American Journal of Civil Engineering and Architecture, 2026, Vol. 14, No. 3, 128-136
Available online at http://pubs.sciepub.com/ajcea/14/3/6
Published by Science and Education Publishing
DOI:10.12691/ajcea-14-3-6

Evaluating the Use of Artificial Intelligence in the Field of Civil Engineering: Basis for a Proposed Comprehensive Professional Organizational Support Program

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Received May 21, 2026; Revised June 25, 2026; Accepted July 02, 2026

Abstract Artificial Intelligence (AI) is increasingly embedded in civil engineering work, yet empirical evidence on how practicing engineers actually use and experience AI remains limited, particularly in emerging-economy settings [1]. This study examined AI utilization in civil engineering practice in Quirino Province, Philippines, and developed a comprehensive professional organizational support program based on the findings. A descriptive-comparative cross-sectional survey was conducted among 150 practicing civil engineers using a structured 24-item questionnaire covering four dimensions: technological, organizational, knowledge and skills, and ethical, cultural, and regulatory aspects. Descriptive statistics, independent-samples t-tests, and one-way analysis of variance with post hoc testing were used to analyze the data. The overall mean score for AI-related conditions was 2.89 on a four-point scale, indicating moderately favorable conditions. Knowledge and skills obtained the highest mean (3.03), followed by technological (2.96) and organizational aspects (2.88), while ethical, cultural, and regulatory aspects obtained the lowest mean (2.69), although they remained in the positive range. Significant differences were observed across demographic and sectoral groups, with younger engineers, those with 10 years or less of experience, and private-sector practitioners reporting more favorable AI-related conditions than older, more experienced, and government-sector counterparts; female respondents also perceived more favorable organizational support than male respondents. The findings indicate an emerging but not yet mature level of AI readiness in civil engineering practice and support the need for multi-dimensional interventions. A comprehensive professional organizational support program is proposed to strengthen AI adoption through capacity-building, stronger institutional backing, improved digital infrastructure, and clearer ethical and regulatory guidance, which may be useful for similar developing-country contexts [2,3].

Keywords: *artificial intelligence, civil engineering practice, technology adoption, organizational support, professional development, Philippines*

Cite This Article: Orlando D. Davin Jr., Genesis S. Jose, and Wilfredo B. Baniqued, “Evaluating the Use of Artificial Intelligence in the Field of Civil Engineering: Basis for a Proposed Comprehensive Professional Organizational Support Program.” *American Journal of Civil Engineering and Architecture*, vol. 14, no. 3 (2026): 128-136. doi: 10.12691/ajcea-14-3-6.

1. Introduction

Artificial intelligence has become an increasingly important enabling technology in civil engineering because it can process large volumes of data, recognize patterns, support prediction, and automate complex tasks that would otherwise demand substantial time and human effort [4]. As civil engineering responds to rapid urbanization, aging infrastructure, and rising expectations for sustainability and efficiency, AI is being considered for a broad range of applications including structural health monitoring, transportation systems, geotechnical analysis, construction planning, cost estimation, construction monitoring, building management, and infrastructure maintenance [1].

Recent review studies show that AI in the construction and civil infrastructure sectors is no longer confined to laboratory or highly specialized tools; it increasingly supports mainstream project functions such as cost estimation, schedule prediction, safety monitoring, risk assessment, and predictive maintenance [5,6]. AI-based computer vision, machine learning, and reinforcement learning methods can detect unsafe conditions, forecast project delays, optimize resource allocation, and identify defects at early stages, thereby augmenting engineers' ability to manage complex project environments [7,8].

Despite these opportunities, AI utilization in civil engineering is not yet widespread or uniform [9]. Implementation is slowed by poor data quality, fragmented information systems, lack of interoperability with existing software, high start-up costs, and varying levels of organizational and workforce readiness [10]. Concerns about explainability, trust, job displacement, and accountability especially for "black-box" AI models further complicate adoption in safety-critical civil engineering decisions [11,12].

Workforce capability and organizational conditions emerge as central determinants of successful AI utilization. Engineers may be aware of AI conceptually but lack the practical skills needed to apply it in design, analysis, and project management, while organizations may have limited strategies, budgets, or support mechanisms for integrating AI into routine workflows [7,13]. Ethical, cultural, and regulatory issues such as data privacy, professional liability, and clarity of rules also influence how comfortable practitioners feel using AI in their work [12,14].

In the Philippine context, and particularly in provincial settings like Quirino, empirical evidence on AI utilization in civil engineering practice remains limited [2,3] Existing studies often focus on technical feasibility or isolated use cases rather than on the broader conditions that shape AI adoption across practitioners and organizations [9,15] Examining the current state of AI utilization among civil engineers in such contexts can generate evidence needed to design relevant capacity-building programs and policies, especially where digital transformation is uneven [1,16].

This study therefore investigates the utilization of AI in civil engineering practice in Quirino Province across four dimensions technological, organizational, knowledge and skills, and ethical, cultural, and regulatory aspects and analyzes differences by sex, age, years of work experience, and work affiliation. The results serve as basis for a proposed comprehensive professional organizational support program intended to strengthen AI utilization in civil engineering

1.1. Objectives

The study aimed to evaluate the utilization of artificial intelligence in civil engineering practice as basis for a comprehensive professional organizational support program. Specifically, it sought to:

1. Describe the demographic profile of civil engineer respondents in terms of age, sex, years of work experience, and work affiliation.
2. Assess the extent of AI utilization in civil engineering in terms of technological, organizational, knowledge and skills, and ethical, cultural, and regulatory aspects.
3. Determine whether significant differences exist in AI utilization when respondents are grouped according to their demographic profile.
4. Propose a comprehensive professional organizational support program to strengthen AI utilization in civil engineering practice.

1.2. Theoretical Framework

The study is informed by several complementary theories. Decision Theory explains how professionals choose among alternatives under risk and uncertainty, emphasizing trade-offs among cost, time, quality, and safety in project environments [17,18]. In such settings, AI serves as a decision aid that processes large volumes of project data to reduce uncertainty and improve judgment [7,19]. This links Turner & Cochrane's work with decisions in projects where goals and methods are not fully defined, which is exactly where AI-supported decision tools become relevant [20].

Systems Theory views civil engineering projects as complex systems composed of interdependent components including people, materials, equipment, procedures, and information flows where changes in one part can affect others [19]. AI-based monitoring, optimization, and simulation tools support this systems view by integrating data from multiple subsystems to reveal how local decisions affect overall project performance [10].

AI-enabled Decision Support Systems (DSS) link AI to project management by describing computer-based systems that help professionals analyze data, explore alternatives, and make better-informed [21]. When AI methods such as machine learning and predictive analytics are embedded in DSS, they enhance capabilities for risk assessment, cost forecasting, progress monitoring, and resource allocation in construction projects [16,21].

The Technology Acceptance Model (TAM) posits that perceived usefulness and perceived ease of use shape individual acceptance of new technologies [22,23]. For civil engineers, perceived usefulness relates to whether AI helps deliver projects more efficiently, safely, and at higher quality, while perceived ease of use reflects the compatibility and learnability of AI tools [13]. Diffusion of Innovations theory explains how new technologies spread across social systems over time, highlighting adopter categories and attributes such as relative advantage and compatibility [24].

Together, these theories support the study's focus on technological, organizational, knowledge and skills, and ethical, cultural, and regulatory aspects of AI utilization and guide the design of the proposed support program [12].

2. Methods

2.1. Research Design

A descriptive-comparative cross-sectional survey design was used. The descriptive component sought to determine the extent of AI utilization across four dimensions, whereas the comparative component examined differences when respondents were grouped by sex, age, work affiliation, and years of work experience. The cross-sectional approach allowed data to be collected at a single point in time without manipulating variables, appropriate given the focus on existing perceptions and conditions rather than causal relationships [25].

2.2. Study Site and Participants

The study was conducted in Quirino Province, Philippines, among practicing civil engineers who are members of the Philippine Institute of Civil Engineers (PICE), Quirino Chapter. Participants included professionals from both government agencies and private construction and consulting firms involved in planning, design, construction, and infrastructure management [12,13].

Sample size was determined using Raosoft and Slovin’s formula, with a 5% margin of error, 95% confidence level, and 50% response distribution, yielding a minimum of approximately 141 respondents. The final sample consisted of 150 civil engineers, exceeding the minimum requirement and enhancing statistical power. A stratified random sampling method was employed to ensure representation across age groups, work affiliation (government vs. private), and years of work experience.

2.3. Instrument

Data were collected using a self-developed structured questionnaire comprising two parts. Part I gathered demographic data (age, sex, years of experience, work affiliation), and Part II consisted of 24 statements measuring four dimensions: technological aspects (7 items), organizational aspects (7 items), knowledge and skills aspects (5 items), and ethical, cultural, and regulatory aspects (5 items). Items were rated on a four-point Likert scale from 1 (Strongly Disagree) to 4 (Strongly Agree), and weighted means were interpreted using defined cut-offs.

The instrument underwent expert validation to assess content relevance and clarity, yielding content validity indices between 0.70 and 0.85, and a pilot test established acceptable internal consistency reliability. These procedures aligned with recommended practices for survey development in engineering management research [9,26].

2.4. Data Collection and Analysis

After pilot testing and refinement, the questionnaire was distributed electronically through professional networks and organizational channels, accompanied by an informed consent statement. Completed responses were screened, coded, and entered into statistical software for analysis.

Frequency and percentage were used to describe the demographic profile of respondents. Weighted means were computed to assess the extent of AI utilization across the four dimensions. Independent-samples t-tests were used to compare AI utilization by sex and work affiliation, and one-way analysis of variance with post hoc tests was used to examine differences by age and years of experience. Statistical significance was evaluated at the 0.05 level.

2.5. Ethical Considerations

The study followed ethical standards for survey research. Participation was voluntary, respondents were informed of the study’s purpose and their rights, and confidentiality and anonymity were assured. No personally identifiable information was reported, and the data were used solely for academic purposes [27].

3. Results

3.1. Demographic Profile

Table 1 shows that half of the respondents (50.00%) were 30 years old and below, while 28.67% were aged 31–40 years, indicating that the sample is composed largely of younger professionals. Most respondents (64.00%) had 10 years or less of work experience, with only 2.00% reporting more than 40 years in service. Male respondents comprised 76.00% of the sample and female respondents 24.00%. Slightly more than half (54.00%) worked in government, and 46.00% worked in the private sector.

Table 1. Demographic Profile of Respondents (N = 150)

Variable	Category	n	%
Age (years)	30 and below	75	50.00
	31–40	43	28.67
	41–50	12	8.00
	51–60	16	10.67
61 and above	4	2.67	
Sex	Male	114	76.00
	Female	36	24.00
Years of work experience	10 years and below	96	64.00
	11–20 years	38	25.30
	21–30 years	9	6.00
	31–40 years	4	2.70
	41 years and above	3	2.00
Work affiliation	Government	81	54.00
	Private	69	46.00

3.2. AI Utilization by Dimension

Table 2–Table 5 present the item-level means for each dimension, and Table 6 summarizes the dimension-level means.

The grand mean of 2.89 indicates that respondents perceive AI-related conditions as moderately favorable overall. Knowledge and skills emerged as the most favorable dimension, followed by technological and organizational aspects, while ethical, cultural, and regulatory aspects were relatively weaker though still positive.

3.3. Differences by Sex and Work Affiliation

Independent-samples t-tests were conducted to examine differences in AI utilization by sex and work affiliation.

Sex-based differences were generally not significant, except for the organizational aspect, where female respondents reported significantly higher mean scores than male respondents ($p = .023$). This indicates more favorable perceptions of organizational support for AI among women in the sample.

Private-sector respondents reported significantly higher mean scores across all four dimensions than government respondents, indicating more favorable AI-related conditions in private organizations.

Table 2. Technological Aspects of AI Utilization (N = 150)

Item	Mean	Interpretation
AI tools specifically designed for civil engineers are readily available.	3.05	Agree
AI algorithms are accurate in solving real problems.	2.96	Agree
AI systems demonstrate consistent accuracy and reliability in civil engineering tasks.	2.94	Agree
Current AI technologies are easy for civil engineers to use.	2.96	Agree
It is easy to connect AI systems with existing civil engineering software.	2.92	Agree
Organizations have the advanced infrastructure needed for AI solutions.	2.97	Agree
AI tools frequently solve civil engineering problems accurately.	2.89	Agree
Category mean	2.96	Agree

Table 3. Organizational Aspects of AI Utilization (N = 150)

Item	Mean	Interpretation
Civil engineering organizations know the benefits of using AI.	3.14	Agree
Senior management fully supports using AI technologies.	2.66	Agree
People in the organization are open to change, which helps with AI adoption.	3.09	Agree
Training employees to use AI tools is affordable and worthwhile.	2.83	Agree
There are enough skilled staff in-house to make AI work well.	2.85	Agree
The organization’s main goals include using new technologies like AI.	2.92	Agree
There is enough funding for new ideas and AI research.	2.69	Agree
Category mean	2.88	Agree

Table 4. Knowledge and Skills Aspects of AI Utilization (N = 150)

Item	Mean	Interpretation
Civil engineers have the training they need to understand and use AI.	2.86	Agree
There are enough training programs about AI in civil engineering.	2.87	Agree
AI is strong and reliable, which encourages its use in civil engineering.	3.01	Agree
Having a good basic understanding of AI helps achieve better civil engineering project results.	3.23	Agree
Hearing about successful uses of AI in civil engineering increases confidence in AI.	3.19	Agree
Category mean	3.03	Agree

Table 5. Ethical, Cultural, and Regulatory Aspects of AI Utilization (N = 150)

Item	Mean	Interpretation
People are comfortable with how AI makes decisions, so there is less resistance to using it.	2.81	Agree
The organization welcomes automation, making it easier to use AI.	2.89	Agree
Employees are not worried about losing their jobs because of AI, so they support its use.	2.59	Agree
There are clear rules for using AI in civil engineering, making it more accepted.	2.65	Agree
People are not worried about data privacy or security when using AI solutions.	2.52	Agree
Category mean	2.69	Agree

Table 6. Summary of AI Utilization by Dimension (N = 150)

Dimension	Mean	Interpretation
Technological aspects	2.96	Agree
Organizational aspects	2.88	Agree
Knowledge and skills aspects	3.03	Agree
Ethical, cultural, and regulatory aspects	2.69	Agree
Grand mean	2.89	Agree

Table 7. AI Utilization by Sex: Independent-samples T-test (N = 150)

Dimension	Sex	Mean	t	p	Decision at 0.05
Techno-logical aspects	Male	2.90	−1.864	.064	Fail to reject H_0
	Female	3.14			
Organ-izational aspects	Male	2.82	−2.305	.023*	Reject H_0
	Female	3.08			
Knowledge and skills aspects	Male	2.98	−1.652	.101	Fail to reject H_0
	Female	3.19			
Ethical, cultural, and regulatory aspects	Male	2.65	−1.307	.193	Fail to reject H_0
	Female	2.82			

$p < .05$.

Table 8. AI Utilization by Work Affiliation: Independent-samples T-test (N = 150)

Dimension	Work affiliation	Mean	t	p	Decision at 0.05
Technological aspects	Government	2.84	−2.273	.024*	Reject H_0
	Private	3.09			
Organizational aspects	Government	2.79	−2.040	.043*	Reject H_0
	Private	2.99			
Knowledge and skills aspects	Government	2.87	−3.232	.002*	Reject H_0
	Private	3.21			
Ethical, cultural, and regulatory aspects	Government	2.55	−2.954	.004*	Reject H_0
	Private	2.87			

$p < .05$.

3.4. Differences by Years of Work Experience

One-way ANOVA was used to examine differences in AI utilization across groups defined by years of work experience.

Post hoc tests (Table 9) showed that respondents with 1–10 years of experience consistently reported significantly higher mean scores than those with longer experience, especially those with 31–40 years and 41 years and above.

Table 9. AI Utilization by Years of Work Experience: One-way ANOVA (N = 150)

Dimension	Years of experience	Mean	F	p	Decision at 0.05
Technological aspects	1–10 years	3.18	21.613	< .001*	Reject H_0
	11–20 years	2.82			
	21–30 years	2.29			
	31–40 years	1.32			
	41 years and above	1.62			
Organizational aspects	1–10 years	3.10	22.211	< .001*	Reject H_0
	11–20 years	2.72			
	21–30 years	2.37			
	31–40 years	1.46			
	41 years and above	1.62			
Knowledge and skills aspects	1–10 years	3.24	22.543	< .001*	Reject H_0
	11–20 years	2.90			
	21–30 years	2.62			
	31–40 years	1.35			
	41 years and above	1.47			
Ethical, cultural, and regulatory aspects	1–10 years	2.85	16.383	< .001*	Reject H_0
	11–20 years	2.70			
	21–30 years	2.20			
	31–40 years	1.05			
	41 years and above	1.27			

$p < .05$.

Table 10 Post hoc Test (Tukey) for AI Utilization by Years of Work Experience

Dimension	Group 1	Group 2	Mean difference	Std. error	p
Technological aspects	1–10	11–20	0.363	0.105	.006
	1–10	21–30	0.897	0.190	.000
	1–10	31–40	1.861	0.278	.000
	1–10	41+	1.564	0.320	.000
	11–20	31–40	1.498	0.287	.000
	11–20	41+	1.201	0.327	.003
	21–30	31–40	0.964	0.328	.031
Organizational aspects	1–10	11–20	0.379	0.093	.001
	1–10	21–30	0.732	0.168	.000
	1–10	31–40	1.632	0.246	.000
	1–10	41+	1.478	0.282	.000
	11–20	31–40	1.254	0.254	.000
	11–20	41+	1.099	0.289	.002
	21–30	31–40	0.901	0.290	.019
Knowledge and skills aspects	1–10	11–20	0.347	0.101	.007
	1–10	21–30	0.619	0.184	.009
	1–10	31–40	1.892	0.269	.000
	1–10	41+	1.775	0.309	.000
	11–20	31–40	1.545	0.277	.000
	11–20	41+	1.428	0.317	.000
	21–30	31–40	1.272	0.317	.001
	21–30	41+	1.156	0.352	.011
Ethical, cultural, and regulatory aspects	1–10	21–30	0.650	0.199	.012
	1–10	31–40	1.800	0.292	.000
	1–10	41+	1.583	0.336	.000
	11–20	31–40	1.650	0.301	.000
	11–20	41+	1.433	0.343	.000
	21–30	31–40	1.150	0.344	.009

Only significant comparisons are shown.

3.5. Differences by Age

One-way ANOVA was also used to examine differences in AI utilization across age groups

Tukey post hoc tests (Table 11) indicated that the youngest age groups (21–30 and 31–40 years) had significantly higher mean scores than older age groups across all dimensions.

Table 11. AI Utilization by Age: One-way ANOVA (N = 150)

Dimension	Age group (years)	Mean	F	p	Decision at 0.05
Techno-logical aspects	21–30	3.21	46.759	< .001*	Reject H_0
	31–40	3.20			
	41–50	2.51			
	51–60	1.76			
	61+	1.71			
Organ-izational aspects	21–30	3.10	39.374	< .001*	Reject H_0
	31–40	3.09			
	41–50	2.45			
	51–60	1.91			
	61+	1.71			
Knowledge and skills aspects	21–30	3.22	46.688	< .001*	Reject H_0
	31–40	3.36			
	41–50	2.60			
	51–60	1.94			
	61+	1.60			
Ethical, cultural, and regulatory aspects	21–30	2.92	23.226	< .001*	Reject H_0
	31–40	2.86			
	41–50	2.38			
	51–60	1.74			
	61+	1.45			

$p < .05$.

Table 12. Post hoc Test (Tukey) for AI Utilization by Age

Dimension	Group 1	Group 2	Mean difference	Std. error	p
Techno-logical aspects	21–30	41–50	0.699	0.142	.000
	21–30	51–60	1.453	0.126	.000
	21–30	61+	1.497	0.234	.000
	31–40	41–50	0.684	0.148	.000
	31–40	51–60	1.437	0.133	.000
	31–40	61+	1.482	0.238	.000
	41–50	51–60	0.759	0.174	.000
	41–50	61+	0.798	0.263	.024
Organ-izational aspects	21–30	41–50	0.650	0.132	.000
	21–30	51–60	1.192	0.117	.000
	21–30	61+	1.389	0.218	.000
	31–40	41–50	0.641	0.139	.000
	31–40	51–60	1.182	0.124	.000
	31–40	61+	1.379	0.222	.000
	41–50	51–60	0.542	0.162	.009
	41–50	61+	0.738	0.245	.025
Knowledge and skills aspects	21–30	41–50	0.621	0.138	.000
	21–30	51–60	1.284	0.122	.000
	21–30	61+	1.621	0.228	.000
	31–40	41–50	0.758	0.145	.000
	31–40	51–60	1.421	0.130	.001
	31–40	61+	1.758	0.232	.001
	41–50	51–60	0.663	0.170	.001
	41–50	61+	1.000	0.257	.001
Ethical, cultural, and regulatory aspects	21–30	41–50	0.534	0.167	.015
	21–30	51–60	1.180	0.148	.000
	21–30	61+	1.467	0.276	.000
	31–40	51–60	1.123	0.158	.000
	31–40	61+	0.933	0.311	.000

Dimension	Group 1	Group 2	Mean difference	Std. error	p
	41–50	51–60	0.646	0.206	.017
	41–50	61+	0.933	0.311	.000

Only significant comparisons are shown.

4. Discussion

The results indicate that civil engineers in Quirino Province operate in an environment that is receptive to AI but still at an emerging stage of readiness. The overall mean of 2.89 suggests that AI-related technological, organizational, knowledge-based, and ethical-regulatory conditions are present but not yet strong. This pattern is consistent with global reviews describing construction as moving toward AI integration while still facing structural, organizational, and cultural barriers [11].

Knowledge and skills received the highest dimension mean (3.03), indicating that respondents recognize the value of AI competence and report some level of AI-related training and awareness. However, the scores remain in the moderate range, implying that deeper, practice-oriented capacity-building is needed if AI is to become part of routine civil engineering workflows[7,13].

Technological aspects also scored favorably (mean 2.96), reflecting perceptions that AI tools are available, reasonably accurate, and usable, and that organizations have some related infrastructure. Nevertheless, the absence of “strongly agree” ratings suggests continuing challenges in interoperability, digital infrastructure, and consistent utilization, which are commonly cited in the literature as barriers to full AI integration [10,28].

Organizational aspects scored slightly lower (mean 2.88), highlighting a familiar gap between recognizing AI’s benefits and providing robust institutional support. The significant differences favoring private-sector respondents across all dimensions underscore the role of sectoral context: private organizations may have more flexible cultures, greater investment capacity, and stronger incentives to experiment with AI than government agencies constrained by bureaucratic procedures and legacy systems [2,3].

Ethical, cultural, and regulatory aspects were the weakest dimension (mean 2.69), though still positive, pointing to ongoing concerns about data privacy, job security, decision transparency, and regulatory clarity. These findings mirror international discussions emphasizing that AI deployment in safety-critical fields like civil engineering must be accompanied by clear guidelines, accountability frameworks, and communication strategies to build trust among professionals and stakeholders [4,12].

The demographic and sectoral differences observed in the study are compatible with innovation-diffusion and technology-acceptance theories. Younger and less experienced engineers reported more favorable AI-related conditions than older, more experienced colleagues, suggesting that newer entrants to the profession may be more open to digital technologies and less tied to traditional methods [23]. The single significant sex difference in organizational aspects (favoring women) warrants cautious interpretation but signals that gender may shape how institutional support for AI is perceived or experienced.

Internationally, the study contributes empirical evidence on AI readiness in a localized civil engineering context, complementing more technically focused research on AI algorithms and applications [1]. By centering on practitioner perceptions and institutional conditions, it underscores that successful AI adoption depends on human and organizational factors as much as on technological potential [2,3].

5. Proposed Comprehensive Support Framework

Based on the findings, a Comprehensive Professional Organizational Support Program is proposed to strengthen AI utilization in civil engineering practice. The framework consists of four pillars designed to address the main gaps identified in the study.

5.1. Capacity-building and Professional Development

The first pillar focuses on sustained AI education for practicing civil engineers. This includes foundational AI literacy, application-focused training for design, analysis, and project management, exposure to relevant case studies, and structured continuing professional development programs delivered through PICE chapters, employers, and academic partners [29,7]. Because knowledge and skills are already the strongest dimension but still only moderately favorable, capacity-building should emphasize hands-on, project-oriented learning rather than purely conceptual coverage.

5.2. Organizational Leadership and Implementation Support

The second pillar emphasizes stronger institutional support. Organizations should move from generic support for innovation to concrete AI implementation plans, including clear leadership commitments, dedicated budgets, change-management strategies, and designated AI “champions” within project teams [13]. These interventions are especially important for government agencies, which lag behind private organizations across all dimensions.

5.3. Digital Infrastructure and Systems Integration

The third pillar addresses digital infrastructure. AI adoption requires adequate hardware, software, data storage, connectivity, and interoperability with tools such as CAD, BIM, project management systems, and monitoring platforms [5,28]. Improving data quality, standardization, and system integration is essential for moving AI from experimental or isolated use toward sustainable, organization-wide practice.

5.4. Ethical, Cultural, and Regulatory Guidance

The fourth pillar concerns ethical, cultural, and regulatory readiness. Professional organizations, employers, and regulatory agencies should collaborate to develop practical guidelines covering data privacy, transparency, accountability, and acceptable AI use in civil engineering decisions [12,14]. These guidelines should explicitly affirm the continuing role of human professional judgment, address worker concerns about job displacement, and offer mechanisms for monitoring and evaluating AI impacts [30].

Together, these four pillars translate the empirical findings into actionable strategies that can be implemented and refined by stakeholders in Quirino Province and similar settings [2,3].

6. Conclusion

Civil engineers in Quirino Province perceive AI-related conditions in their professional environment as moderately favorable overall, with knowledge and skills and technological aspects rated higher than organizational and ethical-regulatory conditions. Significant differences across sex, sector, years of experience, and age show that AI readiness is uneven, with private-sector, younger, and less experienced engineers generally reporting more favorable conditions than government-sector and more senior counterparts.

These results confirm that AI adoption in civil engineering requires more than technological tools; it depends on aligned efforts in capacity-building, organizational systems, infrastructure, and governance. The proposed four-pillar support framework offers a structured response that can guide professional organizations and institutions in advancing toward more strategic, inclusive, and responsible AI integration in civil engineering practice [16].

7. Limitations and Future Research

The study is limited to PICE-affiliated civil engineers in a single Philippine province and used a cross-sectional survey design, which may restrict generalizability and preclude causal inference. Future research could adopt longitudinal designs to track changes in AI readiness over time, employ qualitative methods such as interviews or focus groups to deepen understanding of barriers and enablers, and compare multiple regions or countries to explore contextual differences in AI utilization [29,30].

ACKNOWLEDGEMENTS

The authors extend their sincere appreciation to Quirino State University and La Salette University Inc. for the institutional support provided throughout the conduct of this study. They gratefully acknowledge the assistance of PICE Quirino chapter for facilitating access to participants and endorsing the data collection activities.

Heartfelt thanks are also due to the civil engineers in Quirino Province who generously shared their time and insights by responding to the survey questionnaire; their contributions made this research possible. The authors likewise recognize the constructive comments of colleagues and peers whose suggestions helped refine the research design, analysis, and presentation of findings.

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