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Artificial Intelligence Allowed Structural Health Monitoring for Resilient Infrastructure Systems

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Abstract: Background: The development of Artificial Intelligence (AI)-based Structural Health Monitoring (SHM) systems brings a new advanced system which protects infrastructure sustainability and safety through established performance standards. Methods: Implemented a quantitative cross-sectional survey study through Google Forms, they used to distribute their online questionnaire. The study gathered 175 complete answers from people at worked in engineering and AI and infrastructure-related fields. Descriptive statistical methods which combined frequency distribution with percentage analysis to study people understood things and how they perceived things and their readiness to adopt and their major obstacles. Results: AI-based SHM systems well because damage detection systems received the highest recognition at 76.8%. The survey results demonstrated a strong positive perception because 82.1% of respondents agreed that AI technology boosts structural safety and 79.6% of participants reported better monitoring performance. The survey results showed that 78.9% of participants supported AI technology for smart infrastructure development. The survey showed that 68.6% of participants wanted to use AI-powered SHM systems but 19.4% of them stayed uncertain about their choice. Conclusion: AI-powered SHM systems as effective tools which improve both structural security and operational efficiency and environmental sustainability. The moderate adoption rate exists because financial obstacles combine with technological barriers and infrastructure problems. The worldwide adoption of AI-based resilient infrastructure systems needs barrier elimination because this process enables faster implementation and full system potential achievement.

Keywords: Artificial Intelligence; Structural Health Monitoring; Smart Infrastructure; Predictive Maintenance; Infrastructure Resilience.

1. Introduction

The fast development of global infrastructure systems has created an urgent requirement for monitoring systems which deliver dependable and quick results to protect structural health and maintain sustainability [1]. Structures of bridges together with buildings and dams and transportation systems face ongoing environmental pressures and wear from time and sudden weight changes [2]. Human inspectors must spend their time performing manual inspections which result in high costs and produce inaccurate results because of human mistakes. The market demands intelligent monitoring systems which deliver instant automated structural evaluation through precise real-time assessment [3]. Structural Health Monitoring (SHM) functions as an essential technology which monitors infrastructure system health through its combination of sensor network systems and data collection instruments and signal analysis methods [4], [5]. The SHM system maintains permanent structural monitoring which detects early-stage damage that leads to complete failure prevention. The traditional SHM methods encounter difficulties when they need to handle big data sets and identify complicated patterns which makes them less useful for contemporary infrastructure systems [6].

The modern world has witnessed a major transformation of SHM systems because Artificial Intelligence (AI) brought advanced capabilities through its machine learning and deep learning and predictive analytics systems [7]. AI-enabled SHM systems process extensive sensor data collections to reveal hidden patterns which they use to predict structural failure points with excellent precision [8]. These technologies enable organizations to use their data for better decisions because they can schedule maintenance activities before equipment failure occurs. The system achieves better operational performance through AI integration which also strengthens its defense against threats [9]. AI-powered SHM systems has not reached all parts of the world because different regions have adopted these systems at different speeds. The developed world has started using smart infrastructure systems but numerous developing nations encounter various obstacles which include expensive implementation fees and insufficient technical knowledge and weak digital network systems [10]. The technology faces three major obstacles which prevent people from using it because they worry about data security and system stability and because they struggle to connect it with other systems [11].

AI-enabled SHM systems needs to improve because this knowledge will lead to faster deployment of these systems in modern infrastructure networks. Acceptance of new technologies by both public citizens and professional experts determines well these safety-critical technologies will perform in civil engineering and other similar fields [12]. The study area becomes more understandable for policymakers and researchers and industry stakeholders through their assessment of public knowledge about the matter and their opinions about its benefits and obstacles. AI-based Structural Health Monitoring systems through a digital survey which collected responses from 175 participants who came from different academic and work-related fields. The study investigates essential elements which determine how people recognize things and understand them and their readiness to accept them while also identifying primary obstacles that organizations encounter. This results will help us understand AI technology works best with SHM systems to create smart infrastructure systems which defend their structures while operating efficiently and achieving environmental sustainability.

2. Materials and Methods

2.1 Study design and data source

This study used a quantitative cross-sectional survey design to study worldwide opinions about Artificial Intelligence (AI)-based Structural Health Monitoring (SHM) systems. AI-based infrastructure monitoring systems while tracking their actual usage of these technologies. Primary data collection took place through an online questionnaire which Google Forms distributed to participants [13]. The design selection process chose this method because it enables quick collection of extensive perception data during short time periods. The research analyzed AI system implementation for civil infrastructure networks which include bridges and buildings and transportation systems. Data collection followed a structured method which allowed researchers to gather consistent information for region-based and professional background-based analysis of participant responses [14].

2.2 Sampling and Data Collection

This study at a global level by distributing online surveys which enabled them to reach participants from different parts of the world. The study collected responses from people worked in academic settings and professional fields which consisted of civil engineering and information technology and infrastructure-related professions. The final dataset contained 175 valid responses which researchers obtained through non-probability convenience sampling methods. A structured questionnaire with four parts which asked about demographic information and AI knowledge in SHM and system advantages and adoption readiness with potential obstacles. The survey incorporated fixed-answer questions together with five-point Likert scale items which researchers based on previous studies to create understandable answers.

2.3 Data analysis

The collected data underwent analysis through descriptive statistics which contained frequency distribution and percentage analysis and mean score ranking. These methods to assess how people understood AI-enabled Structural Health Monitoring systems and they perceived these systems and their willingness to use them and the main obstacles they faced [15]. Organized itself into tabular format which helped researchers understand the results through straightforward comparisons [16]. The research team selected a systematic analytical method to track worldwide trends which showed how people responded to infrastructure monitoring AI systems and what they thought about them [17]. This method to study important elements which helped them create valuable conclusions about modern infrastructure AI-based SHM system adoption potential [17].

3. Result

3.1 Demographic Profile of Respondents

Table 1. Demographic Profile of Respondents.

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	102	58.3
	Female	73	41.7
Age	18–25	81	46.3
	26–35	64	36.6
	36–45	20	11.4
	46+	10	5.7
Background	Engineering	98	56.0
	IT/AI	42	24.0
	Civil/Infrastructure	20	11.4
	Others	15	8.6

Demographic profile of the 175 respondents indicates a relatively balanced representation across key socio-demographic variables. The study sample includes 58.3% male respondents represent more than half of the participants while 41.7% females form the remaining group which demonstrates average gender variety according to **Table 1.** The research data shows that most participants belonged to the 18-25 age bracket which made up 46.3% of the sample while 36.6% belonged to the 26-35 age range which shows the research focuses on students and people who started their careers. Most respondents who participated in the study came from engineering fields which represented 56.0% of the sample while 24.0% of participants worked in AI-related fields.

Infrastructure professionals made up 11.4% of the group while other professional groups contributed to the remaining 8.6% of the total.

3.2 Awareness of AI-Enabled Structural Health Monitoring Systems

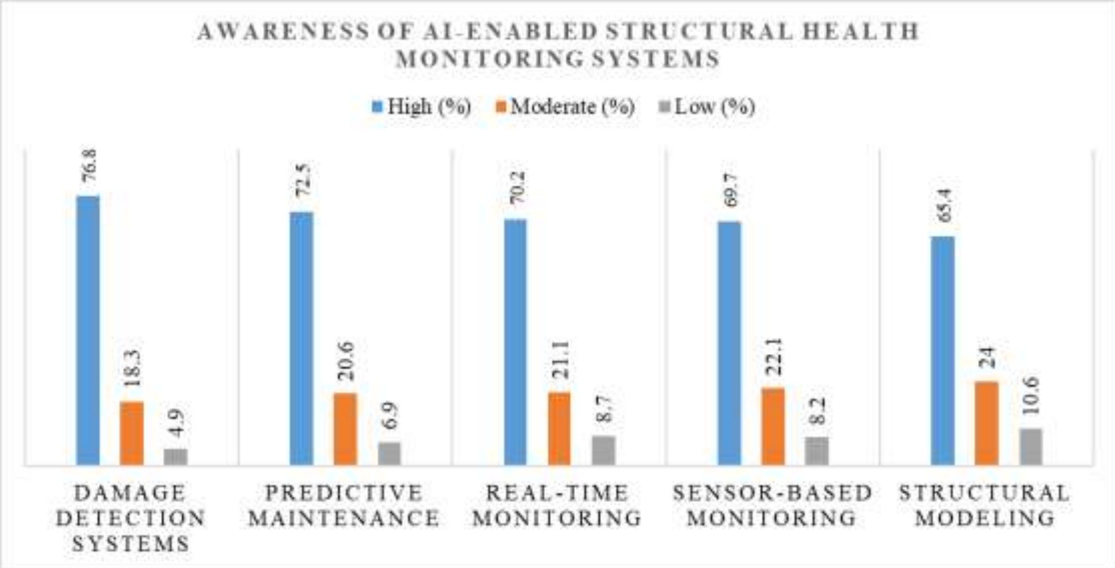

Figure 1. Awareness of AI-Enabled Structural Health Monitoring Systems.

The survey results show that people have a good understanding about AI-powered Structural Health Monitoring (SHM) systems work in their main operational areas. Damage detection systems showed the strongest recognition because 76.8% of people expressed high awareness about them. Awareness about predictive maintenance reached 72.5% which appears in **Figure 1.** The public showed strong awareness of real-time monitoring systems because 70.2% of people reported high recognition which proves that continuous infrastructure monitoring holds major importance. The public showed moderate awareness about sensor-based monitoring systems because 69.7% of people recognized these systems at a high level but 8.2% of people showed minimal understanding about them. The public maintained limited knowledge about structural modeling applications because 65.4% of people showed high recognition while 10.6% of them showed poor understanding about these applications which indicates that people have limited knowledge about advanced analytical functions.

3.3 Perception of AI in Structural Health Monitoring

Table 2. Perception of AI in Structural Health Monitoring.

Statement	Agree (%)	Neutral (%)	Disagree (%)
AI improves structural safety	82.1	12.4	5.5
AI reduces maintenance cost	74.8	18.9	6.3
AI enhances monitoring accuracy	79.6	14.7	5.7
AI enables predictive maintenance	76.5	16.2	7.3
AI supports smart infrastructure development	78.9	14.1	7.0

All indicators of perception about SHM systems are positive among the participants; thus, participants overwhelmingly agree that AI can increase structural safety (82.1% of respondents), thereby showing confidence about AI's place in protecting infrastructure (See **Table 2).** Almost as high with respect to perception that AI will increase the accuracy of monitoring systems, 79.6% of respondents agreed with this statement, establishing a sense of trust in data-based assessment systems. Furthermore, with regard to developing smart infrastructure, a large majority (78.9%) of respondents said they believe AI will play a significant role in this. Likewise, positive ratings of AI's role in providing the ability to provide for predictive maintenance (76.5%) and reduced costs of maintenance (74.8%) were given; however, respondents were neutral (12.4% – 18.9%) on this topic. There is a relatively low number of participants that disagreed with the above mentioned phenomena.

3.4 Willingness to Adopt AI-Enabled SHM Systems

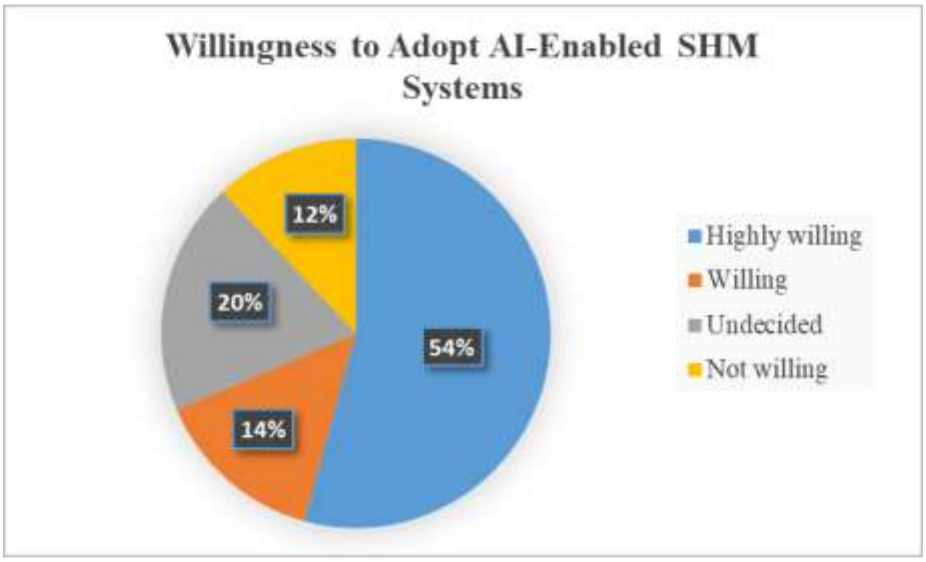

Figure 2. Willingness to Adopt AI-Enabled SHM Systems.

The positive trend of willingness to use AI based Structural Health Monitoring (SHM) systems is demonstrated in the results of our survey. The majority of respondents (54.3%) who have indicated they are very willing to use AI SHM systems means there is significant interest in AI based infrastructure monitoring systems as shown in **Figure 2.** A total of 14.3% indicated a level of willingness to adopt, confirming an overall positive attitude towards the implementation of AI based SHM technologies. Twenty percent of respondents were undecided about their willingness to adopt AI SHM systems perhaps due to a lack of knowledge about the technology or concerns about the costs associated with the implementation of the systems. Only 12.0% indicated they were unwilling to use AI SHM systems meaning the majority of respondents had a willingness to use AI SHM systems and indicated there was a high probability that they would adopt the technology. This indicates that over two-thirds of respondents demonstrated some level of readiness or preparedness to adopt AI based SHM technologies displaying a global acceptance of the technology.

3.5 Barriers to AI-Enabled SHM Adoption

Table 3. Barriers to AI-Enabled SHM Adoption.

Barrier	High (%)	Moderate (%)	Low (%)
High implementation cost	84.2	10.9	4.9
Lack of technical expertise	77.5	15.2	7.3
Cybersecurity risks	69.8	18.6	11.6
Data availability issues	66.3	21.4	12.3
Infrastructure limitations	64.7	22.8	12.5

The results of research on barriers to Artificial Intelligence (AI)-enabled Structural Health Monitoring (SHM) systems demonstrate a number of factors that affect global adoption of such systems. The highest barrier to the implementation of AI-enabled SHM systems was determined to be cost, with 84.2% of all survey respondents identifying this as a major challenge (see **Table 3**). This suggests that financial limitations are still a significant barrier to large-scale implementation of these systems. Respondents expressed agreement that there was a shortage of technical expertise to implement AI-enabled SHM systems (77.5% of respondents indicated that they agree with this). Respondents were also concerned about cybersecurity (69.8% of respondents indicated a concern regarding data security and systems vulnerability). Other respondents pointed out problems with data availability (66.3% of respondents) - meaning that many structural engineers will have difficulty obtaining adequate quality and consistent structural data. Finally, 64.7% of respondents identified infrastructure limitations and technological inequities among regions.

4. Discussion

Generally, the results from this worldwide study show that Artificial Intelligence (AI)-enabled Structural Health Monitoring (SHM) Systems are perceived to have value; however, all levels of perception are generally low (moderate to slightly low levels) [19]. Although there are many advantages; the results indicate AI remains an emerging technology that can be useful but not yet indispensable as a means of infrastructure [20]. Within the value dimension; Safety remains the most recognized value dimension by 82.1%, agreeing that AI increases infrastructure safety. Therefore, AI is primarily associated with reducing risk for infrastructure. AI also increases accuracy in monitoring systems according to 79.6%; therefore, it is perceived as a tool to improve current monitoring systems, not as a means of radical transformation. Regarding Smart Infrastructure Development, 78.9%; although this indicates acceptance with respect to conceptualization, it does not reflect ample experience in practice.

That is to say, some operational benefits are acknowledged. In a somewhat positive vein, 76.5% of respondents believe that AI enables predictive maintenance; clearly, this prospect gave rise to what appears to be substantial usefulness among many respondents. Nevertheless, 74.8% agree that AI will lower maintenance costs, creating an awareness of economic benefits, albeit a hesitant one for all respondents. Further evidence suggests that the knowledge was only moderate in application. About 76.8% confirm high awareness of damage detection systems, with predictive maintenance applications known to 72.5%. These values indicate that generalized AI applications in SHM are known to most respondents. However, awareness declines for more advanced functionalities; with 70.2% for real-time monitoring systems, 69.7% for sensor-based monitoring, and only 65.4% for structural modeling. Such a pattern suggests that knowledge accrues in basic applications rather than in advanced analytical capabilities [21], [22].

People show some hesitance to adopt AI-enabled SHM systems, even if 68.6% of our respondents say they are willing or are willing enough to adopt those systems. The 19.4% of people who are undecided represent a large proportion of people who have not made a fully informed decision about adopting, and the 12.0% of people are not willing to adopt could represent almost one-third of our entire respondent database. Consequently, interest in adoption exists, but firm commitment to adoption does not exist at this time [23]. Barrier analysis data also support these limited value perceptions, with 84.2% of respondents having identified high implementation costs as the dominant factor leading to diminished perceptions of feasibility for adopting AI-enabled SHM systems. Furthermore, 77.5% of respondents have identified a lack of technical expertise as an additional significant barrier to AI-enabled SHM system adoption; thus, the constraints imposed by the limitations of human capabilities are considered to be major barriers to adoption of AI-enabled SHM systems [24], [25].

The perception of AI systems as hard to implement within an actual infrastructure may be exacerbated by expected cyber security threats (69.8%), data unavailability (66.3%) and infrastructure limitations (64.7%), all of which contribute to a lack of confidence in the practical application of AI systems. The respondents, who view SHM systems that leverage AI technologies as providing low-moderate value, recognize the potential benefits but do not see those benefits as sufficiently attractive to encourage widespread use [26]. The technology has been identified as useful; however, cost, lack of skill-sets, and infrastructure all contribute to an overall perception that there is low value associated with AI within SHM today and that further development is needed before it can be regarded as an established solution within the world of infrastructure [27].

5. Conclusion

This study shows that Structural Health Monitoring systems using AI are viewed as a positive way to provide better safety, accuracy, and predictability of critical infrastructure. However, there is a moderate level of adoption of such systems due to high implementation costs, and lack of supporting infrastructure. They would be willing to utilize AI-based SHM technology in the future, providing a strong signal that these systems will continue to gain prominence. AI-based SHM systems are an evolving solution to strengthening infrastructure, but further advances in their affordability, and implementation support will be imperative for them to become a mainstream solution.

References

[1] M. Azimi, A. Eslamlou, and G. Pekcan, "Data-Driven Structural Health Monitoring and Damage Detection through Deep Learning: State-of-the-Art Review," *Sensors*, vol. 20, no. 10, p. 2778, 2020, doi: 10.3390/s20102778.

[2] M. Flah, I. Nunez, W. B. Chaabene, and M. L. Nehdi, "Machine Learning Algorithms in Civil Structural Health Monitoring: A Systematic Review," *Archives of Computational Methods in Engineering*, vol. 28, no. 4, pp. 2621–2643, 2021, doi: 10.1007/s11831-020-09471-9.

[3] M. F. Bado and J. R. Casas, "A Review of Recent Distributed Optical Fiber Sensors Applications for Civil Engineering Structural Health Monitoring," *Sensors*, vol. 21, no. 5, p. 1818, 2021, doi: 10.3390/s21051818.

[4] P. Kot, M. Muradov, M. Gkantou, G. S. Kamaris, K. Hashim, and D. Yeboah, "Recent Advancements in Non-Destructive Testing Techniques for Structural Health Monitoring," *Applied Sciences*, vol. 11, no. 6, p. 2750, 2021, doi: 10.3390/app11062750.

[5] E. M. Dogo, A. F. Salami, N. I. Nwulu, and C. O. Aigbavboa, "Blockchain and Internet of Things-Based Technologies for Intelligent Water Management System," in *Transactions on Computational Science and Computational Intelligence*. Cham, Switzerland: Springer, 2019, pp. 129–150, doi: 10.1007/978-3-030-04110-6_7.

[6] P. Jiao, K. I. Egbe, Y. Xie, A. M. Nazar, and A. H. Alavi, "Piezoelectric Sensing Techniques in Structural Health Monitoring: A State-of-the-Art Review," *Sensors*, vol. 20, no. 13, p. 3730, 2020, doi: 10.3390/s20133730.

[7] M. A. Mousa *et al.*, "Application of Digital Image Correlation in Structural Health Monitoring of Bridge Infrastructures: A Review," *Infrastructures*, vol. 6, no. 12, p. 176, 2021, doi: 10.3390/infrastructures6120176.

[8] Y. Yang, Y. Zhang, and X. Tan, "Review on Vibration-Based Structural Health Monitoring Techniques and Technical Codes," *Symmetry*, vol. 13, no. 11, p. 1998, 2021, doi: 10.3390/sym13111998.

[9] M. Azimi and G. Pekcan, "Structural Health Monitoring Using Extremely Compressed Data Through Deep Learning," *Computer-Aided Civil and Infrastructure Engineering*, vol. 35, no. 6, pp. 597–614, 2020, doi: 10.1111/mice.12517.

[10] S. Hassani, M. Mousavi, and A. H. Gandomi, "Structural Health Monitoring in Composite Structures: A Comprehensive Review," *Sensors*, vol. 22, no. 1, p. 153, 2021, doi: 10.3390/s22010153.

[11] P. Jiao and A. H. Alavi, "Artificial Intelligence in Seismology: Advent, Performance and Future Trends," *Geoscience Frontiers*, vol. 11, no. 3, pp. 739–744, 2020, doi: 10.1016/j.gsf.2019.10.004.
[12] H. Li, L. Ren, Z. Jia, T. Yi, and D. Li, "State-of-the-Art in Structural Health Monitoring of Large and Complex Civil Infrastructures," *Journal of Civil Structural Health Monitoring*, vol. 6, no. 1, pp. 3–16, 2016, doi: 10.1007/s13349-015-0108-9.
[13] D. Goyal and B. S. Pabla, "The Vibration Monitoring Methods and Signal Processing Techniques for Structural Health Monitoring: A Review," *Archives of Computational Methods in Engineering*, vol. 23, no. 4, pp. 585–594, 2016, doi: 10.1007/s11831-015-9145-0.
[14] T. Yigitcanlar and F. Cugurullo, "The Sustainability of Artificial Intelligence: An Urbanistic Viewpoint from the Lens of Smart and Sustainable Cities," *Sustainability*, vol. 12, no. 20, p. 8548, 2020, doi: 10.3390/su12208548.
[15] M. Callcut, J. C. Agliozzo, L. Varga, and L. McMillan, "Digital Twins in Civil Infrastructure Systems," *Sustainability*, vol. 13, no. 20, p. 11549, 2021, doi: 10.3390/su132011549.
[16] H. Alami *et al*., "Artificial Intelligence in Health Care: Laying the Foundation for Responsible, Sustainable, and Inclusive Innovation in Low- and Middle-Income Countries," *Globalization and Health*, vol. 16, no. 1, p. 52, 2020, doi: 10.1186/s12992-020-00584-1.
[17] M. Andronie, G. Lăzăroiu, M. Iatagan, C. Uță, R. Ștefănescu, and M. Cocoșatu, "Artificial Intelligence-Based Decision-Making Algorithms, Internet of Things Sensing Networks, and Deep Learning-Assisted Smart Process Management in Cyber-Physical Production Systems," *Electronics*, vol. 10, no. 20, p. 2497, 2021, doi: 10.3390/electronics10202497.
[18] M. A. Akbar, U. Qidwai, and M. R. Jahanshahi, "An Evaluation of Image-Based Structural Health Monitoring Using Integrated Unmanned Aerial Vehicle Platform," *Structural Control and Health Monitoring*, vol. 26, no. 1, p. e2276, 2019, doi: 10.1002/stc.2276.
[19] J. Li, H. Hao, K. Fan, and J. Brownjohn, "Development and Application of a Relative Displacement Sensor for Structural Health Monitoring of Composite Bridges," *Structural Control and Health Monitoring*, vol. 22, no. 4, pp. 726–742, 2015, doi: 10.1002/stc.1714.
[20] K. Wang, Y. Zhao, R. K. Gangadhari, and Z. Li, "Analyzing the Adoption Challenges of the Internet of Things (IoT) and Artificial Intelligence (AI) for Smart Cities in China," *Sustainability*, vol. 13, no. 19, p. 10983, 2021, doi: 10.3390/su131910983.
[21] A. Pigola *et al*., "Artificial Intelligence-Driven Digital Technologies to the Implementation of the Sustainable Development Goals: A Perspective from Brazil and Portugal," *Sustainability*, vol. 13, no. 24, p. 13669, 2021, doi: 10.3390/su132413669.
[22] G. D. Sharma, A. Yadav, and R. Chopra, "Artificial Intelligence and Effective Governance: A Review, Critique and Research Agenda," *Sustainable Futures*, vol. 2, p. 100004, 2020, doi: 10.1016/j.sftr.2019.100004.
[23] S. E. Chang, T. McDaniels, J. Fox, R. Dhariwal, and H. Longstaff, "Toward Disaster-Resilient Cities: Characterizing Resilience of Infrastructure Systems with Expert Judgments," *Risk Analysis*, vol. 34, no. 3, pp. 416–434, 2014, doi: 10.1111/risa.12133.
[24] S. S. Ali and B. J. Choi, "State-of-the-Art Artificial Intelligence Techniques for Distributed Smart Grids: A Review," *Electronics*, vol. 9, no. 6, p. 1030, 2020, doi: 10.3390/electronics9061030.
[25] T. Yigitcanlar, L. Butler, E. Windle, K. C. Desouza, R. Mehmood, and J. M. Corchado, "Can Building 'Artificially Intelligent Cities' Safeguard Humanity from Natural Disasters, Pandemics, and Other Catastrophes? An Urban Scholar's Perspective," *Sensors*, vol. 20, no. 10, p. 2988, 2020, doi: 10.3390/s20102988.
[26] Q. Mei, M. Gül, and N. Shirzad-Ghaleroudkhani, "Towards Smart Cities: Crowdsensing-Based Monitoring of Transportation Infrastructure Using In-Traffic Vehicles," *Journal of Civil*

Structural Health Monitoring, vol. 10, no. 4, pp. 653–665, 2020, doi: 10.1007/s13349-020-00411-6.
[27] T. Yigitcanlar, K. Desouza, L. Butler, and F. Roozkhosh, "Contributions and Risks of Artificial Intelligence (AI) in Building Smarter Cities: Insights from a Systematic Review of the Literature," *Energies*, vol. 13, no. 6, p. 1473, 2020, doi: 10.3390/en13061473.