Artificial Intelligence Readiness and Maintenance Performance among Critical Infrastructure Engineers: The Mediating Role of Trust in Artificial Intelligence

Karim Mohamed Moustafa [1*] **Mahmoud Abdelaziz Hussein Mohamed Ibrahim** [2]

[1] Senior QA/QC Civil Engineer, Saudi Binladen Group, Makkah, Saudi Arabia.
Email: karimsand68@gmail.com | https://orcid.org/0009-0004-6963-6362
[2] Senior Planning Engineer, Saudi Arabian Parsons Limited, Makkah, Saudi Arabia.
Email: maziz52011@gmail.com | https://orcid.org/0009-0003-3381-4000

ABSTRACT: The aim of this study was to fill the gap in the existing literature by investigating the mediating effect of Trust in Artificial Intelligence on the association between Artificial Intelligence Readiness and Maintenance Performance of Critical Infrastructure Engineers in Makkah, Saudi Arabia. This study utilized cross-sectional correlational research design and purposive sampling approach. Data was obtained from engineers working in the critical infrastructure industry, such as energy, transport, water, manufacturing, telecommunication, oil and gas, and public utility companies. Male and female engineers who have attained a minimum of a bachelor's degree and at least one year of experience in their respective areas participated in this study. The standardized tools used were Artificial Intelligence Readiness Scale (Wang et al., 2026), Trust in Automated Systems Survey (Jian et al., 2000) and the Individual Work Performance Questionnaire (Koopmans et al., 2014) modified items. Ethical standards were adhered to throughout the study in line with APA 7th edition. Of 350 targeted participants, 300 filled the questionnaire. The data was analyzed using IBM SPSS Statistics Version 29 and Hayes PROCESS Macro (Model 4). It was found from the Pearson product-moment correlation that there are significant positive associations between AI Readiness, Trust in AI, and Maintenance Performance. Mediation analysis proved that Trust in AI is a partial mediator for the relationship between AI Readiness and Maintenance Performance. There were no significant gender differences regarding Artificial Intelligence Readiness, Trust in AI, and Maintenance Performance from the independent-samples t-tests.

KEYWORDS: Artificial Intelligence Readiness, Trust in Artificial Intelligence, Maintenance Performance, Critical Infrastructure Engineers, Predictive Maintenance, Artificial Intelligence

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Corresponding Author
Karim Mohamed Moustafa
karimsand68@gmail.com

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Introduction

Critical infrastructure such as transportation, energy, water, manufacturing, telecommunications, and industrial facilities is a vital component of any country in terms of economic development and public security (Olawale et al., 2023). The increase in complexity of these infrastructures, together with the problems associated with the aging of the infrastructures, growing demand on services provided by the infrastructures, climate disturbances, and cyber-attacks, has revealed the insufficiency of the traditional methods of maintenance based on either a reactive approach or preventive maintenance (Crichton et al., 2024; Gerstein & Leidy, 2024). For this reason, artificial intelligence (AI) is applied more widely to enhance the resilience of infrastructure, improve the maintenance processes, and provide better decisions regarding infrastructure operations (Ahmad, 2025; Ajayi et al., 2025; Ali et al., 2026; Sharma et al., 2025). Recent research findings have shown the efficiency of AI usage in transportation maintenance, civil infrastructure, construction projects, the oil and gas industry, and intelligent maintenance systems (Alnaser & Elmousalami, 2025; Anick, 2026; Bhatti & Cheema, 2026; Bhatti & Otamurodov, 2025; Zhou et al., 2026).

Despite all these technological developments, the implementation of AI not only depends on technology but also on the organization's ability to incorporate AI within its engineering processes. Artificial Intelligence Readiness (AIR) can be defined as the organization's capacity to implement and employ AI via proper technological infrastructure, organizational capability, human skills, governance frameworks, leadership support, and high-quality data (Oliva, 2023; Pal & Islam, 2025). The more AI-ready the organization is, the better chances there are to turn AI investments into organizational effectiveness due to the presence of strategic resources needed for AI implementation. The literature shows that organizational infrastructure, management support, AI governance, collaborative environment, financial readiness, and workforce capability are the key factors affecting AI readiness and AI implementation (Pal & Islam, 2025). Policy reports stress that organizations dealing with critical infrastructure should develop their governance, cybersecurity, workforce capability, and compliance prior to implementing AI in their mission-critical operations (Crichton et al., 2024; Gerstein & Leidy, 2024). The research evidence from infrastructure management, predictive maintenance, cybersecurity, and risk management confirms that AI readiness positively impacts organizational resilience, intelligent decision-making, and organizational performance (Gul & Umer, 2026; Islam & Biswas, 2023; Odekunle et al., 2025; Tarek & Rahman, 2023).

Even though organizational readiness provides the base for implementing AI technologies, it is the readiness of engineers to use recommendations generated by AI that can make these technologies helpful for improving maintenance processes. This issue is reflected in Trust in Artificial Intelligence, which measures users' confidence in the reliability, transparency, consistency, and effectiveness of the systems that are supported by artificial intelligence. Explainable AI is one of the most critical instruments used for developing users' trust in AI because it allows users to understand how AI models make recommendations and predictions (Hu et al., 2026). In addition, Rahaman (2026) showed that explainable AI, along with digital twin technology, improved predictive maintenance and lifecycle management and increased operators' engagement. Furthermore, Waqar et al. (2026) found that algorithmic transparency and explainability contributed to the development of trust, which in turn contributed to better decision-making in relation to infrastructure. The same results were obtained by studying cybersecurity and cloud infrastructure, in which explainable AI led to greater user trust, effectiveness of response, and organizational resilience (Nalini, 2025; Rahman & Haque, 2025).

Maintaining good maintenance performance is one of the key organizational outcomes from implementing AI. Proper maintenance will help reduce downtime, improve equipment reliability, increase asset availability, and keep maintenance costs low. The use of AI predictive maintenance will enable engineers to constantly monitor the state of their equipment, plan effectively, and make good decisions regarding maintenance. While previous literature has looked at the topic of Artificial Intelligence, digital twins, cybersecurity, and infrastructure resilience, there is a lack of empirical literature that has explored how Artificial Intelligence Readiness Impacts Maintenance Performance through the medium of Trust in Artificial Intelligence. This study seeks to fill this gap. Most previous literature on the topic has paid attention only to the technological side of things (Oliva, 2023; Pal & Islam, 2025; Waqar et al., 2026). In addition, empirical studies on transportation, healthcare, cybersecurity, and industrial control systems cannot be generalized to engineers who maintain different critical infrastructure assets (Ajayi et al., 2025; Gergov et al., 2026). Consequently, the current study explores the impact of Artificial Intelligence Readiness on Maintenance Performance, while examining the mediating effect of Trust in Artificial Intelligence of Critical Infrastructure Engineers. The results of the study will make a significant contribution to the existing body of knowledge by combining the concept of organizational readiness and behavioral trust in one model.

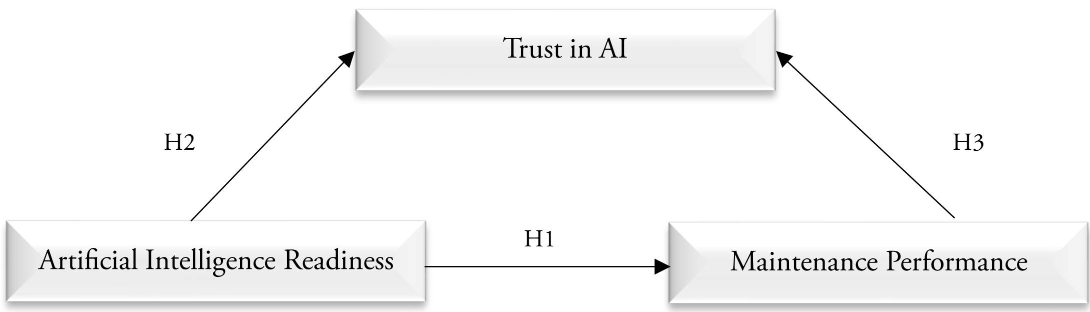
Hypotheses

H1: Artificial Intelligence Readiness has a significant positive effect on Maintenance Performance among Critical Infrastructure Engineers.

H2: Artificial Intelligence Readiness has a significant positive effect on Trust in Artificial Intelligence among Critical Infrastructure Engineers.

H3: Trust in Artificial Intelligence positively mediates the relationship between Artificial Intelligence Readiness and Maintenance Performance among Critical Infrastructure Engineers.

Figure 1



Methodology

A correlational study was designed for this study, which adopted a quantitative research methodology to investigate the linkage between Artificial Intelligence Readiness (AIR) and Maintenance Performance (MP) among Critical Infrastructure Engineers, where Trust in Artificial Intelligence (TAI) acted as a mediator. To collect the data, a convenience sampling technique was applied through which data was collected from engineers operating in various critical infrastructure sectors in Makkah (Saudi Arabia), such as energy, transportation, water, manufacturing, telecommunications, oil and gas, and utilities. The inclusion criterion for participation in the survey included having a minimum educational qualification of a bachelor's degree in engineering or another relevant field, along with a minimum of one year of work experience in maintenance, operations, or asset management. Overall, 350 engineers were surveyed, out of which only 300 responded to the questionnaire.

Instruments

Artificial Intelligence Readiness Scale (AIRS) by Wang et al. (2026) included 13 items spread over four subscales: Self-efficacy and Cognition, Optimism, Collaborative Learning and Working, and Comfort. Items were assessed on a 7-point Likert scale that ranged from 1 (Strongly Disagree) to 7 (Strongly Agree). The initial scale exhibited high internal consistency (Cronbach's $\alpha = .91$). In the current research, Cronbach's alpha was .86.

Trust in Automated Systems Survey by Jian et al. (2000) consisted of 12 items measured on a 7-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). The initial scale indicated a high Cronbach's alpha (.92). The current study revealed a reliability of .87.

Maintenance Performance was measured by 10 items adapted from the Individual Work Performance Questionnaire (IWPQ) by Koopmans et al. (2014). Items were measured on the 5-point Likert scale that ranged from 1 (Seldom) to 5 (Always). The initial scale indicated reliability coefficients between .79 and .89. In the current study, Cronbach's alpha was .90.

Procedure and Data Analysis

Ethical guidelines that coincide with the guidelines of APA 7th edition were maintained during the research process. Permission to administer the scales was sought in advance where necessary. Participants were briefed on the research aims, the confidentiality of the answers provided, and that they were not obligated to take part and had the freedom to leave at any point in time. Data were then analyzed using IBM SPSS Statistics Version 29 through descriptive statistics, reliability, correlation, independent sample t-tests, and Hayes PROCESS Model 4 for assessing the mediating effect of Trust in Artificial Intelligence. Significance was set at the .05 level.

Results

Table 1

Socio-demographic Characteristics of the Respondents

		Frequency	Percent	Mean	SD
Age				2.07	.968
	21–30 Years	101	33.7		
	31–40 Years	105	35.0		
	41–50 Years	65	21.7		
	Above 50 Years	29	9.6		
Gender					
	Male	237	79.0		
	Female	63	21.0		
Qualification					
	Bachelor's Degree	162	54.0		
	Master's Degree	87	29.0		
	MS/MPhil	33	11.0		
	PhD	9	3.0		
	Other	9	3.0		
Engineering Discipline					
	Mechanical	74	24.7		
	Electrical	70	23.3		
	Civil	35	11.7		
	Electronics	33	11.0		
	Chemical	33	11.0		
	Industrial	26	8.7		
	Mechatronics	19	6.3		
	Other	10	3.3		
Organization Sector					
	Energy	64	21.3		
	Oil & Gas	36	12.0		
	Water	44	14.7		

	Transportation	53	17.7
	Manufacturing	36	12.0
	Telecommunications	31	10.3
	Public Utilities	31	10.3
	Other	5	1.7
Current Position			
	Engineer	107	35.7
	Senior Engineer	65	21.7
	Maintenance Supervisor	62	20.7
	Maintenance Manager	44	14.7
	Asset Manager	15	5.0
	Other	7	2.3
Work Experience			
	1–5 Years	91	30.3
	6–10 Years	93	31.0
	11–15 Years	55	18.3
	16–20 Years	30	10.0
	More than 20 Years	31	10.3

Table 1 illustrates the socio-demographic profile of the 300 respondents. The biggest percentage of respondents fell into the age bracket 31 – 40 years (35.0%), followed by 21 – 30 years (33.7%), with the average age being 2.07 (SD = 0.97). Most respondents were men (79.0%), while females formed 21.0% of the respondents. Most of the respondents possessed a bachelor's degree (54.0%), followed by a master's degree (29.0%). The disciplines of Mechanical Engineering (24.7%) and Electrical Engineering (23.3%) were the dominant engineering fields among the respondents. The respondents worked within various vital infrastructure industries, with the highest representation in the Energy industry (21.3%) and the Transportation industry (17.7%). Many of the respondents were Engineers (35.7%), and the largest percentage had 6 – 10 years (31.0%) or 1 – 5 years (30.3%) of professional experience.

Table 2

Correlation among Study Variables

1. Artificial Intelligence Readiness	1	.428**	.409**
2. Trust in Artificial Intelligence		1	.536**
3. Maintenance Performance			1

Note: $N = 300$. $p < .01$ (two-tailed). AI = Artificial Intelligence. Correlations are based on Pearson's product–moment correlation coefficients. $p < .01$ indicates a statistically significant correlation.

The Pearson correlation coefficients between the variables under study can be seen in Table 3. The outcomes show that Artificial Intelligence Readiness is significantly and positively correlated with Trust in Artificial Intelligence ($r = .428$, $p < .01$) and Maintenance Performance ($r = .409$, $p < .01$). In addition, Trust in Artificial Intelligence is significantly and positively correlated with Maintenance Performance ($r = .536$, $p < .01$). These associations reflect a moderate level of correlation between the variables, offering justification for the hypotheses to be tested through mediation analysis.

Table 3

Mediation Analysis of Trust in Artificial Intelligence between Artificial Intelligence Readiness and Maintenance Performance (N = 300)

Path	B	SE	t	p	95% CI	F	R^2
AIR → TAI	0.467	0.057	8.165	< .001	[0.354, 0.579]	66.658	.183
AIR → MP	0.216	0.052	4.178	< .001	[0.114, 0.318]	72.055	.327
TAI → MP	0.397	0.047	8.388	< .001	[0.304, 0.491]	72.055	.327

Note: AIR = Artificial Intelligence Readiness; TAI = Trust in Artificial Intelligence; MP = Maintenance Performance.

Based on the output of the mediation analysis through the Hayes PROCESS Macro (Model 4), it was found that Artificial Intelligence Readiness exerted a significant effect on Trust in Artificial Intelligence (B = 0.467, SE = 0.057, t = 8.165, $p < .001$) and explained 18.3% of the variance ($R^2 = .183$). The total model is significant, $F(1, 298) = 66.66$, $p < .001$. Furthermore, Artificial Intelligence Readiness (B = 0.216, $p < .001$) and Trust in Artificial Intelligence (B = 0.397, $p < .001$) significantly predict Maintenance Performance and explain 32.7% of its variance ($R^2 = .327$). The total model is significant, $F(2, 297) = 72.06$, $p < .001$. Hence, it can be inferred that Trust in Artificial Intelligence is the mediator between Artificial Intelligence Readiness and Maintenance Performance.

Table 4

Indirect Effect

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Indirect Path	Effect	β	Boot LLCI	Boot ULCI
Trust in Artificial Intelligence	.19	.47	.13	.25

Note: N = 300.

The effect of Artificial Intelligence Readiness on Maintenance Performance via Trust in Artificial Intelligence was positive and significant (effect = 0.19, β = 0.47), and the bootstrap confidence interval did not contain zero (Boot LLCI = 0.13, Boot ULCI = 0.25). This shows that Trust in Artificial Intelligence is a significant mediator of the association between Artificial Intelligence Readiness and Maintenance Performance for Critical Infrastructure Engineers.

Table 5

Gender Differences in Artificial Intelligence Readiness, Trust in Artificial Intelligence, and Maintenance Performance

Variable	Men (n = 237)		Women (n = 63)		t (298)	p	Cohen's d
	M	SD	M	SD			
Artificial Intelligence Readiness	4.77	0.84	4.84	0.85	-0.56	.578	-0.08
Trust in Artificial Intelligence	4.03	0.93	4.02	0.88	0.07	.948	0.01
Maintenance Performance	3.48	0.84	3.65	0.76	-1.47	.141	-0.21

Note: N = 300. M = Mean; SD = Standard Deviation.

Table 5 displays the gender differences in the variables investigated in this research. In both Artificial Intelligence Readiness and Trust in Artificial Intelligence, there were no statistically significant gender differences among male and female engineers; t (298) = -0.56, p = .578, Cohen's d = -0.08 for Artificial Intelligence Readiness and t (298) = 0.07, p = .948, Cohen's d = 0.01 for Trust in Artificial Intelligence; with both measures displaying negligible effect sizes. There was no statistically significant gender difference in Maintenance Performance; t (298) = -1.47, p = .141, Cohen's d = -0.21. However, female engineers had a slightly higher mean score than male engineers in this variable.

Discussion

The current study examined the relationship between Artificial Intelligence Readiness (AIR) and Maintenance Performance (MP) of Critical Infrastructure Engineers by considering the mediating role of Trust in Artificial Intelligence (TAI). The findings of the current study supported Hypothesis 1, which stated that there was a significant positive relationship between Artificial Intelligence Readiness, Trust in Artificial Intelligence, and Maintenance Performance. Engineers who scored high on the AI readiness scale trusted AI systems and performed their tasks effectively. Such findings are consistent with existing literature showing that organizational readiness is an important factor for successful implementation of AI and its impact on operations (Oliva, 2023; Pal & Islam, 2025). In a similar way, Ahmad (2025), Ali et al. (2026), Ajayi et al. (2025), and Zhou et al. (2026) have stated that the use of artificial intelligence in predictive maintenance increases the reliability of infrastructure and maintenance efficiency. Also, Bhatti and Otamurodov (2025) found that the use of digital twins increases the level of operational resilience by providing intelligent maintenance management. The above results suggest that engineers possessing AI knowledge, organizational readiness, and technical skills are better prepared to apply AI technologies for improvement of maintenance plans, fault detection, and equipment reliability.

Hypothesis 2 was also proven true since there is mediation of Trust in Artificial Intelligence on the relationship between Artificial Intelligence Readiness and Maintenance Performance. While there is direct influence of Artificial Intelligence Readiness on Maintenance Performance, there is also indirect influence through Trust in Artificial Intelligence, which makes it partial mediation. This implies that in the absence of engineers' trust in AI-generated recommendations, organizational readiness will not be enough to maximize maintenance performance. These results agree with Waqar et al. (2026), who explain that transparency and explainability increase trust in AI and enhance infrastructure decision-making quality. As such, Hu et al. (2026) and Rahaman (2026) concluded that explainable AI increases user trust, predictive maintenance performance, and infrastructure management due to increased transparency and explainability of the AI system. The same results were obtained by Rahman and Haque (2025), which show that explainable AI increases analyst trust, cybersecurity performance, and organizational resilience. Hence, trust is an important behavioral mechanism for mediating organizational AI readiness on maintenance performance.

Hypothesis 3 was aimed at determining the gender differences in the study variables. It was found that there were no statistically significant differences in the level of Artificial Intelligence Readiness, Trust in Artificial Intelligence, and Maintenance Performance among male and female engineers. While female engineers had higher mean levels of Artificial Intelligence Readiness and Maintenance Performance, the difference was not statistically significant. Therefore, it can be concluded that both male and female engineers have the same levels of artificial intelligence readiness, trust in AI, and effectiveness in maintenance. This may be because they have equal education, training, job experience, and AI-enabled maintenance technologies.

Therefore, the results provide additional insight into the literature on critical infrastructure AI adoption by showing that organizational readiness and behavioral trust are crucial to obtaining successful maintenance performance. In general, past research has mainly concentrated on technologies, including predictive analytics, digital twins, infrastructure monitoring, and intelligent maintenance systems (Bhatti & Cheema, 2026; Gergov et al., 2026;

Sharma et al., 2025). However, the current paper shows that Artificial Intelligence Readiness positively impacts Maintenance Performance and increases its level both directly and indirectly through Trust in Artificial Intelligence. The results are consistent with Technology-Organization-Environment (TOE) theory, Dynamic Capabilities Theory, and Technology Acceptance Model (TAM). Specifically, organizational capabilities and behavioral trust play a vital role in the successful deployment of AI. From a practical perspective, it is critical for critical infrastructure organizations to build AI readiness and thus increase maintenance performance by way of training programs, governance structures, explainability, and building trust in AI technology.

Limitations and Recommendations

Despite achieving its goals, there are some limitations that should be noted in the current study. First, the cross-sectional correlational research design was used in the study, which makes it impossible to make any conclusions about the causal relationships between Artificial Intelligence Readiness, Trust in Artificial Intelligence, and Maintenance Performance. It is recommended for further research to use a longitudinal or experimental research design to investigate the changes in these constructs over time. Second, the purposive sampling technique was used, and data were collected from 300 Critical Infrastructure Engineers in Makkah (Saudi Arabia). Thus, the results can be applicable only to this country or industry. To improve the generalizability of the findings, probability sampling techniques and a larger sample size should be used in future research across various infrastructure sectors and geographical areas. Lastly, self-reports have been chosen as the means of data collection in the research, which creates the risk of encountering problems associated with common methods bias and social desirability biases. The researchers conducting future studies may consider such aspects as supervisor evaluations and performance indicators in their studies. Finally, the researchers conducting future studies may focus on other aspects like AI competency, etc.

Implications

There are both practical and theoretical implications of the findings of this study. From a practical point of view, the high correlations between AI Readiness, Trust in Artificial Intelligence, and Maintenance Performance indicate the fact that organizations responsible for maintenance of important infrastructures should not only invest in the sphere of AI technologies but also in staff training, AI literacy, AI governance, and Explainable AI so that engineers could feel comfortable making maintenance decisions with the help of artificial intelligence technologies. From the point of view of the mediation analysis, the findings reveal the importance of trust in artificial intelligence and thus suggest that organizations should ensure transparency and reliability of AI technologies to get the highest performance in the field of maintenance. In addition, the absence of gender differences indicates the possibility for organizations to develop an AI strategy that can be applied by both males and females.

Theoretically speaking, this study makes contributions to the theory of the TOE Framework, Dynamic Capabilities Theory, and TAM by establishing that Trust in Artificial Intelligence acts as a vital behavioral pathway for Artificial Intelligence Readiness affecting Maintenance Performance. The contribution of this research to the current literature is twofold since this work contributes to the body of knowledge about AI adoption in critical infrastructure, while considering both organizational readiness and user trust in one framework.

References

Ahmad, I. (2025). Artificial intelligence in civil engineering: Transforming infrastructure development and maintenance. *Turing Ledger Journal of Engineering & Technology*, *1*(2), 59–71. https://doi.org/10.63056/tljet.1.2.2025.64

Ajayi, O. O., Kurien, A., Djouani, K., & Dieng, L. (2025). Artificial intelligence for infrastructure resilience: Transportation systems as a strategic case for policy and practice. *Sustainability*, *17*(20), 8992. https://doi.org/10.3390/su17208992

Ali, A., Ali, S., Ali, M., Ahmed, F., Ismail, M., & Ali, S. (2026). Predictive Maintenance of Civil Infrastructure using Digital Twin Technology and AI-Based Structural Performance Modeling Techniques. *Spectrum of Engineering Sciences*, *4*(5), 1394-1405. https://thesesjournal.com.medicalsciencereview.com/index.php/1/article/view/2848

Alnaser, A. A., & Elmousalami, H. (2025). Exploring critical success factors of AI-integrated digital twins on Saudi construction project deliverables: A PLS-SEM approach. *Buildings*, *15*(19), 3543. https://doi.org/10.3390/buildings15193543

Anick, K. M. (2026). Sustainable infrastructure through intelligent maintenance and energy optimization frameworks. *American Journal of Scholarly Research and Innovation*, *05*(01), 156-197. https://doi.org/10.63125/zdb6zb58

Bhatti, M. A. A., & Cheema, A. T. (2026). Impact of Artificial Intelligence-Driven Project Management on Operational Performance in Oil and Gas Projects: A Structural Equation Modeling Approach. *Advance Journal of Econometrics and Finance*, *4*(1), 2137-2143. https://www.ajeaf.com/index.php/Journal/article/view/429

Bhatti, M. A., & Otamurodov, S. (2025). Digital twin adoption for mechanical maintenance management: A capability-based approach to enhancing operational resilience. *Reports in Mechanical Engineering*, *6*(2), 37-52. https://doi.org/10.31181/rme509

Crichton, K., Ji, J., Miller, K., Bansemer, J., Arnold, Z., Batz, D., Choi, M., Decillis, M., Eke, P., Gerstein, D. M., Leblang, A., McGee, M., Rattray, G., Richards, L., & Scott, A. (2024). *Securing Critical Infrastructure in the Age of AI*. Center for Security and Emerging Technology (CSET). https://doi.org/10.51593/20240032

Gergov, I., Sharabov, M., Rusev, A., & Tsochev, G. (2026). Critical Infrastructure Restoration and Artificial Intelligence Systems: Applications and Practical Limitations. *Sustainability*, *18*(11), 5297. https://doi.org/10.3390/su18115297

Gerstein, D. M., & Leidy, E. N. (2024). Emerging Technology and Risk Analysis: Artificial Intelligence and Critical Infrastructure. Homeland Security Operational Analysis Center, RAND Corporation. https://doi.org/10.7249/RRA2873-1

Gul, H., & Umer, M. (2026). AI-driven Zero-Trust cybersecurity architecture for protecting Pakistan's critical digital infrastructure: The roles of threat intelligence, cyber resilience, and regulatory readiness. *Spectrum of Engineering Sciences, 4*(2), 1606–1622. https://thesesjournal.com/index.php/1/article/view/3569

Hu, Y., Atta, Z., Rahman, T. U., Qiu, S., Wang, J., Wei, W., Liang, Z., & Zaheer, Q. (2026). Shedding light on explainable AI: Insights, challenges, and the future of infrastructure management. *ISPRS International Journal of Geo-Information*, *15*(3), 100. https://doi.org/10.3390/ijgi15030100

Islam, S. N., & Biswas, A. (2023). Artificial Intelligence for Critical Power Infrastructure: Challenges and Opportunities. *Applied IT and Engineering Review, 1*(1), 1–8.

Jian, J., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an empirically determined scale of trust in automated systems. *International Journal of Cognitive Ergonomics*, *4*(1), 53-71. https://doi.org/10.1207/s15327566ijce0401_04

Koopmans, L., Bernaards, C. M., Hildebrandt, V. H., De Vet, H. C., & Van der Beek, A. J. (2014). Construct validity of the individual work performance questionnaire. *Journal of Occupational & Environmental Medicine*, *56*(3), 331-337. https://doi.org/10.1097/jom.0000000000000113

Nalini, T. (2025). AI Powered Holistic Cognitive Framework for Intelligent Cloud Network Security Self Healing Enterprise Infrastructure and Digital Trust Systems. *International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)*, *8*(5), 12929-12938. https://doi.org/10.15662/IJRPETM.2025.0805031

Odekunle, Y. O., Omotola, A. S., Edeh, C. G., & Chinonyerem, C. A. (2025). Leveraging Artificial Intelligence and Predictive Analytics for Dynamic Risk Management in Complex Infrastructure Projects. *MPRI-EDIR International Journal of Earth Design and Innovation Research,* *9*(4). https://doi.org/10.70382/mejedir.v9i4.054

Olawale, M. A., Ayeh, A. A., Adekola, F. O., Precious, A. S., Joshua, A. O., & Oladosu, O. T. (2023). A review on the intersection of artificial intelligence on building resilient infrastructure, promoting inclusive and sustainable industrialization and fostering innovation. *International Journal of Engineering and Modern Technology*, *9*(3), 44-74. https://doi.org/10.56201/ijemt.v9.no3.2023.pg44.74

Oliva, D. (2023). *Readiness assessment for the Artificial Intelligence Act: with a requirements catalogue in the field of critical infrastructure* (Doctoral dissertation, Technische Universität Wien). https://doi.org/10.34726/hss.2023.107330

Pal, T., & Islam, M. M. (2025). Assessing organizational AI readiness in critical infrastructure: An integrated maturity framework for healthcare systems and supply chain management. *American Journal of Scholarly Research and Innovation*, *04*(01), 613-621. https://doi.org/10.63125/vh7x5h50

Rahaman, T. (2026). Explainable AI (XAI) digital twin framework for predictive failure detection and lifecycle management of U.S. drinking water treatment infrastructure. *American Journal of Data Science and Analytics*, *07*(06), 156-181. https://doi.org/10.63125/v6bmnt68

Rahman, M. A., & Haque, B. M. (2025). Adaptive cybersecurity threat intelligence using explainable artificial intelligence for resilient protection of U.S. critical information systems. *American Journal of Advanced Technology and Engineering Solutions*, *01*(02), 216-261. https://doi.org/10.63125/wbaw3w65

Sharma, A., Boora, A., & Kumar, Y. (2025). Artificial intelligence and machine learning for resilient transportation infrastructure. *Cureus Journal of Computer Science*. https://doi.org/10.7759/s44389-025-09490-2

Tarek, J. H., & Rahman, W. (2023). AI-driven cybersecurity, IoT networking, and resilience strategies for industrial control systems: A systematic review for U.S. Critical infrastructure protection. *International Journal of Scientific Interdisciplinary Research*, *04*(04), 144-176. https://doi.org/10.63125/mbyhj941

Wang, I., Hung, C., Lin, H., Lai, W., & Wang, Y. (2026). Artificial intelligence readiness in management education: Scale development and validation. *The International Journal of Management Education*, *24*(3), 101429. https://doi.org/10.1016/j.ijme.2026.101429

Waqar, A., Ali, A. S., Alrasheed, K. A., & Hanid, M. (2026). Socio-technical determinants of explainable artificial intelligence for infrastructure decision support. *Scientific Reports*. https://doi.org/10.1038/s41598-026-60853-8

Zhou, J., Wang, C., Guo, J., & Qin, P. (2026). Examining the impact of artificial intelligence technology on sustainable development in highway maintenance industry: A structural equation modelling approach. *Sustainability*, *18*(2), 889. https://doi.org/10.3390/su18020889