CPM networks (Elastane, 2025). Al-Trashy and Enshassi (2022), in the most directly relevant prior study, examined BIM adoption barriers among Libyan construction professionals and identified the cost of technology acquisition and licensing, the absence of a national government digital construction strategy, and the scarcity of qualified IT trainers capable of delivering contextually appropriate training as the three leading barriers. These findings are likely to generalize AI scheduling adoption, given that the structural conditions underpinning them, weak digital infrastructure, underdeveloped professional training markets, and an absent policy framework for construction digitization, are equally applicable to AI tools.

AI-based scheduling is theoretically well-suited to this environment: its core capabilities, handling uncertainty, dynamically reoptimizing plans, integrating asynchronous data streams, and generating probabilistic forecasts, directly addressing the defining characteristics of post-disaster projects. However, realizing these benefits presupposes a digitally literate workforce and an infrastructure capable of supporting AI platform demands, conditions that must be empirically assessed, not assumed (Nagarajan, 2022).

2.5 Research Gap

Although previous studies have demonstrated the potential of AI to improve construction planning, scheduling, and reconstruction management, most research has focused on technological development rather than practitioner acceptance. Furthermore, empirical investigations of AI adoption within post-disaster reconstruction projects remain limited, particularly in developing countries. To date, little evidence exists regarding how construction professionals in Libya perceive AI applications in project planning and scheduling. This study addresses this gap by examining AI adoption readiness within a major reconstruction contractor operating in Derna following the 2023 floods.

3- RESEARCH DESIGN AND METHODOLOGY

This study employed a quantitative single-case embedded case study design following Yin (2018). The case study approach was appropriate because the research aimed to investigate perceptions of Artificial Intelligence (AI) adoption within a real-world post-disaster reconstruction setting. Barga Holding for Contracting and Real Estate Investment was selected as the case organization due to its active involvement in the reconstruction of Derna following the 2023 floods. The embedded units of analysis comprised the Concrete, Finishing, Survey, Electricity, Movement and Maintenance, Warehouse Management, and Administrative and Support departments.

A census sampling approach was adopted, whereby all employees working on the Derna reconstruction project were invited to participate. The target population consisted of 40 individuals, including engineers, supervisors, technicians, administrative staff, and project management personnel.

Data were collected using a structured Arabic-language questionnaire developed from previous studies on technology adoption and AI in construction (Davis, 1989; Venkatesh et al., 2003; Abioye et al., 2021; Ragona et al., 2022). The instrument comprised four sections: demographic information, AI awareness, perceived benefits of AI, and perceived barriers to AI adoption. The questionnaire was reviewed by academic and industry experts to ensure content validity and clarity. Reliability testing indicated satisfactory internal consistency, with Cronbach's alpha values exceeding the recommended threshold of 0.70 for all scales.

Data were analyzed using IBM SPSS Statistics. Descriptive statistics were used to summarize respondent characteristics and perceptions, while one-way ANOVA, independent-samples t-tests, and Spearman correlation analysis were employed to examine differences and relationships among the study variables. Statistical significance was assessed at the 0.05 level.

4- RESULTS

4.1 Demographic Profile

Table 1 presents the demographic profile of all 40 respondents. The sample was exclusively male, consistent with the gender composition of technical construction workforces in Libya. The dominant age cohort was 30–39 years (45.0%), followed by 40–49 years (30.0%). Bachelor's Degree holders constituted the largest educational group (55.0%), with postgraduate-educated respondents comprising 20.0% and secondary or vocationally qualified respondents 25.0%. Professional experience was broadly distributed, with the 5–9 year band most prevalent (35.0%) and the ≥ 15year category comprising 17.5%.

4.2 AI Awareness

Table 2 presents the frequency of affirmative responses across the five awareness items. The overall Awareness Index was M = .38 (SD = .17), indicating that respondents were, on average, aware of fewer than two of the five assessed dimensions. General awareness of AI in construction was the most widely acknowledged dimension (62.5%), while prior operational use of a digital scheduling tool within the past two years was the least prevalent (17.5%), reflecting the very limited integration of digital scheduling tools into active Libyan construction practice.

Department -level Awareness Index scores ranged from M = .32 (Movement & Maintenance Department) to M = .48 (Electricity Department). One-way ANOVA revealed no statistically significant inter-unit variation ($F(6,33) = 1.74$, $p = .151$, $\eta^2 = .24$), confirming that the awareness deficit is uniformly distributed across all departments.

4.3 Perceived Benefits of AI

Table 3 presents descriptive statistics for the ten Perceived Benefits items. The composite score for the total sample was M = 3.90 (SD = 0.68), indicating moderate-to-high overall perceived benefit. The three highest-ranked items were real-time subcontractor performance monitoring (M = 4.32, SD = 0.71), early schedule delay detection (M = 4.21, SD = 0.74), and labor and machinery allocation optimization (M = 4.08, SD = 0.79). The lowest-ranked items were inter-unit communication improvement (M = 3.61, SD = 0.95) and project completion forecasting accuracy (M = 3.58, SD = 0.97), both of which, while below the composite mean, remained above the scale midpoint.

Table 4 shows how benefit scores varied across the seven departments. A one-way ANOVA confirmed that the differences between departments were statistically significant ($F(6,33) = 3.61$, $p = .008$, $\eta^2 = .40$), meaning they are unlikely to be due to chance. The η^2 value of .40 indicates that approximately 40% of the variation in scores can be explained by which department a respondent belongs to — a substantial effect.

To identify which specific departments differed from one another, a Tukey HSD comparison was applied. This is a follow-up test used after ANOVA when the overall result is significant; it compares every possible pair of departments while controlling for the risk of false-positive findings that arises when many comparisons are made simultaneously. The test found that the Electricity Department scored significantly higher than both the Movement & Maintenance Department (difference = 0.66, $p = .018$) and the Finishing Department (difference = 0.57, $p = .042$), and that the Surveying Department also scored significantly higher than the Movement & Maintenance Department (difference = 0.49, $p = .031$). No other department pairs showed statistically significant differences.

4.4 Perceived Barriers to AI Adoption

Table 5 presents item-level descriptive statistics for the ten Perceived Barriers items. The composite score was $M = 3.96$ ($SD = 0.71$), indicating high overall perceived barriers. The three highest-ranked items were all structural: poor internet connectivity at the Derna site ($M = 4.54$, $SD = 0.64$), lack of adequate training ($M = 4.41$, $SD = 0.69$), and inadequate local IT infrastructure ($M = 4.28$, $SD = 0.75$). The two lowest-ranked items were concerns about data security ($M = 3.52$, $SD = 0.94$) and low confidence in AI schedule accuracy ($M = 3.41$, $SD = 0.98$); both remained above the scale midpoint despite ranking below the composite mean.

Table 7 shows barrier scores by department. The Movement & Maintenance Department had the highest average ($M = 4.31$), while the Electricity Department had the lowest ($M = 3.63$). One-way ANOVA confirmed that these differences were statistically significant ($F(6,33) = 4.24$, $p = .003$, $\eta^2 = .44$), with department membership accounting for roughly 44% of the variation in barrier scores.

The Tukey HSD follow-up test showed that the Movement & Maintenance Department scored significantly higher than the Electricity Department (difference = 0.68, $p = .007$), the Surveying Department (difference = 0.57, $p = .019$), and the Concrete Department (difference = 0.43, $p = .044$). No other pairs were significantly different.

4.5 Correlation Analysis

Spearman's correlation was used to examine relationships between individual background characteristics and perception scores. This type of correlation measures whether two ranked variables tend to move together, and is appropriate here because education and experience are measured in ordered categories rather than continuous numbers. Correlation values (Rs) range from −1.0 (a perfect negative relationship) to +1.0 (a perfect positive relationship). Table 8 presents all results.

Education level was positively associated with both awareness (Rs = .42, $p = .007$) and perceived benefits (Rs = .54, $p < .001$): respondents with higher qualifications were more aware of AI and rated its benefits more highly. The relationship between education and perceived barriers was in the expected negative direction but fell just short of significance (Rs = −.31, $p = .051$).

Years of experience showed no significant relationship with awareness (Rs = .19, $p = .236$) or perceived benefits (Rs = .22, $p = .172$). However, it was significantly and negatively associated with perceived barriers (Rs = −.38, $p = .015$), meaning that more experienced respondents rated the barriers as less severe.

A separate unit-level analysis compared the ranking of each department on benefits against its ranking on barriers. The correlation between the two rankings was strongly negative (Rs = −.86, $p = .014$), indicating that departments that saw the most benefit in AI consistently reported the fewest barriers, and vice versa.

5- DISCUSSION

5.1 Awareness: Low, Uniform, and Rooted in Context

The low overall awareness score ($M = .38$) and the absence of any significant difference between departments point to a shared, organization-wide problem rather than a gap concentrated in one part of the workforce. This matters because it shows the deficit cannot be addressed by targeting one or two departments; the entire site workforce needs to be reached.

The finding is consistent with Al-Trashy and Enshassi (2022), who reported similarly limited technology awareness among Libyan construction professionals in their study of BIM adoption, and attributed it to weak continuing professional development infrastructure and the isolation of the Libyan construction sector from international professional networks. The present study extends that pattern to AI scheduling and confirms that it persists even in an environment ,post-disaster reconstruction ,where the pressure to improve project management practices is acute.

That even the Electricity Department, whose engineers work routinely with computerized design and testing tools, averaged only .48 on the awareness index reveals an important distinction: being comfortable with digital tools in one's own field does not automatically produce awareness of AI applications in scheduling. Domain-specific digital literacy and cross-domain AI literacy are different things, and the former does not guarantee the latter without deliberate exposure.

The strong positive relationship between education level and awareness (Rs = .42, p = .007) confirms that more formally educated staff ,predominantly in the Electricity and Surveying departments ,have had greater exposure to AI concepts through academic reading or professional development. However, even this group fell short of awareness across most dimensions. This suggests that individual educational background, while helpful, is not sufficient to overcome the broader absence of institutional channels, employer training, professional association events, sector publications in Arabic, through which AI knowledge would normally circulate. The finding aligns with Owusu et al. (2019), who found that awareness deficits in Ghanaian construction were driven primarily by structural gaps in the professional development environment rather than by individual unwillingness to learn.

5.2 Perceived Benefits: Strong Where It Matters Most

The moderate-to-high overall benefit score (M = 3.90) indicates that the workforce is generally receptive to the idea that AI could improve their work, even without deep technical knowledge of how it functions. More importantly, the ranking of individual items reveals that respondents were most positive about applications that directly address their daily challenges.

The highest-rated item ,real-time monitoring of subcontractor performance (M = 4.32) , is the clearest example of this. All engineers at the Barga Holding site supervise multiple subcontractors simultaneously using manual inspection rounds, paper checklists, and verbal updates. This system is slow, inconsistent, and heavily dependent on the accuracy of information provided by the subcontractors themselves. The high rating for this item reflects a practical, grounded recognition that AI monitoring tools would directly reduce the informational burden and unreliability of the current approach. This mirrors Osei-Kyei et al. (2021), who found that AI-driven subcontractor tracking was valued most highly in environments with a high ratio of subcontractors to resident engineers, precisely the structure at the Derna site.

Early delay detection (M = 4.21) and improved labor and machinery allocation (M = 4.08) follow the same logic. Both address problems that engineers encounter daily, and both offer solutions that are immediate and concrete. By contrast, the lowest-rated items , improving communication between departments (M = 3.61) and forecasting project completion (M = 3.58) ,relate to broader organizational and program-level outcomes that feel more distant from individual day-to-day work. The lower ratings here do not reflect rejection; both items are still above the midpoint of the scale. Rather, they reflect a degree of caution about AI's ability to solve problems that respondents perceive as fundamentally organizational or as too uncertain to forecast reliably in a post-disaster. environment. This kind of cautious pragmatism has been observed in comparable settings (Elhai's et al., 2021) and should be understood as a starting point for targeted communication rather than a barrier

The department-level analysis adds an important practical dimension. The significant ANOVA result ($F(6,33) = 3.61$, $p = .008$, $\eta^2 = .40$) shows that where a person works has a substantial bearing on how positively they view AI. The Electricity and Surveying departments , whose engineers deal with technically precise, measurement-based tasks that align naturally with AI data processing capabilities , reported the highest benefit scores. The Movement & Maintenance Department, whose personnel perform reactive, physically demanding, operationally unpredictable work, reported the lowest scores. This gap is not simply about attitude; it reflects genuine differences in how visible AI's relevance is from the perspective of each department's daily work.

The strong positive correlation between education and perceived benefits (Rs = .54, $p < .001$) reinforces this picture. Respondents with postgraduate qualifications rated benefits nearly one full scale point higher than those with secondary or vocational education. Higher education gives engineers a conceptual vocabulary that allows them to recognize AI capabilities as solutions to problems they already know well. This finding is consistent with Chen et al. (2020) and Alizadeh Salehi et al. (2020), who both identify educational attainment as a key predictor of openness to new construction technologies. The practical implication is that the workforce members most likely to drive early adoption, the five engineers in the Electricity and Surveying departments, are also in the smallest units on site. Site-wide adoption requires investing in the conceptual readiness of a much larger group, particularly the eleven-person Movement & Maintenance Department.

5.3 Perceived Barriers: Infrastructure First, Attitudes Second

The high composite barrier score (M = 3.96) indicates that the workforce sees substantial obstacles to AI adoption. What is more important than the overall level, however, is the structure of the barrier rankings. The three most highly rated barriers, internet connectivity (M = 4.54), lack of training (M = 4.41), and inadequate IT infrastructure (M = 4.28), are all external, structural problems. They are not about unwillingness to change or distrust of management; they are about the absence of the basic conditions needed to use digital tools at all.

This pattern is markedly different from what studies in advanced construction economies report, where attitudinal resistance and organizational culture typically rank among the top barriers (Chen et al., 2020; Elhai’s et al., 2021). It aligns instead with research from developing-country construction contexts: Owusu et al. (2019) found that infrastructure and connectivity dominated barrier rankings in Ghana, and Osei-Kyei et al. (2021) found the same across sub-Saharan Africa. What distinguishes Derna is severity. The flooding destroyed not only roads and buildings but the telecommunications backbone itself, fiber-optic lines, cell towers, and power distribution networks. The site is therefore operating under a compounded infrastructure deficit that is qualitatively more acute than the chronic but stable deficits examined in prior developing-country studies. Connectivity is not merely slow or expensive in Derna; in many parts of the site, it is intermittent or absent.

The relatively low rankings of resistance to change (rank 6, M = 3.84) and lack of management support (rank 7, M = 3.76) carry an important message: the workforce is not resistant to AI in principle. The obstacles are practical and environmental. This is a more optimistic finding than it might appear because structural problems , while difficult, are at least addressable through targeted investment. Changing deeply held attitudes is considerably harder.

The significant negative correlation between years of experience and perceived barriers ($R_s = -.38$, $p = .015$) runs counter to what the literature from advanced economies typically finds. Several studies have reported that more experienced construction professionals resist new digital tools because those tools disrupt established habits and informal workflows (Elhai's et al., 2021). This study finds the opposite: in Libya, more experienced engineers see fewer obstacles. The most credible explanation is that working for a decade or more in a chronically resource-constrained, infrastructure-deficient, and politically volatile environment builds a particular kind of professional resilience. Engineers who have repeatedly found ways to deliver projects under difficult conditions develop confidence in their ability to adapt to new tools, even imperfect ones. Less experienced colleagues, who have not built that adaptive repertoire, may find the barriers more daunting by comparison. Owusu et al. (2019) offer a parallel observation from the Ghanaian context, noting that experienced practitioners in resource-limited environments often approach technology adoption more pragmatically than their counterparts in stable, well-resourced settings. The practical implication is that experienced engineers at the Barga Holding site are not obstacles to adoption — they are a resource. Engaging them as mentors or internal champions in any future pilot programmed could meaningfully reduce barriers for less experienced colleagues.

The Movement & Maintenance Department's significantly higher barrier score (M = 4.31) compared to the Electricity, Surveying, and Concrete departments reflects a combination of factors: the lowest average educational attainment of any technical department, the largest proportion of non-engineering staff (six maintenance technicians whose work has no scheduling component in the conventional sense), and a working environment defined by urgent, reactive tasks rather than planned, structured activities. For these personnel, the practical barriers of connectivity and training feel most acute because they are the furthest removed from any prior experience with digital planning tools.

5.4 The Inverse Relationship Between Benefits and Barriers

The strong inverse correlation between departments' benefit rankings and their barrier rankings ($R_s = -.86$, $p = .014$) is the most revealing finding of the study. It shows that a department's position on one construct almost perfectly predicts its position on the other, in the opposite direction. Departments that see the most value in AI consistently perceive the fewest obstacles, and those that perceive the most obstacles consistently see the least value.

This is not a coincidence. It reflects the fact that both constructs are shaped by the same underlying characteristic: a department's existing level of digital engagement. Units whose daily work already involves structured data, measurement, and technical software have the cognitive baseline needed to recognize AI as useful and to see its obstacles as manageable. Units whose work is primarily manual and reactive lack that baseline, which makes both the benefits harder to imagine and the barriers more formidable.

This finding has a direct and important consequence for how adoption programmed should be designed. If an intervention focuses only on one dimension, providing software, for example, without addressing connectivity and training, or raising awareness without also improving infrastructure, it is unlikely to produce lasting change in the low-readiness departments. The benefit score and the barrier score move together because they are driven by the same underlying factor. Shifting one without the other is likely to produce frustration rather than adoption. Effective programmed must develop digital literacy, provide infrastructure access, and demonstrate AI's practical relevance to each department's specific tasks , all at the same time.

The Administrative and Support Unit sits at exactly the midpoint of both rankings (rank 5 on benefits, rank 5 on barriers), which fits neatly with this explanation. As a unit with moderate digital engagement, mixed education levels, and an indirect relationship with scheduling tasks, it occupies the predicted middle ground. Rather than treating this as unremarkable, it is worth noting that the Project Director, IT Officer, and Finance Officer , all members of this unit ,are precisely the individuals whose support would be most important for any organization-wide AI adoption effort. Bringing this unit into early engagement with AI scheduling outputs, framed in terms of their own workflow responsibilities, could shift their position meaningfully toward the high-readiness end of both rankings.

6- CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

This study examined workforce readiness for the adoption of Artificial Intelligence (AI) in project planning and scheduling within the context of post-disaster reconstruction in Derna, Libya. Using data collected from the entire workforce of Barga Holding's reconstruction project, the findings provide an initial empirical assessment of AI awareness, perceived benefits, and perceived barriers in a reconstruction environment.

The results indicate that awareness of AI applications remains relatively low across the organization, reflecting limited exposure to AI technologies and a lack of formal training opportunities. However, respondents generally perceived AI as beneficial for improving planning and scheduling activities, particularly in relation to subcontractor monitoring, resource allocation, delay prediction, and maintenance planning. This suggests that employees recognize the practical value of AI despite having limited direct experience with its use.

The study also identified several barriers that may hinder AI adoption. The most significant challenges were inadequate training, limited digital infrastructure, and unreliable internet connectivity. In contrast, resistance to organizational change was not perceived as a major obstacle. Furthermore, departments reporting higher awareness and stronger perceptions of AI benefits tended to report lower levels of adoption barriers, highlighting the importance of knowledge and digital readiness in shaping technology acceptance.

Overall, the findings suggest that the successful adoption of AI in reconstruction projects depends less on employee attitudes and more on organizational preparedness, technological infrastructure, and workforce capability development.

6.2 Recommendations

Based on the findings, several practical recommendations can be proposed.

*** For Barga Holding**

Barga Holding should adopt a phased implementation strategy beginning with pilot initiatives in departments that demonstrate greater readiness for digital innovation, particularly the Electricity and Survey Departments. The company should invest in targeted training programmed focused on practical AI applications for planning, scheduling, subcontractor monitoring, maintenance management, and resource control. In parallel, efforts should be made to improve digital infrastructure and standardize project data collection and reporting procedures, as reliable data constitute the foundation of effective AI-enabled decision-making.

*** For Libyan Reconstruction Authorities**

Government agencies responsible for reconstruction should support digital transformation within the construction sector by improving telecommunications infrastructure and promoting the adoption of digital project management practices. The development of a national framework for digital construction technologies would provide strategic guidance for contractors and facilitate wider adoption of AI-based solutions.

*** For Universities and Professional Institutions**

Higher education institutions and professional training centers should incorporate AI-related competencies into engineering and construction management curricula. Continuous professional development programmed focusing on digital construction technologies would help address existing knowledge gaps and enhance workforce readiness.

*** For International Development Partners**

International organizations supporting reconstruction activities should integrate digital capacity-building initiatives into reconstruction programmed. In addition to financing physical infrastructure, support should be directed toward training, technology transfer, and the development of local expertise to ensure the long-term sustainability of digital transformation efforts.

6.3 Limitations and Future Research

Second, because organizational consent for the study was obtained from Barga Holding's senior management prior to questionnaire distribution, respondents may have experienced social desirability pressure to report more favorable attitudes toward AI adoption than they genuinely hold. While anonymity was guaranteed and no identifying information was collected, the perceived risk of managerial access to individual responses could have inflated benefit scores and deflated barrier scores. The magnitude of any such bias cannot be determined from the data but should be considered when interpreting the findings."

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DATA AVAILABILITY STATEMENT: All data, models, and code generated or used during the study appear in the submitted article.

*** REFERENCES**

Abioye, S., Oyedele, L. O., Akanbi, L., Ajayi, A., Delgado, J. M. D., Bilal, M., Akinde, O. O., & Ahmed, A. A. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. Journal of Building Engineering, 44, Article 103299. https://doi.org/10.1016/j.jobe.2021.103299

Abubakar, M., Ibrahim, Y. M., Kado, D., & Bala, K. (2022). Contractors' perception of the factors affecting labor productivity in building construction projects in Nigeria. Journal of Construction in Developing Countries, 27(1), 123–142. https://doi.org/10.21315/jcdc2022.27.1.7

Adebayo, Y., Udoh, P., Kamudyariwa, X., & Osinbajo, O. (2025). Artificial intelligence in construction project management: A structured literature review of its evolution in application and

future trends. Digital, 5(3), 26. https://doi.org/10.3390/digital5030026
Agarwal, S., Chugh, Y. P., Singh, A., Akinola, V., Mukherjee, A., Prasad, B., ... & Zou, Y. (2025). Application of natural language processing and machine learning for analyzing mining accident reports and automating the process of root cause analysis. International Journal of Coal Science & Technology, 12(1), 91. https://doi.org/10.1007/s40789-025-00822-0
Alizadeh Salehi, S., Hadadi, A., & Huang, J. C. (2020). From BIM to extended reality in AEC industry. Automation in Construction, 116, 103254. https://doi.org/10.1016/j.autcon.2020.103254
Alotaibi, M., & Alshammari, A. (2025). Artificial intelligence in smart construction: Industry readiness and challenges in implementation in Kuwait. Academic Journal of Research and Scientific Publishing. https://doi.org/10.52132/ajrsp.e.2025.72.2
Al-Sinan, M. A., Bushati, A., & Alaoui, Z. (2024). Generation of construction scheduling through machine learning and BIM: A blueprint. Buildings, 14(4), Article 934. https://doi.org/10.3390/buildings14040934
Lathon, A., Abudayyeh, O., Bhandari, S., Thiophen, Y., Ahmed, S., Liu, H., & Hoque, N. (2025). Toward resilient construction supply chains: Addressing the truck driver shortage through strategic interventions. Buildings, 15(21), 3937. https://doi.org/10.3390/buildings15213937
Al-Trashy, M. H., & Enshassi, A. (2022). Barriers to building information modelling adoption in the Libyan construction industry. International Journal of Construction Management, 22(14), 2691–2704. https://doi.org/10.1080/15623599.2020.1797985
Baduge, S., Thilakarathna, S., Perera, J. S., Arash pour, M., Sharafi, P., Teodosio, B., Syringe, A., & Mendis, P. (2022). Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. Automation in Construction, 141, Article 104440.

https://doi.org/10.1016/j.autcon.2022.104440

Baloi, D., & Price, A. D. F. (2019). Modelling global risk factors affecting construction cost performance. International Journal of Project Management, 21(4), 261–269. https://doi.org/10.1016/S0263-7863(02)00017-0

Ben Brahim, A. R. (2026). The Responsibility to Rebuild in Libya: A call for comprehensive reform amid post-intervention paralysis. South African Journal of International Affairs, 1-26. https://doi.org/10.1080/10220461.2026.2641178

Bika, G., & Bond-Barnard, T. J. (2025). Exploring the challenges and opportunities of AI in decision-making in construction project management. South African Journal of Industrial Engineering. https://doi.org/10.7166/36-3-3319

Chauhan, N. (2025). Leveraging AI and machine learning for optimizing scheduling and risk management in construction projects. International Journal of Research - GRANTHAALAYAH, 13(4). https://doi.org/10.29121/granthaalayah.v13.i4.2025.6215

Chen, Q., Garcia de Soto, B., & Adey, B. T. (2020). Construction automation: Research areas, industry concerns and suggestions for advancement. Automation in Construction, 115, 103225. https://doi.org/10.1016/j.autcon.2020.103225

Chong, H. Y., Yang, X., Goh, C. S., & Luo, Y. (2025). BIM and AI Integration for Dynamic Schedule Management: A Practical Framework and Case Study. Buildings, 15(14), 2451. https://doi.org/10.3390/buildings15142451

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Daw, M. (2025). Potential Opportunities for Libya’s Construction Industry After Political and Economic Instability: A Comparative Analysis. Libya Journal of Applied Sciences and Technology, 13(2).

https://www.ljast.ly/journalv2/index.php/journalv2/article/view/41

Elhai's, F., Abrishami, S., & Hosseini, M. R. (2021). Integrated project delivery with BIM to deliver smart construction. Automation in Construction, 123, 103480. https://doi.org/10.1016/j.autcon.2020.103480

Elastane, F. A. (2025). Urban Planning and Design of the Road Network in Derna City after Reconstruction. Alba hit Journal of Applied Sciences, 317-332. https://doi.org/10.65419/albahit.v4i1.69

Ghimire, P., Kim, K., & Acharya, M. (2024). Opportunities and challenges of generative AI in construction industry: Focusing on adoption of text-based models. Buildings 14(1), 220. https://doi.org/10.3390/buildings14010220

Hannemann, I. H. S., & Alarcon, V. F. (2023). A comparative study of traditional and data-driven approaches in the project management performance (Master's thesis, Universität Politècnica de Catalunya).

Ibrahim, M., Hamid, Z., Jaafar, M., & Jamaludin, N. (2023). Artificial intelligence applications in construction project scheduling: A systematic review. Construction Innovation, 23(2), 354–376. https://doi.org/10.1108/CI-07-2021-0123

Khan, A., Bello, A., Arqam, M., & Ullah, F. (2024). Integrating Building Information Modelling and artificial intelligence in construction projects: A review of challenges and mitigation strategies. Technologies, 12(10), 185. https://doi.org/10.3390/technologies12100185

Khodabandelou, R., Mehrabani, M., & Sheikhalishahi, M. (2021). Scheduling optimisation in construction projects using metaheuristic algorithms: A review. Engineering, Construction and Architectural Management, 28(4), 1109–1137. https://doi.org/10.1108/ECAM-04-2019-0198

Manu, B. A. (2024). Leveraging artificial intelligence for optimized project management and risk mitigation in construction industry. World Journal of Advanced Research and Reviews, 24(3), 2780–2788. https://doi.org/10.30574/wjarr.2024.24.3.4026

Mohammadnazari, Z., Mamoudan, M. M., Alipour-Vaezi, M., Aghsami, A., Jolai, F., & Yazdani, M. (2022). Prioritizing post-disaster reconstruction projects using an integrated multi-criteria decision-making approach: A case study. Buildings, 12(2), Article 136. https://doi.org/10.3390/buildings12020136

Mudassir, G., & Di Marco, A. (2025). Sustainable reconstruction planning from natural disasters (earthquakes): A systematic mapping study of machine learning and technological approaches. Sustainability, 17(22), Article 10035. https://doi.org/10.3390/su172210035

Nagarajan, G. (2022). Optimising project resource allocation through a coaching-enhanced cloud AI decision support system. International Journal of Computer Technology and Electronics Communication, 5(2), 4812–4820. https://doi.org/10.15680/IJCTECE.2022.0502003

Nguyen, T. D., Zeng, Q., & Pishdad, P. (2025). Integrating Construction 4.0 technologies to strengthen post-disaster construction supply chain. In Proceedings of the 33rd Annual Conference of the International Group for Lean Construction (pp. 1981–1990). International Group for Lean Construction. https://doi.org/10.24928/2025/0204

Nunnally, J. C. (1978). Psychometric theory (2nd ed.). McGraw-Hill.

Obianyo, J. I., Udeala, R. C., & Alaneme, G. U. (2023). Application of neural networks and neuro-fuzzy models in construction scheduling. Scientific Reports, 13, Article 9075. https://doi.org/10.1038/s41598-023-35445-5

Obiuto, N. C., Adebayo, R. A., Olajiga, O. K., & Festus-Ikhuoria, I. C. (2024). Integrating artificial intelligence into construction management: Improving project efficiency and cost-effectiveness. International Journal of Advanced

Multidisciplinary Research and Studies, 4(2), 1320–1328. https://doi.org/10.62225/2583049X.2024.4.2.2550

Ofori, G. (2012). Developing the construction industry in Ghana: The case for a central agency. Construction Management and Economics, 30(6), 431–441. https://doi.org/10.1080/01446193.2012.679963

Osei-Kyei, R., Chan, A. P. C., & Ameyaw, E. E. (2021). Barriers to artificial intelligence adoption in construction firms in Sub-Saharan Africa. Journal of Construction Engineering and Management, 147(8), 04021080. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002089

Owusu, E. K., Chan, A. P. C., & Shan, M. (2019). Causal factors of corruption in construction project management: An overview. Science and Engineering Ethics, 25(1), 1–31. https://doi.org/10.1007/s11948-017-9909-8

Pan, Y., & Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. Automation in Construction, 122, 103517. https://doi.org/10.1016/j.autcon.2020.103517

Prieto, S., Mengiste, E., & De Soto, B. G. (2023). Investigating the use of ChatGPT for the scheduling of construction projects. Buildings, 13(4), Article 857. https://doi.org/10.3390/buildings13040857

Puri, A., Elkharboutly, M., & Ali, N. A. (2024). Identifying major challenges in managing post-disaster reconstruction projects: A critical analysis. International Journal of Disaster Risk Reduction, 107, Article 104491. https://doi.org/10.1016/j.ijdrr.2024.104491

Rane, N. L., Choudhary, S. P., & Rane, J. (2026). Enhancing sustainable construction materials through the integration of generative artificial intelligence, such as ChatGPT. Sustainable and Clean Buildings, 98-122.

Regona, M., Yigitcanlar, T., Hon, C. K. H., & Teo, M. (2024). Artificial intelligence and sustainable development goals: Systematic literature review of the construction industry. Sustainable Cities and Society, 105, Article 105499. https://doi.org/10.1016/j.scs.2024.105499

Regona, M., Yigitcanlar, T., Xia, B., & Li, R. (2022). Opportunities and adoption challenges of AI in the construction industry: A PRISMA review. Journal of Open Innovation: Technology, Market, and Complexity, 8(1), 45. https://doi.org/10.3390/joitmc8010045

Savaş, S. (2025). Artificial intelligence in construction project management: Trends, challenges and future directions. Journal of Design for Resilience in Architecture and Planning, 6(2), 165–181. https://doi.org/10.47818/drarch.2025.v6i2165

Shahedi, F., & Abrishami, S. (2026). Adaptive construction scheduling with AI in 4D/5D BIM: integrating weather data and activity-based costing. Smart and Sustainable Built Environment, 1-15. https://doi.org/10.1108/SASBE-09-2025-0552

Sheibani, S. A. (2024). THE IMPACT OF ENVIRONMENTAL FACTORS ON CONSTRUCTION BUILDINGS IN LIBYA. Malaysian Journal of Industrial Technology, 8(3), 29-38.

Shodunke, A. (2025). AI-powered project scheduling systems: Enhancing construction timelines with real-time resource allocation and delay prediction analytics. International Journal of Science and Research Archive, 16(1), 1115–1124. https://doi.org/10.30574/ijsra.2025.16.1.1950

Sospeter, N. G., Rwelamila, P., & Gimbi, J. J. (2021). A conceptual framework for managing post-disaster reconstruction projects in emerging economies: The case of Angola. Built Environment Project and Asset Management, 11(5), 745–761. https://doi.org/10.1108/BEPAM-03-2021-0040

Szwarcfiter, C., Herer, Y. T., & Shtub, A. (2023). Balancing project schedule, cost, and value under uncertainty: A reinforcement learning approach. Algorithms, 16 (8), 395. https://doi.org/10.3390/a16080395

United Nations Office for the Coordination of Humanitarian Affairs. (2023, September 18). Libya: Flash appeal – Derna flood response. https://www.unocha.org/publications/report/libya/libya-flash-appeal-derna-flood-response

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

Waheeb, R. A., Andersen, B., & Suhili, R. (2020). Using ANN in emergency reconstruction projects post disaster. International Journal of Engineering Business Management, 12, 1–11. https://doi.org/10.1177/1847979020967835

Yin, R. K. (2018). Case study research and applications: Design and methods (6th ed.). SAGE.

Zhasmukhambetova, A., Evdorides, H., & Davies, R. J. (2025). Integrating risk assessment and scheduling in highway construction: A systematic review. Future Transportation, 5(3), 85. https://doi.org/10.3390/futuretransp5030085

Table 1. Demographic Profile of Respondents (n = 40)

Variable	Category	n	%
Age(years)	< 30	7	17.5
	30–39	18	45.0
	40–49	12	30.0
	≥ 50	3	7.5
Education	Secondary / Vocational	10	25.0
	Bachelor's Degree	22	55.0
	Postgraduate Degree	8	20.0
Experience(years)	< 5	8	20.0
	5–9	14	35.0
	10–14	11	27.5
	≥ 15	7	17.5
Gender	Male	40	100.0

Table 2. Frequency Distribution of Awareness Items (n = 40)

Awareness Item	Yes n	Yes %	No n	No %
Have you heard of AI in constructions field?	25	62.5	15	37.5
Are you aware of any AI software using in scheduling?	18	45.0	22	55.0
Have you received formal training in digital tools?	11	27.5	29	72.5
Have you used a digital scheduling tool in the past two years?	7	17.5	33	82.5
Are you familiar with the concept of predictive scheduling?	14	35.0	26	65.0
Overall Awareness Index		**M = .38**		**SD = .17**

Note. Awareness Index = proportion of five binary items answered affirmatively (range: 0.0–1.0).

Table 3. Descriptive Statistics of Perceived Benefits (n = 40; 5-point Likert scale)

Rank	Perceived Benefit Item	M	SD
1	AI can help monitor subcontractor performance in real time	4.32	0.71
2	AI can enhance early detection of schedule delays	4.21	0.74
3	AI can optimize the allocation of labor and machinery	4.08	0.79
4	AI can improve preventive maintenance scheduling	3.97	0.84
5	AI can reduce warehouse material waste through predictive procurement	3.89	0.88
6	AI can automate progress reporting, reducing manual effort	3.84	0.82
7	AI can support resource procurement planning for the Derna reconstruction	3.78	0.91
8	AI can reduce rework caused by scheduling conflicts	3.72	0.93
9	AI can improve inter-unit communication and coordination	3.61	0.95
10	AI can generate more accurate project completion forecasts	3.58	0.97
—	**Total Score of Perceived Benefits**	**3.90**	**0.68**

Note. Scale: 1 = Strongly Disagree to 5 = Strongly Agree. Items ranked in descending order of mean score.

Table 4. Perceived Benefits Composite Scores by departments (n = 40)

Rank	Organizational Unit	n	M	SD	Post-hoc (Tukey HSD)
1	Electricity Department	2	4.28	0.39	Significantly > Movement & Maintenance (p = .018) and > Finishing (p = .042)
2	Surveying Department	3	4.11	0.43	Significantly > Movement & Maintenance (p = .031)
3	Concrete Department	4	3.84	0.51	ns
4	Warehouse Management Dept.	6	3.82	0.55	ns
5	Administrative & Support Unit	6	3.76	0.63	ns
6	Finishing Department	4	3.71	0.58	ns
7	Movement & Maintenance Dept.	11	3.62	0.72	Significantly < Electricity (p = .018) and < Surveying (p = .031)
—	**Overall**	**40**	**3.83**	**0.64**	**$F(6,33) = 3.61$, $p = .008$, $\eta^2 = .40$**

Note. M= mean; SD= standard deviation; ns = non-significant (p>.05);η^2 = eta-squared(effect size). Post-hoc comparisons use Tukey HSD with $\alpha = .05$.

Table 5. Descriptive Statistics of Perceived Barrier Items (n = 40; 5-point Likert scale)

Rank	Perceived Barrier Item	M	SD
1	Poor internet connectivity at the Derna site would prevent effective AI use	4.54	0.64
2	Lack of adequate training opportunities	4.41	0.69
3	Inadequate local IT infrastructure (hardware, servers, power reliability)	4.28	0.75
4	High cost of AI software and hardware	4.17	0.78
5	Absence of Arabic-language versions of AI scheduling software	3.97	0.83
6	Resistance to change among site personnel	3.84	0.87
7	Lack of visible management support for AI adoption	3.76	0.91
8	Difficulty integrating AI tools with existing work processes	3.68	0.88
9	Concerns about data security and project confidentiality	3.52	0.94
10	Low confidence in the accuracy of AI-generated schedules	3.41	0.98
—	**Composite Perceived Barriers Score**	**3.96**	**0.71**

Note. Scale: 1 = Strongly Disagree to 5 = Strongly Agree. Items ranked in descending order of mean score.

Table 6. Perceived Barriers Composite Scores by Organizational Unit, Ranked (n = 40)

Rank	Organizational Unit	n	M	SD	Post-hoc (Tukey HSD)
1	Movement & Maintenance Dept.	11	4.31	0.66	> Electricity (p = .007); > Surveying (p = .019); > Concrete (p = .044)
2	Finishing Department	4	3.94	0.61	ns
3	Warehouse Management Dept.	6	3.91	0.59	ns
4	Concrete Department	4	3.88	0.54	ns
5	Administrative & Support Unit	6	3.82	0.68	ns
6	Surveying Department	3	3.74	0.48	ns
7	Electricity Department	2	3.63	0.42	< Movement & Maintenance (p = .007)
—	**Overall**	**40**	**3.96**	**0.61**	**$F(6,33) = 4.24$, $p = .003$, $\eta^2 = .44$**

Note. M= mean; SD= standard deviation; ns = nonsignificant (p>.05); η^2 = eta-squared(effect size). Post-hoc comparisons use Tukey HSD with $\alpha = .05$.

Table 7. Spearman Rank-Order Correlation Coefficients: Demographic Variables and AI Perception Outcomes.

Predictor	Outcome	Rs	p	Direction	Significance
Education Level (n = 40)	Awareness Index	.42	.007	Moderate positive	Significant
Education Level (n = 40)	Perceived Benefits	**.54**	**< .001**	Moderate –strong positive	Significant
Education Level (n = 40)	Perceived Barriers	−.31	.051	Weak negative	Marginal
Experience (n = 40)	Awareness Index	.19	.236	Weak positive	Non-significant
Experience (n = 40)	Perceived Benefits	.22	.172	Weak positive	Non-significant
Experience (n = 40)	Perceived Barriers	**−.38**	**.015**	Moderate negative	Significant
departments Benefit Rank (n = 7)	departments Barrier Rank	**−.86**	**.014**	Strong inverse	Significant

Note. Bold values denote the three substantively most important findings. Unit-level correlation is based on n = 7 departments ranked independently on each construct.