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Engineering Leadership Orientation and Perceived Organizational Enablement for Responsible Artificial Intelligence Use in Iraq

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Abstract: The integration of artificial intelligence (AI) into engineering practice is bringing new dimensions to the role of a leader, including professional judgment, collaboration, and responsibility for decisions made with AI's support. However, desirable personal leadership orientations do not necessarily correlate with desirable work conditions. This study examines this perceived capability–enablement divide among engineers in Iraq. Survey data were collected from 144 engineers working in Iraq using 39 Likert-scale questions. The primary within-respondent comparison used bootstrap estimation, the Wilcoxon signed-rank test, and a cumulative ordinal fixed-effects model covering 5,616 item responses. Adjusted associations were examined using ordinary least squares regression with heteroskedasticity-consistent type 3 (HC3) standard errors and complete-profile permutation tests. Individual Leadership Orientation (ILO) was rated more favorably (M = 3.789, standard deviation [SD] = 0.435) than Organizational Enablement (OE) (M = 3.479, SD = 0.848). The mean paired difference was 0.309 points (95% bootstrap confidence interval [CI] [0.187, 0.443], $p < .001$; Cohen's d_z = 0.394). Using the ordinal model, and controlling for respondent and item differences, the same directionality was found; that is, endorsement of Organizational Enablement was associated with lower odds (odds ratio [OR] = 0.450, 95% CI [0.380, 0.534], $p <$ .001). AI-use frequency was associated with ILO, but its association did not differ significantly from that with OE (p = .242). Education was associated much more strongly with individual orientation than enablement. The results suggest that there is a perceived gap in capability and enablement among the engineers participating, rather than any broad opposition to AI. The results indicate that leadership orientation and perceived organizational support are separate factors to consider when designing responsible AI implementation for engineering organizations.

Keywords: Responsible artificial intelligence; Sociotechnical alignment; Human–artificial intelligence collaboration; Workplace support; Engineering workforce; Iraq

1 Introduction

Artificial intelligence (AI) is transforming both the technical aspects of engineering and the professional judgment and leadership needed to navigate its implementation. In the field of architecture, engineering, and construction (AEC), AI is being developed for analysis, design, prediction, monitoring, and decision-making via building information modeling, digital twins, computer vision, automation, and integrated project platforms [1, 2]. While these applications may offer probable advantages, the outputs may be imprecise or misjudged, potentially affecting, safety, quality, contractual responsibility, and public welfare. Engineers need to do more than simply apply existing technologies. They need to assess their findings, recognize their broader implications, and accept their responsibilities in decision-making that involves AI.

The growing availability of AI does not necessarily mean that engineers are prepared to use it responsibly. An engineer might rely on an application without having the chance to check its principles, recognize when outputs are unreliable or insecure, safeguard sensitive information, or determine when human verification is needed. Organizations can also encourage experimentation, but lack the tools, reliable data, formal training, technical support, or formal accountability. Digital transformation is thus an organizational process and not the deployment of individual

technologies [3, 4]. It is the combination of the technology, workforce capability, managerial commitment, data practices, workflows and organization learning that makes it successful [5].

In this setting, engineering leadership is crucial for meeting the challenges involved in the responsible use of AI. Leaders participate in interpreting unclear evidence, coordinating and applying specialized knowledge, contesting defective recommendations, communicating findings, and taking ownership of the consequences of decisions supported by AI. The level of skills to be acquired is not just technical, but also encompasses adaptability, teamwork, systems thinking, evidence-based decisions and accountable decisions [6, 7]. Adaptive leadership plays a crucial role in complex construction settings where technological, organizational, and safety factors can vary rapidly [8].

Individual capability, however, cannot substitute for organizational enablement. Even a good engineer may resort to unstandardized practices when reliable guidance is absent. Organizational investment alone is also insufficient when engineers lack the ability to interpret and critically assess the outputs generated by automated systems. Consistently successful implementation requires the alignment of the expectations of the engineer and what the workplaces allow the engineer to achieve. It can help to conceptualize these levels and indicate if the perceived deficit is largely related to professional orientation, workplace enablement, or both.

Other requirements for digital project leadership identified by competency research include interoperability, data governance, cybersecurity, predictive analysis, stakeholder collaboration and lifecycle awareness [9]. However, the study of adoption and professional capability and organizational readiness are often separated. Professional competence is not necessarily a sign of frequent use of AI, and infrequent use of AI in the workplace does not automatically mean resistance.

For the purposes of this study, leadership in the age of AI is not limited to a managerial role, supervisory capacity or formal authority. It is interpreted to be a general career attitude that manifests itself in adaptability, systems thinking, teamwork, responsible use of technology, evidence-based decision making, self-efficacy and technical credibility. This is applicable in any engineering field, as professionals need to consider new technologies, plan and manage complex activities and use their professional judgment, when formal guidance is scarce. The leadership focus is, therefore, not only on the presence of engineers in leadership roles but on the extent to which their leadership styles for change are reinforced by the organizational culture and arrangements that enable them to be put into effect.

This study examines the results of the responses of 144 engineers from Iraq. The 39-item survey covers the following areas of leadership: adaptive and responsible leadership; human–AI collaboration; evidence-based judgment; technical credibility; organizational enablement; and supporting institutional perceptions. The study contrasts a wide-ranging, theory-based Individual Leadership Orientation (ILO) composite score with an independent measure of perceived Organizational Enablement (OE), measured on the same individuals.

The study addresses three research questions:

RQ1. Do participating engineers report more favorable ILO than perceived OE?

RQ2. How are AI-use frequency, formal training, and professional characteristics associated with ILO and OE, and do their adjusted associations differ?

RQ3. To what extent do the measured respondent characteristics jointly account for ILO, OE, and the capability–enablement divide?

2 Literature Review

2.1 Engineering Leadership in the Artificial Intelligence Era

Engineering leadership in AI-enabled settings involves more than technical competence or formal authority. It includes making inferences based on ambiguous evidence, coordinating different expertise, conveying implications, and taking responsibility for implications [10–12].

The Four Capabilities Model describes leadership through sensemaking, relating, visioning, and inventing [13]. The relevance of these capacities depends on the context of a project, the quality of the data, professional standards, and the effects of using it in work supported by AI . Engineers need to grasp the technical findings, explain their limitations, and decide whether they are sufficient to support action. Leadership can also be transferred between team members depending on the type of expertise needed for a project and not only with the designated manager [14].

Interdisciplinary coordination is thus one of the key skills. Complex projects involve designers, contractors, clients, regulators, data specialists and users in operation, who may have diverse views on the same problem. Collaboration demands that engineers make their assumptions visible, bring their evidence together and build a common understanding of the task [15]. The inclusion of AI introduces another set of knowledge boundaries: domain experts need to work with digital experts and at the same time stay in charge of the engineering interpretation.

This general profile is in line with recent competency research that relates project leadership in the digital world with the concepts of interoperability, data governance, cybersecurity, stakeholder collaboration, and lifecycle awareness [9]. Related frameworks are a combination of technical, cognitive, interpersonal, ethical, and managerial competencies necessary for Construction 4.0 [6, 7, 16]. The study thus regards the leadership for the age of AI

as a general professional attitude, which represents adaptability, systems thinking, collaboration, responsible use, evidence-based judgment, self-efficacy, and technical credibility.

2.2 Artificial Intelligence Adoption and Human–Artificial Intelligence Collaboration in Architecture, Engineering, and Construction

The uses of AI are not restricted to any specific stage of the AEC lifecycle but span through the entire process: from the design phase to forecasting, document processing, risk identification, monitoring, maintenance, and asset management [1, 17–19].

These capabilities are expanded by generative AI. Engineers can use it to summarize documents, structure project information, evaluate alternatives, produce a preliminary report, or pinpoint possible risks. Construction risk identification has been offered as an example of evidence that demonstrates both its value and its limitations. While generative systems increase the number of risks that can be considered, the engineer will still need to determine what risks are relevant, prioritize the threats, and choose responses appropriate to the project [20]. The system can give extended attention, but not take the responsibility for the final decision.

This perspective of human-AI collaboration is therefore more helpful than the substitution perspective alone. AI can handle vast amounts of data, recognize patterns, and offer insights, whereas humans can provide context, ethical considerations, communication, and accountability. Task allocation, explainability, calibrated trust and procedures for verification are crucial to effective collaboration [2]. Human-centered AI research also shows that systems should be built around the work and decision-making needs of professionals, and not just because an algorithm is technically possible [21].

AI familiarity and use demonstrate technological engagement and do not establish critical assessment of AI outputs, management of uncertainty, and professional accountability of engineers. For this reason, the frequency of AI use and formal training are included in this study as potential correlates of the reported leadership orientation but not as direct measures of professional capability.

2.3 Organizational Enablement for Artificial Intelligence Transformation

Digital transformation extends beyond acquiring software. In construction, it involves integrating digital technologies with organizational capabilities, project workflows, stakeholder coordination, and data-driven decision-making [3, 4, 22].

Digital transformation is difficult during construction due to the temporary nature of project configurations and the integration of various systems and contractual obligations involving clients, consultants, contractors, regulators, and stakeholders. Limited interoperability between digital systems, fragmented data, skills shortages, high implementation costs, and difficulties coordinating project stakeholders can restrict digital transformation in construction [23–25]. The strategic direction, leadership commitment, competence of the workforce, quality of data, and sensemaking of the organization are therefore important factors for adoption [5, 26, 27].

There are additional governance considerations added by AI. Organizations need to define which tools to use and what information can go into the tool, and who is responsible for reviewing the outcomes and where those should go. Integration with existing workflows is also important. An isolated pilot may demonstrate technical feasibility without delivering organizational value if it is not integrated into planning, design, quality, safety, or risk management processes. Coordinated value creation also relies on partners with different resources and incentives to share information, as construction delivery is a multi-organizational process [28]. For this study, OE is the individual's perception of the tools, data, guidance, training and support from management that are present in the workplace, not necessarily an objective measure of the digital maturity of the organization.

2.4 Sociotechnical Alignment

The implementation of AI is sociotechnical because there are interactions between technical performance and professional practice. An accurate system can be ignored if employees do not have confidence in it, do not understand what it is producing, or feel it's incompatible with current responsibilities. Responsible use cannot be maintained by a motivated workforce without the assistance of information, tools and rules of the organization. The alignment between people, technologies, workflows and institutions is then the relevant issue. The capability–enablement distinction is employed here to explore sociotechnical alignment as a function of leadership orientation and perceived support in the workplace.

Misalignment may occur in a number of ways, where it is possible that organizations invest in technology prior to governance and training. Furthermore, experiments can be made by the employees without formal systems being developed. Or, managers may support innovation rhetorically but provide little time, assistance, or protection for responsible experimentation. In these instances, AI adoption may be both visible and lack organizational structures for reliable deployment.

Gender-related workplace conditions provide another example of sociotechnical alignment. Previous construction research has documented persistent workplace barriers and gendered organizational practices, even where support for inclusion is expressed [29–31]. Accordingly, gender-equality beliefs and perceived gender barriers were retained as contextual dimensions rather than components of the primary capability–enablement comparison.

2.5 Research Gap and Conceptual Positioning

Previous studies have examined engineering competencies and organizational digital transformation using different research approaches. Zhu et al. [13] conducted a study of 23 practicing engineers from Chinese industries in order to investigate the engineering leadership by sensemaking, relating, visioning and inventing. Muzulon et al. [7] produced a synthesis on 59 publications to obtain 47 competencies for digital engineers. Owais et al. [9] extracted 55 digital project-management competencies from the literature and aligned them with the requirements for digital twins. These studies provide valuable information on professional competencies, but none directly compares engineers' reported leadership orientations with their perceptions of workplace support.

Another aspect of this relationship is discussed in research on organizational transformation. Olanipekun and Sutrisna [3] analyzed 36 publications to explore the enablers and barriers of digital transformation in construction. Li et al. [26] analyzed literature and expert judgments and identified influencing factors on construction digitalization. Zulu and Saad [5] investigated organizational sensemaking by analyzing the qualitative responses of 59 construction practitioners in the United Kingdom. Together, these studies demonstrate the value of organizational resources, management and workplace processes, but they focus on different outcomes than those explored in this study.

Azimi et al. [32] provide the closest empirical comparison. They surveyed 501 AEC professionals on their personal level of AI familiarity, usage, and training, as well as on firm size, work arrangements, AI maturity, and other organizational factors. Their findings validate the importance of the organizational context in the process of AI adoption. The current study aims to answer a related but different question. It explores wider leadership orientations: adaptability, systems thinking, collaboration, responsible use of AI, and evidence-based judgment, and perceived enablement in the work place. Instead of measuring the AI adoption as the main outcome, it compares these two reported dimensions within the same respondents.

This study investigates the relationship between leadership orientation and organizational support as perceived by 144 participants with an engineering background in Iraq. This study provides paired comparisons and complementary analyses for their reported alignment, without equating their perceptions with demonstrated professional competence, or objectively assessed organizational capacity.

3 Methodology

3.1 Research Design and Study Context

This research used a cross-sectional quantitative survey method to determine whether individual engineers' leadership orientations aligned with the organizational context that supports responsible practice when using AI tools. The participants were engineers in Iraq from different age groups, career stages, professional settings, and engineering disciplines. Data were collected in 2026. The design was not aimed at testing causality, maturity in the digital space or even objectively auditing digital maturity but rather capturing respondents' perceptions at one point in time.

The analysis did not combine the items of ILO and OE into a readiness score; instead, it analyzed them as two separate theory-guided analytical families. The ILO reflected the reported orientation toward adaptive, collaborative, responsible, evidence-informed and technically credible leadership. OE was defined as perceived access to workplace support, guidance, training, data and appropriate technological conditions. The separation enabled the study to examine if positive individual attitudes and orientations could co-exist with less positive organizational support. A pair-wise comparison and respondent level regression were conducted at the individual engineer level. Each response to a substantive questionnaire item was the unit for the ordinal item-level analysis.

3.2 Participants, Sampling, and Data Collection

Eligibility criteria were being a graduate of an engineering program and previous or current experience in an engineering-related role. Data were collected from January to April 2026. The Arabic version of the questionnaire was sent electronically via professional networks to engineers in various professional contexts and organizations. Respondents were asked to respond voluntarily and were asked to answer based on their own experience working in the job, not on behalf of their employer.

The final analytical sample consisted of 144 engineers, 92 from the public sector, 39 from the private sector, 7 from mixed public–private organizations, and 6 from academic institutions. 66.0% of the participants were civil engineers, and 63.9% worked in the public sector. Despite civil engineering being the largest discipline, insufficient data was available to identify the number of respondents who were involved in construction-related activities. Thus, the sample is considered as a multidisciplinary engineering sample and not a construction-industry sample. Of

the 144 respondents who met the eligibility requirements, 144 respondents provided complete responses to the 39 substantive questionnaire items. No item responses were missing, and no exact duplicate records were identified, yielding 5,616 item-level observations. Participants were not selected from a complete sampling frame but through professional contacts. The study therefore used a nonprobability sampling approach, and a conventional response rate could not be calculated. When interpreting the findings, the recruitment approach and the relatively high proportion of civil engineers and public-sector employees are important considerations. The results, therefore, refer to the engineers who participated in the study and cannot be generalized to the broader engineering workforce in Iraq.

3.3 Questionnaire Development and Expert Review

The questionnaire was based on literature concerning engineering leadership, human–AI collaboration, responsible AI, digital transformation, and gender in engineering workplaces. Conceptual overlap, ambiguous language, unnecessary technical jargon and suitability for the engineers working in Iraq were the first criteria used to review the initial item pool.

Content and face validity of the questionnaire were assessed by eight experts (five men and three women). They were experts in engineering, leadership, research methods, digital transformation, and AI related to professional practice. The Arabic questionnaire was individually evaluated by each expert by means of a structured evaluation form. They rated the item relevance and clarity on four-point scales and determined the importance of items as: essential, useful but not essential, or unnecessary. Written comments and suggestions also were gathered. All evaluations, including discrepancies in the experts' opinions and recommendations for improvement, were taken into account. The authors examined discrepancies in expert judgments, in conjunction with the written comments, and incorporated the expert feedback to clarify items that needed rewording or conceptual distinctions. The issues raised in the feedback included item wording, conceptual overlap, and clarity of AI-related professional responsibilities. Items were shortened, standardized and distinctions between individual capability and organizational support were clarified during the process of questionnaire refinement. The finalized questionnaire was administered in Arabic. An English translation was then developed for publication by the authors. The English language wording was cross-checked with the final Arabic questionnaire for accurate and consistent meaning and suitable technical terminology.

There were 39 substantive statements in the questionnaire, which were initially coded into 11 conceptual areas: Future Engineering Leadership, Digital Collaboration and AI Teaming, Adaptive Leadership, Systems Thinking, Responsible AI Leadership, Evidence-Based Judgment, Leadership Self-Efficacy, OE, Gender Equality Beliefs, Perceived Gender Barriers, and Technical Credibility. Responses were made on a 5-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

Twenty nine items in the ILO family were used in the main analysis, measuring Future Engineering Leadership, Digital Collaboration and AI Teaming, Adaptive Leadership, Systems Thinking, Responsible AI Leadership, Evidence-Based Judgment, Leadership Self-Efficacy, and Technical Credibility. There were four items that measured OE, three that measured Gender Equality Beliefs, and three that measured Perceived Gender Barriers.

No items were deleted following data collection or as a consequence of the results of N = 144. ILO was used as a theory-based general construct and not a single dimensional reflective scale. Its eight component domains represented related aspects of reported professional orientation, but the analysis did not assume that all 29 items measured one latent trait. OE was regarded as a unique four-item family representing perceived workplace support.

3.4 Measures, Construct Families, and Coding

Items of the questionnaire were grouped into theory-derived analytical families. The 29 items about digital collaboration, future-oriented engineering leadership, adaptive leadership, systems thinking, responsible leadership in the context of AI, evidence-based judgment, leadership self-efficacy, and technical credibility were aggregated as ILO. The three factors of OE, Gender Equality Beliefs, and Perceived Gender Barriers were analyzed separately, as they represented organization/institutional dimensions. The scores of the relevant items were averaged to obtain the respondent-level scores. The four items of the OE family achieved high internal consistency (Cronbach's alpha, α = 0.872) [33], whereas the broad ILO composite also exhibited high internal consistency (α = 0.896). These coefficients are indicators of score consistency and are not indicators of unidimensionality. The Kaiser–Meyer–Olkin (KMO) measure based on Spearman correlations was 0.874. Parallel analysis supported retaining three diagnostic factors, which did not reproduce the 11 theory-guided domains [34]. The item families were thus kept as theory-informed analytical groupings, not as scales. Domain-level reliability summaries, parallel-analysis results, and exploratory factor loadings are presented in Supplementary Tables S2, S3A, and S3B, respectively.

ILO is not a measurement of actual leadership competency but rather a reflection of the self-reported professional orientations of the respondents. OE is a perception of workplace conditions and not an objective organizational audit. While the two families have the same five-point response scale, their scope and coverage of items are different. The comparison between the two does not, therefore, represent a comparison of the individual or organizational ability but rather a reported difference in dimensions.

AI-use frequency and use of other digital tools were measured using a 0–4 scale (0 = never and 4 = always). Formal AI or digital-transformation training was coded as a binary variable. Education had four ordered levels: bachelor's, master's, doctorate, or other. The same results on education were obtained when the single respondent who chose 'Other' was excluded from the complete-case sensitivity check. The ordered survey categories for engineering experience were maintained. Leadership responsibility varied from no leadership decision role through to team, project, department and executive responsibility. Gender was coded as a woman indicator where men were coded as the reference group. The four categories recorded for employment sector were public, private, mixed public–private, and academic. These were aggregated into two categories: public (n = 92) and non-public (n = 52) due to the limited numbers of respondents in each of the mixed or academic categories. The distribution of the original four categories is maintained as shown in Table 1. The relationship between age and engineering experience was strong. However, engineering experience was included in the principal models, as it was more closely related to the professional processes being studied and age was introduced in a sensitivity specification. There was no significant multicollinearity in the other variance-inflation factors.

Table 1. Selected sample characteristics

Characteristic	Category	n	%
Gender	Men	92	63.9
	Women	52	36.1
Age	Under 36 years	70	48.6
	36–45 years	43	29.9
	46 years or older	31	21.5
Education	Bachelor's	85	59.0
	Master's	35	24.3
	Doctorate	23	16.0
	Other	1	0.7
Discipline	Civil engineering	95	66.0
	Other engineering disciplines	49	34.0
Employment sector	Public	92	63.9
	Private	39	27.1
	Mixed public–private	7	4.9
	Academic	6	4.2
Leadership responsibility	None	57	39.6
	Any formal responsibility	87	60.4
AI use	Never or rarely	39	27.1
	At least occasionally	105	72.9
Formal AI/digital training	No	126	87.5
	Yes	18	12.5

Note: AI = artificial intelligence.

3.5 Statistical Analysis

Participant characteristics were described by means of frequencies and percentages. Means, standard deviations, and percentages of agree or strongly agree were used to describe the results for each item. The 95% confidence interval (CI) for each family mean was estimated using 10,000 respondent-bootstrap resamples. CIs were calculated using the percentile method by resampling respondents with replacement. The same resampling structure for the respondents was employed for paired differences. These summaries outlined the response pattern but were not considered to be sufficient for determining the statistical significance on their own.

The primary capability–enablement comparison was paired within respondents. For each engineer, the OE mean was subtracted from the ILO mean. A positive value indicated that individual orientation was rated more favorably than workplace enablement. The mean paired difference and its bootstrap CI quantified the divide. The Wilcoxon signed-rank test provided a rank-based paired comparison [35]. The distribution of paired differences was examined for symmetry. Because it was positively skewed, an exact sign test was added as a sensitivity analysis that did not depend on the symmetry condition of the signed-rank test. Cohen's d_z and the rank-biserial coefficient were reported to describe standardized magnitude and direction. As a sensitivity analysis, each of the eight theoretically defined capability-domain means was compared separately with OE using the same paired bootstrap and Wilcoxon procedures. A further sensitivity analysis calculated each respondent's ILO score by first averaging items within each of the eight domains and then assigning equal weight to every domain. This tested whether the principal result depended on domains containing different numbers of items.

The main item-level robustness analysis was carried out using a cumulative ordinal fixed-effects model. It maintained 5,616 ordered responses and estimated the odds of choosing a higher response category. Respondent fixed effects accounted for differences in participants' general response tendencies. Item effects were defined as within-family deviations that sum to zero within each family of items. This parameterization enabled the effect of OE to be estimated separately from the item effects. ILO was the reference family, while the two gender-context item families were included as additional adjustment categories. The OE odds ratio (OR) was tested by comparing the full model with a model in which its family coefficient was constrained to zero. A likelihood-ratio test and profile-likelihood 95% CI evaluated this contrast. This model maintained the ordinal response structure and minimized the risk that the outcome was due to a few especially difficult items [36]. Cumulative logit model specifications assume that the family effect is consistent across response thresholds. The paired respondent-level comparison was used as the primary inferential test with the ordinal model used as an item-adjusted robustness test.

Ordinary least squares regression with heteroskedasticity-consistent type 3 (HC3) standard errors was used to estimate adjusted respondent level associations, suitable for modest samples with potentially unequal variance of the residuals [37]. Adjusted differences in the complete standardized 39-item profile were tested using Freedman–Lane permutation procedures with 9,999 permutations [38]. AI use was evaluated while adjusting for the remaining respondent characteristics. Supporting gender and training profile tests are reported in the supplementary material.

Direct coefficient-contrast tests were obtained by regression on the paired difference. The paired-difference model directly tested whether outcome coefficients differed. The AI-use contrast was also evaluated using 10,000 respondent-bootstrap resamples. The study was not powered specifically for the trained-versus-untrained contrast. Because only 18 respondents reported formal training, training coefficients were treated as exploratory estimates with CIs rather than evidence for or against training effectiveness.

4 Results

4.1 Respondent Profile and Artificial Intelligence Exposure

The sample comprised 144 engineers, including 92 men (63.9%) and 52 women (36.1%). Almost half were younger than 36 years (48.6%), while 29.9% were aged 36–45 and 21.5% were 46 or older. Of the total sample, 59.0% held a bachelor's degree; 24.3% had a master's degree; 16.0% had a doctorate; and one respondent mentioned another type of degree. Civil engineering was the most common major (66.0%). The largest employment group was public-sector employees, and 60.4% had formal leadership roles. Most participants reported using AI at least occasionally (72.9%), whereas only 12.5% reported receiving formal AI or digital-transformation training. The complete profile is included in Table 1.

4.2 The Capability–Enablement Divide

The mean score for ILO was 3.789 (standard deviation [SD] = 0.435) while the mean score for OE was 3.479 (SD = 0.848). The mean paired difference is 0.309 points with a 95% respondent-bootstrap CI [0.187, 0.443]. A Wilcoxon signed rank test confirmed a nonzero difference (W = 3,252, $p < .001$). The standardized paired effect was small to moderate (Cohen's d_z = 0.394) and the rank-biserial coefficient was 0.208. The difference between the scale measures of leadership orientation and organizational enablement was 0.309 points on the 5-point response scale, which is a modest yet consistent separation between the reported leadership orientation and the perceived organizational enablement. Practical significance must be interpreted based on specific organizational conditions rated by the respondents, not only in terms of statistical significance. The paired differences were positively skewed with a skewness of 1.17. However, an exact sign test showed the same direction: 86 with positive differences, 56 with negative differences, and two with a tie, p = .015. The item-level ordinal analysis confirmed the direction of the major paired comparison (five response categories, controlling for response tendency and item endorsement). OE items had 55.0% lower odds of receiving a response in a higher agreement category than ILO items (OR = 0.450, profile-likelihood 95% CI [0.380, 0.534]). The likelihood-ratio test was significant, χ^2 = 83.517, $p < .001$. Table 2 combines the paired and ordinal results. Seven of the eight theory-guided capability domains were rated more favorably than OE, providing broad domain-level support for the principal comparison. The equal-domain-weighted sensitivity score also remained higher than OE, with a mean paired difference of 0.272, 95% bootstrap CI [0.144, 0.401], Wilcoxon p = .001. The result therefore did not depend on assigning greater weight to domains containing more items. Complete domain, assumption, weighting, and reliability results are reported in Supplementary Tables S2, S4, and S4B and Figure S1. The main statistical results are summarized in Table 2, and the paired scores of the respondents and the distribution of their difference are shown in Figure 1.

4.3 Adjusted Associations with Capability and Enablement

Controlling for formal training, frequency of using digital tools, gender, engineering experience, education, leadership responsibility, and sector, the frequency of using AI was positively associated with ILO (b = 0.101, 95% CI [0.032, 0.171], p = .005). Its association with OE was nonsignificant (b = 0.027, 95% CI [-0.121, 0.174], p =

.722). The direct comparison between these coefficients was not statistically significant (b = 0.075, 95% CI [-0.051, 0.201], p = .242). Therefore, the results do not establish that AI-use frequency has different associations with ILO and OE.

There was a positive relationship between education and ILO (b = 0.148, 95% CI [0.048, 0.248], p = .004), but not with OE. The direct capability-versus-enablement contrast was significant (b = 0.221, 95% CI [0.027, 0.415], p = .026), showing that education was associated more strongly with individual orientation than with perceived enablement. Engineering experience was negatively associated with OE (b = -0.144, 95% CI [-0.271, -0.016], p = .027), while its direct contrast was nonsignificant (p = .055). Leadership responsibility showed a positive but nonsignificant association with ILO (p = .051).

Formal-training coefficients were imprecisely estimated and were not statistically significant for ILO, OE, or their paired difference. Because only 18 respondents reported formal training, these results do not provide evidence for or against training effectiveness. The selected adjusted coefficients are provided in Table 3 and the full set of predictor estimates across the three outcomes are plotted in Figure 2.

Table 2. Primary evidence for the capability–enablement divide

Analysis	Estimate	Value	95% CI	Test
Family score	ILO	3.789 (0.435)	[3.716, 3.859]	–
	OE	3.479 (0.848)	[3.340, 3.618]	–
Paired comparison	ILO minus OE	0.309	[0.187, 0.443]	W = 3,252; $p < .001$
Effect size	Cohen's d_z	0.394	–	–
	Rank-biserial coefficient	0.208	–	–
Ordinal item-level model	OE relative to ILO	OR = 0.450	[0.380, 0.534]	LR χ^2 = 83.517; $p < .001$
Sign-test sensitivity	Positive/negative/tied	86/56/2	–	Exact p = .015
Equal-domain sensitivity	Equal-domain ILO minus OE	0.272	[0.144, 0.401]	W = 3,510; p = .001

Note: CI = confidence interval; ILO = Individual Leadership Orientation; LR = likelihood ratio; OE = Organizational Enablement; OR = odds ratio. Scores are M (standard deviation). CIs used 10,000 respondent-bootstrap resamples. The en dash (–) indicates that the corresponding entry is not applicable.

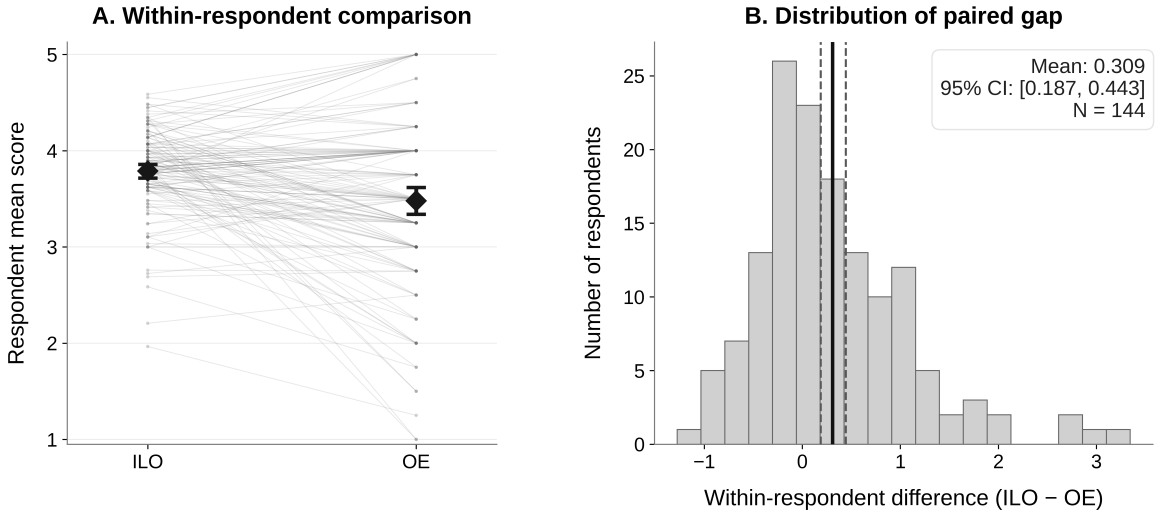


Figure 1. Respondent-level comparison of individual leadership orientation and organizational enablement

Note: ILO = Individual Leadership Orientation; OE = Organizational Enablement; CI = confidence interval; N = total sample size. (A) Paired respondent scores; light gray lines connect scores from the same respondent, and diamonds with error bars show group means and 95% bootstrap confidence intervals. (B) Distribution of respondent-level differences (ILO–OE).

Table 3. Selected adjusted associations with capability, enablement, and their paired difference

Predictor	ILO	OE	Paired Difference
AI use	0.101 [0.032, 0.171], p = .005	0.027 [-0.121, 0.174], p = .722	0.075 [-0.051, 0.201], p = .242
Formal training	0.066 [-0.214, 0.346], p = .640	0.040 [-0.482, 0.563], p = .879	0.026 [-0.446, 0.498], p = .914
Education	0.148 [0.048, 0.248], p = .004	-0.073 [-0.286, 0.140], p = .501	0.221 [0.027, 0.415], p = .026
Engineering experience	-0.026 [-0.084, 0.031], p = .360	-0.144 [-0.271, -0.016], p = .027	0.117 [-0.003, 0.237], p = .055

Note: ILO = Individual Leadership Orientation; OE = Organizational Enablement; CI = confidence interval; AI = artificial intelligence. Values are unstandardized regression coefficients (*b*) with 95% CIs. Models include simultaneous adjustment for eight respondent characteristics.

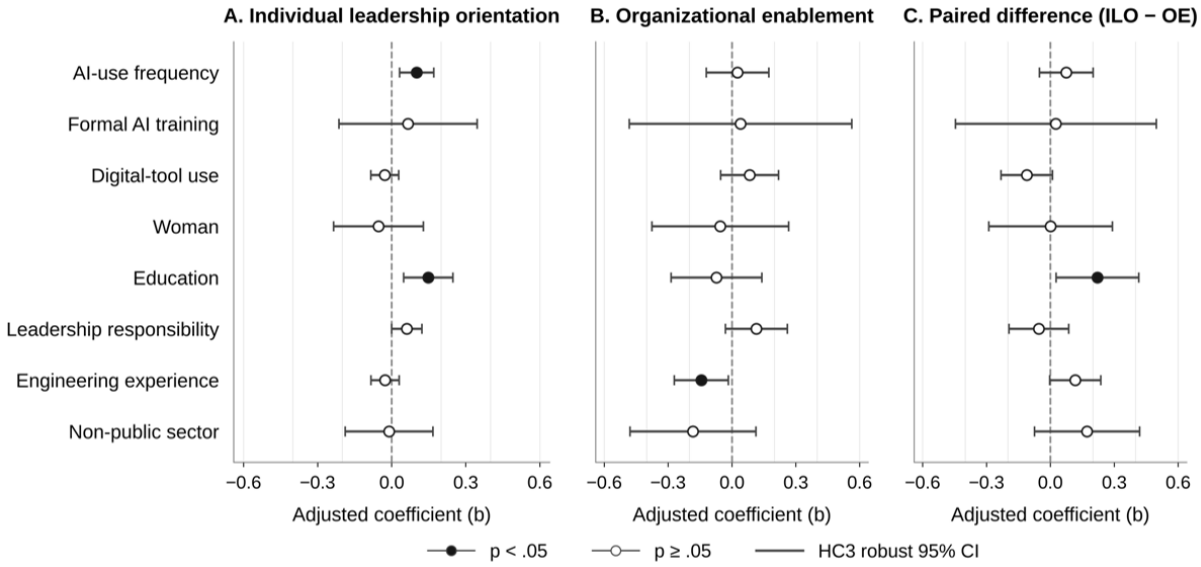


Figure 2. Adjusted predictor associations across leadership orientation and organizational enablement outcomes

Note: AI = artificial intelligence; b = unstandardized regression coefficient; CI = confidence interval; HC3 = heteroskedasticity-consistent type 3 standard errors; ILO = Individual Leadership Orientation; OE = Organizational Enablement. Estimates are shown for Individual Leadership Orientation, Organizational Enablement, and their paired difference. Points represent unstandardized regression coefficients (b); horizontal lines indicate HC3 robust 95% confidence intervals. Filled circles indicate $p < .05$; open circles indicate $p \geq .05$. Binary predictors compare formal AI training (yes vs. no), woman (vs. man), and non-public employment (vs. public employment). AI-use frequency, digital-tool use, education, leadership responsibility, and engineering experience were entered as ordered predictors.

4.4 Model-Level and Complete-Profile Evidence

The eight respondent characteristics were jointly associated with ILO, $F(8, 135) = 3.481$, $p = .001$, adjusted $R^2 = .116$. They were not jointly associated with OE, $F(8, 135) = 1.728$, $p = .097$, adjusted $R^2 = .041$. The predictor set was jointly associated with the paired capability–enablement difference, $F(8, 135) = 3.752$, $p < .001$, although the explained variance was modest (adjusted $R^2 = .093$). The adjusted R^2 values for ILO (.116), OE (.041), and the difference between them (0.093) suggest that the measured respondent characteristics account for only a small portion of the variance in the outcomes. The particularly low value for OE suggests that perceived workplace support depends on factors beyond the individual characteristics included in the models. In the adjusted complete-profile permutation analysis, AI use produced a significant but small global association (pseudo-$F = 3.019$, partial $R^2 = .022$, permutation $p = .007$). Supporting profile tests for gender and formal training are reported in the supplementary material. Table 4 presents the joint outcome tests and adjusted AI-use profile test.

For further context to the adjusted analyses, Table 5 compares ILO and OE by leadership responsibility, by sector of employment and by education groups. The results indicate that the mean differences are comparable across groups of leadership responsibility and that there is a slightly larger difference for public-sector respondents than for those in the private sector. A greater descriptive difference was observed between the two qualification groups, bachelor's versus postgraduate. These comparisons are not adjusted and should not be interpreted as evidence of statistically significant differences between the subgroups.

Gender was not significantly associated with ILO, OE, or their paired difference. Gender equality beliefs and perceived gender barriers have been analyzed as secondary contextual dimensions, not as part of the primary comparison. The supporting results are reported in Supplementary Table S6.

Table 4. Joint outcome tests and adjusted artificial intelligence-use profile test

Analysis	Outcome or Predictor	Statistic	Model/Effect Size	p
Joint HC3 test	ILO	$F(8, 135) = 3.481$	Adjusted $R^2 = .116$	.001
Joint HC3 test	Organizational enablement	$F(8, 135) = 1.728$	Adjusted $R^2 = .041$	.097
Joint HC3 test	Capability–enablement difference	$F(8, 135) = 3.752$	Adjusted $R^2 = .093$	$<.001$
Permutation profile test	AI use	Pseudo-$F = 3.019$	Partial $R^2 = .022$	.007

Note: AI = artificial intelligence; ILO = Individual Leadership Orientation; HC3 = heteroskedasticity-consistent type 3 standard errors. Joint tests use HC3 robust inference. The profile test used 9,999 Freedman–Lane permutations.

Table 5. Descriptive comparison of Individual Leadership Orientation and Organizational Enablement, by respondent groups

Characteristic	Group	n	ILO Mean	OE Mean	Difference
Leadership responsibility	No leadership decision role	57	3.722	3.421	0.301
	Any leadership decision role	87	3.832	3.517	0.315
Employment sector	Public	92	3.792	3.467	0.325
	Private	39	3.752	3.583	0.169
Education	Bachelor's	85	3.718	3.609	0.110
	Postgraduate (master's or doctorate)	58	3.912	3.319	0.593

Note: ILO = Individual Leadership Orientation; OE = Organizational Enablement. Difference = ILO minus OE. Values are unadjusted group means on the five-point scale. The mixed-sector ($n = 7$) and academic ($n = 6$) respondents are omitted from the sector comparison, and one respondent reporting another education category is omitted from the education comparison. These respondents remain included in the overall analyses. No inferential comparisons between subgroups were performed.

5 Discussion

5.1 From Artificial Intelligence Adoption to Capability–Enablement Alignment

Respondents reported more favorable ILO than OE. The paired comparison, item-adjusted ordinal model, separate domain comparisons, equal-domain-weighted sensitivity analysis, and exact sign test all supported the same direction. Together, these analyses support the observed difference between reported ILO and perceived organizational enablement without implying that the two measures are conceptually or psychometrically equivalent.

The difference provides further context for the individual OE items. Clear organizational guidance for responsible use of AI was rated as the lowest average (3.375), followed by data and digital tools (3.493) and organizational training (3.507). Management encouragement of new technological solutions received a slightly higher rating (3.542). Based on these findings, guidance, digital tools and training should be a focus in workplace readiness assessments. All four item means, however, were above the neutral midpoint, suggesting that the findings reflect relatively less positive perceptions of organizational conditions rather than a lack of support.

These findings were a departure from focusing solely on AI adoption to focusing on the alignment between professional orientations and workplace support. Azimi et al. [32] surveyed AEC professionals on their familiarity with AI, its usage and conditions for organizational adoption. The current study builds on this by examining the relationship between self-reported leadership orientation and perceived organizational enablement, among the same respondents. These results indicate that it was not possible to automatically conclude that visible AI engagement is a sign of equally positive organizational conditions for responsible AI use.

5.2 Artificial Intelligence Engagement, Training, and Uneven Capability Development

Frequencies of AI use were positively related to ILO and the complete response profile, but not to OE. The direct capability-enablement coefficient comparison was not significant. Results, therefore, reflect an association with engagement with AI and the overall response pattern, rather than AI use improving capability, exacerbating the gap, or growing at a faster rate than organizational support. There was no significant relationship between the principal outcomes and formal training, although only 18 respondents had undergone such preparation. The most revealing descriptive pattern was between those who reported using AI at least occasionally (72.9%) and those who had formal AI training (12.5%). This distinction underscores the need to explore the connection between formal training and workplace support to reported AI use, although the effectiveness of specific training arrangements was not evaluated in this study.

The discrepancy between the use of AI and the formal participation in training raises a question on how AI knowledge is acquired by engineers. This pattern may be attributed to informal learning by personal experimentation, online, colleagues, or software providers. The questionnaire, however, did not explore these learning pathways or evaluate the competence acquired through them. Their possible role is therefore a question for future studies.

5.3 Engineering Management Implications and Organizational Action

Education had a positive association with ILO and was more associated with individual orientation than perceived enablement. More highly educated respondents had more favorable ILO scores, but this cross-sectional study cannot establish whether education caused this difference. OE was negatively associated with engineering experience, perhaps because experienced engineers had greater exposure to institutional constraints or higher expectations of organizational support. This interpretation is still preliminary as the design was cross-sectional. A positive, but nonsignificant, relationship was observed between ILO and Leadership responsibility.

The descriptive subgroup results provide further context for these associations. The mean capability–enablement difference was similar for respondents with and without leadership decision responsibilities (0.315 and 0.301, respectively). Public-sector respondents showed a larger difference (0.325) than private-sector respondents (0.169). The most prominent descriptive difference was between the postgraduate (0.593) and the bachelor (0.110) respondents. It is possible that these patterns are related to differences in professional expectations and workplace conditions, but the descriptive comparisons alone do not provide any indication of the statistical significance of these differences or of their causes.

The capability–enablement divide has practical consequences for engineering project management too. For construction risk identification, engineers might be willing to apply AI to get a list of potential risks. Yet, there are needs for reliable project information and a process to check and approve the list that AI produces. AI could potentially support quality checks by identifying potential defects, but engineers must ensure they have defined roles and responsibilities for verification, reporting, and corrective measures during inspections. The same applies to design reviews, as AI suggestions need to be reviewed and validated against technical requirements and reviewed through established procedures. Positive individual orientations will not always result in consistent use in project decisions without good organizational guidance, technical support, and defined responsibilities. These examples illustrate possible implications of the perception gap identified by the survey, rather than outcomes directly measured in this study [2, 9, 20].

The following management actions are informed by the literature and the findings of this survey. Their effectiveness was not evaluated in the present study. First, organizations can list existing AI tasks, approve suitable applications, outline acceptable data usage, mandate verification procedures, and establish who is accountable for final decisions. Then, training can be linked to real-world activities and governance needs, and not presented as a technology showcase.

It may be helpful for organizations to look at professional capability and workplace enablement separately. In areas of perceived lack of enablement, support might be directed to tools, data, guidance, technical assistance, and workflow incorporation. There may be a need for task-specific development and supervised application in the case of limited capability.

5.4 Theoretical Contribution, Limitations, and Future Research

Promoting a more general understanding of leadership in engineering practice in the age of AI could be considered the primary contribution of this study. Leadership is not just a position of formal managerial authority. It is also a mindset that is characterized by adaptability, systems thinking, collaboration, responsible use of technology, judgment based on evidence, self-efficacy, and technical credibility. The results indicate that engineers can express positive leadership orientations and less favorable perceptions of organizational support for enacting those orientations. This distinction can be used as a starting point for identifying where AI-related change is supported through professional capability, workplace enablement, or their alignment.

The regression models also have limited explanatory power, particularly for OE. Other variables such as organizational size, characteristics of a project, digital infrastructure, and internal procedures have not been measured. These work factors should be considered in future studies and could contribute to differences in perceived enablement.

Evidence is drawn from cross-sectional responses from 144 engineers, and thus is representative of patterns within the participating sample. Given the differences in breadth of the two item families, the central comparison was explored in a number of complementary analyses. The results of the paired comparison, item-adjusted ordinal, separate domain comparisons, exact sign test, and equal-domain-weighted analyses indicated generally the same direction, thus lending stability to the main finding across the various analytical approaches.

Future research may use the capability–enablement lens on larger and more diverse professional samples, and explore the nature of the gap as the organizational systems evolve. Combining employee assessments with training records, approved-tool inventories, governance arrangements, and evidence of workplace implementation would extend the organizational analysis. Additional research with larger trained samples might help to elucidate the relationship between training type, quality, and organizational support and the two sides of the divide. Interviews might also include information on how engineers without formal AI training gain knowledge of AI through self-learning, peer exchange, online resources, informal workplace support, etc.

6 Conclusion

This study identified a consistent perceived capability–enablement difference among the participating engineers. ILO received higher ratings than OE. Additionally, the finding remained consistent across the paired respondent analysis and the ordinal item-level model. The results show that favorable professional orientations do not necessarily coincide with equally favorable perceptions of organizational support. Because participants came from different engineering disciplines and professional settings, these findings should not be interpreted as estimates specific to the construction industry or the wider engineering workforce.

AI-use frequency association with ILO was positive. However, the direct comparison did not establish a statistically significant difference between its associations with the two outcomes (p = .242). AI exposure should therefore not be interpreted as a direct explanation for the observed divide.

The findings have three implications for engineering managers. First, organizations can evaluate their employees' AI-related leadership orientations and perceptions of workplace support to determine any potential misalignment. Secondly, managers should evaluate the availability of suitable AI tools, reliable data, and clear organizational guidance, especially since the guidance for responsible use of AI was rated lowest among the OE items. Finally, institutions can integrate AI training into specific engineering tasks, such as risk identification, quality inspection, and design review, while establishing technical verification procedures and clear accountability for final decisions. These recommendations follow from the study findings and the practical implications discussed above; their effectiveness was not evaluated in this survey.

Author Contributions

Conceptualization, K.A.A.; methodology, K.A.A. and M.N.A.; validation, K.A.A., M.N.A., and F.M.K.; formal analysis, K.A.A., M.N.A., and F.M.K.; investigation, K.A.A. and F.M.K.; resources, F.M.K.; data curation, K.A.A. and M.N.A.; writing, original draft preparation, K.A.A.; writing, review and editing, M.N.A. and F.M.K.; visualization, K.A.A. and M.N.A.; supervision, K.A.A.; project administration, K.A.A. All authors have read and agreed to the published version of the manuscript.

Informed Consent Statement

Informed consent was obtained from all participants involved in the study. Participation was voluntary, and responses were collected anonymously.

Ethical Approval

The study was conducted in accordance with the Declaration of Helsinki and approved by the Scientific Research Ethics Committee, at College of Engineering—University of Thi-Qar; protocol code # EC-SREC-2025-39; approved on 30 November 2025.

Data Availability

Deidentified data are available from the corresponding author upon reasonable request, subject to ethical and institutional restrictions.

Conflicts of Interest

The authors declare no conflicts of interest.

Declaration on the Use of Generative AI and AI-assisted Technologies

During the preparation of this manuscript, the authors used AI to assist with language editing and improving clarity and readability. All AI-assisted content was reviewed and verified by the authors, who take full responsibility for the accuracy, integrity, and final content of the manuscript.

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Supplementary Information

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