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ISSUES ON IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE (AI) IN INDONESIA CONSTRUCTION PROJECTS

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Abstract

Facing the acceleration of infrastructure development in the recent decade, the Indonesia Construction Industry keeps innovating by adopting technology. It is linear with the current development from Industry 4.0 to Society 5.0. The use of Artificial Intelligence (AI) to manage construction project works is a reflection of Society 5.0's requirements. This paper aims to discuss the supply and demand, awareness, commitment, policy, and also readiness level of human resources based on AI tools in construction projects. Several subfields of AI can be adopted, such as machine learning, knowledge-based systems, computer vision, robotics, natural language processing, automated planning and scheduling, and optimization. Machine learning is the most frequently used that can be applied to planning, construction, monitoring evaluation, and also operation maintenance. Aside from their benefits, AI subfields also have limitations in construction, such as machine learning from streaming data, dealing with high-dimensional data, scalability of models, and distributed computing. A critical review of the available literature is being compared with site surveys on construction projects related to AI applications such as activity monitoring, risk management, resource, and waste optimization. This study provides insights into key AI applications as they apply to construction-specific challenges, as well as the readiness to realize the benefit of AI in the construction industry. The goal of this research is to optimize issues in AI applications throughout the whole lifecycle of the actual complex project.

Keywords: Artificial Intelligence, AI applications, machine learning, construction industry, optimization

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INTRODUCTION

The transformation of construction projects from traditional to modern construction along with the use of information technology are the current trends. This is because effective and punctual analysis and tracking of labor activities is an important contribution to increasing productivity and safety on construction sites (Yang et al., 2019). Construction workers are facing high ergonomic risks that can harm their welfare and productivity. Therefore, it is important to assess ergonomic risks accurately. Observations, sensors, and depth cameras are the three main posture data collection methods, but they face the challenges of low accuracy, inconvenience, and unsuitability for outdoor environments (Yang et al., 2019). Research related to employee assessment by integrating technology and machine intelligence began 10 years ago, and several related studies (Antwi-Afari et al., 2020, 2022; T. Cheng et al., 2013a; Guo et al., 2017; Jebelli et al., 2018, 2019; Kurien et al., 2018; Luo et al., 2018a; Shakerian et al., 2021; Valero et al., 2017; X. Wang & Zhu, 2021) have been carried out.

Several studies related to employee assessment with the assistance of technology continue to develop. Generally, researchers try to utilize technology as a tool that makes it easier to monitor the performance of construction workers. Sensors, algorithms, and artificial intelligence are used to monitor worker activities throughout the day (Z. Yang et al., 2019a). In addition, the dynamic and complex work environment in construction projects means that workers' fatigue status tends to have a more serious impact on their performance compared to other sectors. A sustainable management of fatigue levels for construction workers is essential to improve safety management in projects (Xing et al., 2020).

Figure 1 showed an implementation of AI in the construction stage. Workers observation using sensor and camera to monitor worker's behaviour to evaluate the site layouts. Job-site layout provisions are made to put temporary site offices, heavy equipment locations, storage and workshop areas, access points and safety areas (Small & Baqer, 2016). Since construction workers will perform manual labor and repetitive activities, an assessment of the ever-changing activities and movements of workers is needed to measure individual productivity as input to improve their performance on construction projects (Cho, 2020). A manual productivity data collection was carried out using daily reports from monitoring project achievements. Every day, the quantity surveyor (QS) will observe the time, cost, and progress of the work to be evaluated using the work plan that has been prepared. Using this manual method will take time and there is also a possibility of high human error factor from QS in the field.

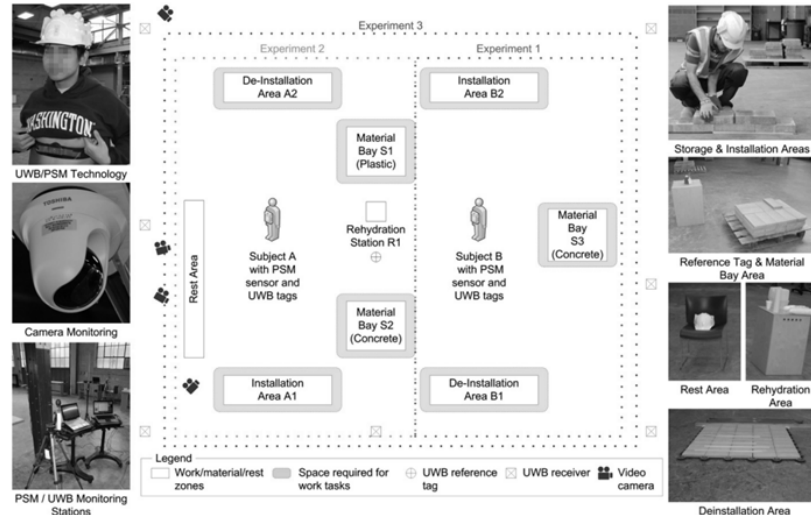


Figure 1: Examples of Worker Observations with the Use of Sensors and Use of Worker Behavior References

Source: (Wong, 2019)

Furthermore, algorithms for job classification can also be used to predict construction worker productivity. This assessment method utilizes a deep learning algorithm to classify time series data from worker inertia measurements (Jacobsen et al., 2023). However, the majority of construction workers' assessments with the help of information technology and machine intelligence lead to mitigation in reducing work accidents. Thus, the assessment of construction workers to increase productivity is rarely carried out. Several productivity assessments with the help of information technology and machine intelligence are carried out by assessing the activities of heavy equipment used on projects (Bai et al., 2021; Chen et al., 2020; Sabillon et al., 2020; D. Wang et al., 2022).

BACKGROUND PROBLEM

Based on the Government AI Readiness Index 2023, Indonesia is ranked 42nd out of 193 surveyed with a total score of 61,03 from 3 (three) evaluation dimensions, such as the government pillar, technology sector pillar, and data infrastructure pillar. This survey was developed based on government public sector performance. In the meantime, there has not been any evaluation regarding the performance of AI used at construction project sites in the construction sector. Several on site data showed that AI's implementation in the construction site start from planning until operation and maintenance. An example from the developed country, Virtual Reality (VR) has begun to be used to evaluate worker performance in construction projects. Documentation of worker movement shots

at the project location was then assessed for ergonomic risks which later became the input in developing the project layout (Wong, 2019). This was done to increase work efficiency so that unnecessary repetition of movements and effective distances in the project layout could be optimized. The urgency of using automated technology to assess the performance of construction workers is high, considering that development is increasing massively. This study provides insights into key AI applications as they apply to construction-specific challenges, as well as the readiness to realize the benefit of AI in the construction industry. The extensive adoption of AI is experiencing a rapid digital transformation in the construction industry. The goal of this research is to optimize issues in AI applications throughout the whole lifecycle of the actual complex project. This research outcome contributes to opportunities, challenges, and threats to implementing AI in Indonesia's construction industry.

LITERATURE

Figure 2 showed manual productivity data collection is done using daily reports of project achievement monitoring results. Every day the quantity surveyor (QS) will observe the achievement of time, cost, and work progress to be evaluated later with the work plan that has been prepared. The use of this manual method will take time and there is also a high human error factor from the QS in the field. The transformation of construction projects from traditional to intelligent construction and the use of information technology is a current trend. This is done because effective and timely analysis and tracking of labor activities is an important contribution to improving productivity and safety on construction sites (Yang et al., 2019).

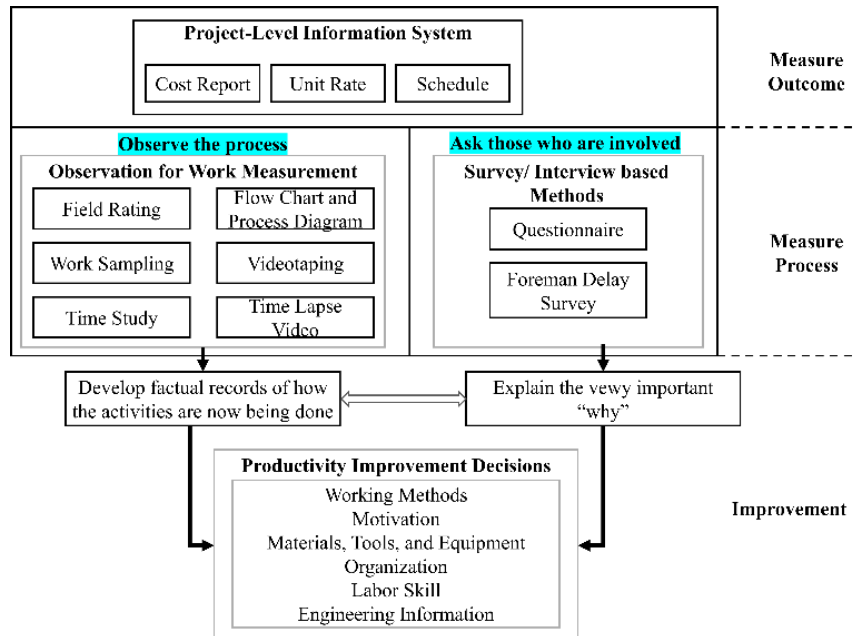


Figure 2 Traditional Productivity Data Collection Methods

Source: (de Araujo et al., 2021)

Studies on automatic models for recognizing construction worker movements were conducted using the Long Short-Term Memory (LSTM) network designed to learn sequential information. The LSTM network can recognize worker movements from motion sensor data by measuring the inherent inertia of each worker (Kinam Kim¹ and Yong K. Cho, 2021). Observing worker movements via Internet of Things (IoT)-based cameras is often linked to the need for Occupational Safety and Health management to be able to control worker ergonomics. The use of Smart Work Packaging (SWP) in construction HSE applications is usually carried out to monitor construction worker fatigue factors, which then create safety warnings (Li et al., 2021). In addition, the work safety monitoring model was also carried out by predicting the level of severity based on images and video clips determined through visual data of workers' body posture, use of personal protective equipment, workers' interactions with tools and materials, construction activities being carried out, and the presence of dangers in the surrounding workplace (Tang & Golparvar-Fard, 2021).

Construction labor requires heavy work which easily makes workers exhausted (Jiang et al., 2015). When they are exhausted, workers' ability to do physical work tends to decrease, along with their awareness of safety, which can trigger dangerous behavior that might lead to accidents. Therefore, fatigue is considered a negative factor in Occupational Safety and Health as one of the main causes of behavior in construction workers (Anwer et al., 2021). In the

construction industry, the lack of a comprehensive framework, standards, and independent task types to produce serial productivity estimation models is a challenge. The proposed model cannot be replicated for all types of projects and it requires time and effort to adapt to new project conditions (Sadatnya et al., 2023). When studied comprehensively, the successful prediction of models used in labor productivity must be supported by algorithmic learning from previous relevant research about the use of ML in construction project case studies (Adebowale & Agumba, 2021). The key success to use machine learning is the algorithms. Research from Ja'far, et.al (2021) identified the most selected algorithm used for cost prediction is Random Forest (RS) that has less error than others. Because the accurate cost estimation is a critical aspect of successful construction projects (Salleh, 2023).

Artificial intelligence, often called AI, is revolutionizing the manufacturing, retail, telecommunications, and construction industries. The construction industry faces many challenges which cause its productivity levels to be lower when compared to manufacturing (Abioye et al., 2021). The lack of digitalization and technology adoption in the construction industry is also associated with cost inefficiencies, project delays, poor quality performance, uninformed decision-making, and low productivity and work safety. AI is a significantly beneficial tool. With the help of algorithms, AI can help solve construction life cycle problems like showed in the Figure 3 (Oluleye et al., 2023). Recognition of various activities can used CCTV to monitor the worker productivity in the construction site.

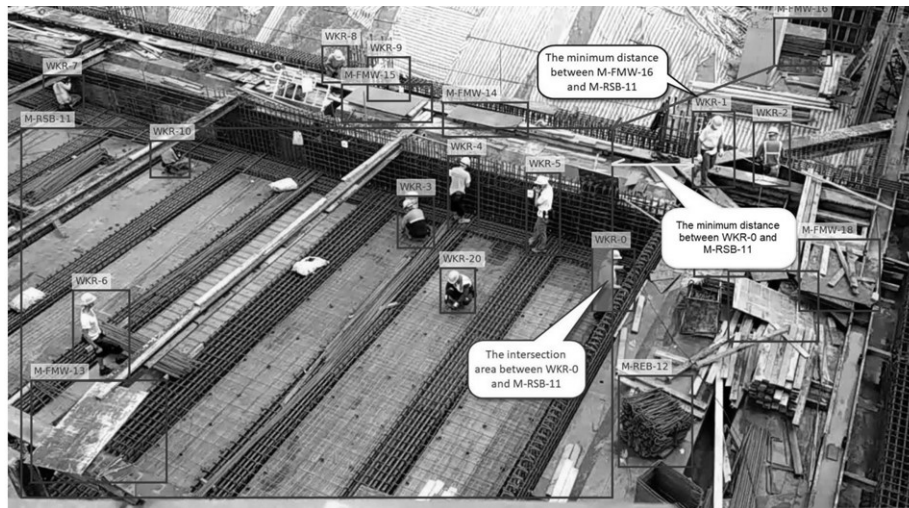


Figure 3: Recognition of Various Activities in Construction Projects via Object Relevance Networks Using Convolutional Neural Networks

Source: (Luo et al., 2018)

In the context of Industry 4.0, the construction industry continues to innovate towards digitalization and intelligence to realize major improvements in automation, productivity, and reliability (Zhang et al., 2021). The emergence of AI will certainly have implications for social, ethical, policy, legal, and even human resources. Apart from the need for digitalization to speed up construction work, it was revealed that the use of AI also poses a risk to the transition from using manual workers to technology. Even in developed countries, the risk of automation in reducing manual workers reaches 51-52% (Nazareno & Schiff, 2021).

RESEARCH METHODOLOGY

This research used a questionnaire to evaluate the construction project readiness levels. The variable was constructed based on the pillars of the government AI Readiness Index and the Construction Industry 4.0 Readiness Index (CI4.ORI). There are three pillars related to the government AI Readiness Index, namely the technology sector, data, and infrastructure. Meanwhile, in CI4.ORI, there are five pillars used to assess the level of readiness to implement Industry 4.0 in the construction industry, which are management and organization, human resources and culture, products and services, technology, and onsite and offsite operations. Both the Government AI Readiness Index and Construction Industry Readiness Index 4.0 (CI4.ORI) determined the research variables. Subsequently, those pillars were combined with an updated implementation in the construction project. The detailed variable is shown in Table 3 along with the research results.

Each of the indicators was evaluated using four scale levels related to the readiness level. Research data was collected through an online questionnaire using Google Forms. The pilot survey was designed before the distribution of the main questionnaire. The respondents were contractors, consultants, and stakeholders related to the construction industry. In total, 75 samples contributed to this research. The respondent has at least 5 (five) years of working experience in the construction industry. The basic questions of this questionnaire asked about the company's level of readiness in implementing AI, which included 43 questions using a level scale from 0 to 4, which ranges from whether they are ready or not to whether it has been implemented already.

The result of the evaluation phase was later verified using the Spider Web Method. The Spider Web method was developed by Bernstein in 1986 as a qualitative technique in the field of management to produce decision-making. In general, spider web methods tend to adopt a four-stage process:

- 1) Problem recognition;
- 2) Strategy development;
- 3) Execution of action plans; and
- 4) Implementation.

The Spider Web diagram was used to map the results of the readiness level of construction industry players based on the average value of each pillar. Based on the average value, the results of the overall readiness level of each pillar were divided into five categories, with level 0 indicating unreadiness and level 4 indicating complete implementation. Those five pillars were broken down into indicators and sub-indicators (see Table 1).

Table 1: Level Scale

Index	Level		Description
$0,0 < \text{Mean} \leq 0,8$	Level 0	Not Ready	Not supported yet
$0,8 < \text{Mean} \leq 1,6$	Level 1	Early Readiness	Have a plan to transform to Industry 4.0
$1,6 < \text{Mean} \leq 2,4$	Level 2	Medium Readiness	Start transforming to Industry 4.0
$2,4 < \text{Mean} \leq 3,2$	Level 3	Ready	Transformed to Industry 4.0
$3,2 < \text{Mean} \leq 4,0$	Level 4	Already Applied	Already implemented all Industry 4.0

RESULTS AND DISCUSSION

Society 5.0 requires three main abilities such as creativity, critical thinking, communication, and collaboration (Yulianto, 2021). The adoption of Society 5.0 has several rules in the construction industry:

- 1) Creativity in the construction industry is actualized through various innovations in project implementation such as methods, equipment, and increased productivity.
- 2) The use of intelligent technology with the concept of Machine Learning and Deep Learning in the implementation of the project continues to develop as a reflection of critical thinking in the construction industry.
- 3) Using Building Information Modelling as a tool for communication and collaboration between project parties is one of the steps of readiness level construction industry for Society 5.0.

The literature review showed that there are 4 (four) types of AI used in the construction industry, such as machine learning, Building Information Modelling (BIM), computer applications, and statistics. Machine learning is frequently used to detect and classify human activities using wearable inertial measurement units (IMUs). An algorithm is needed to determine the object and it can also be used for direct assessment tools. As for BIM, it is frequently used for drawing and calculating construction objects and it needs software to translate into industry foundation classes (IFC) format. Recently, BIM has been used to assess cost and time in construction projects. While machine learning started to be used as an assessment tool at the beginning of 2018 to identify activity recognition that connects to productivity analysis, BIM was used in advance of machine learning but it focused more on drawing and estimating. Based on the recent condition of a construction project, manual assessment is not

recommended because it cannot show the comprehensive and tracking results of the worker's assessment.

The construction industry in most countries accounts for the highest share of employment. Indonesia, as a developing country, has approximately 203,403 construction companies, from small to large scale. Data for 2020 states that the number of construction workers in Indonesia reached 1,133,290 people (BPS, 2021). The average growth trend in the construction sector workforce is 2.38%, so it is projected that in 2023, the construction sector can absorb 8,769,798 workers. The large number of workers and high labor wages cause labor costs in construction projects to be large. Additionally, project delays due to lost labor productivity can result in additional costs. Therefore, human resource management is necessary to increase worker productivity in construction projects (Gurmu & Ongkowijoyo, 2020). Based on (Risnu et al., 2016), two stages in construction projects have been carried out with the assistance of AI, namely the planning and execution stages.

Table 2: AI Implementation in Construction Projects.

Planning Phase	AI Implementation	Execution Phase	AI Implementation
Design Planning	PMCS Tools: Cost Estimating	Quality Control	CAE: Structural Modeling
	Billing & Payment System Tools		PMCS Tools: Scheduling
Engineering Design	PMCS Tools: Cost Estimating Billing & Payment System Tools		
Risk Planning	PMCS Tools: Cost Estimating Billing & Payment System Tools		

Several AI implementations have been performed in construction projects. Survey technology that implements AI is often found in construction projects. Generally, AI is implemented to speed up surveys, especially for hard-to-reach project locations. Based on the results of the questionnaire evaluation, it was found that the technology infrastructure variable is in the first place with a value of 3.301. This shows that the technology infrastructure has been implemented comprehensively in construction projects. The human resource development variable, the level of BIM implementation, and the AI implementation policy came after technology infrastructure, respectively. It was revealed that these variables were ready but had not been implemented comprehensively. The last variable, the AI implementation policy, was carried out through the construction and post-construction stages, which were categorized as the planning stage of transformation in the construction industry.

This is a common concern because the evaluation results revealed that the policy and preparation of technology infrastructure have led to the implementation of AI in the construction industry but have not been able to be fully applied yet in construction projects.

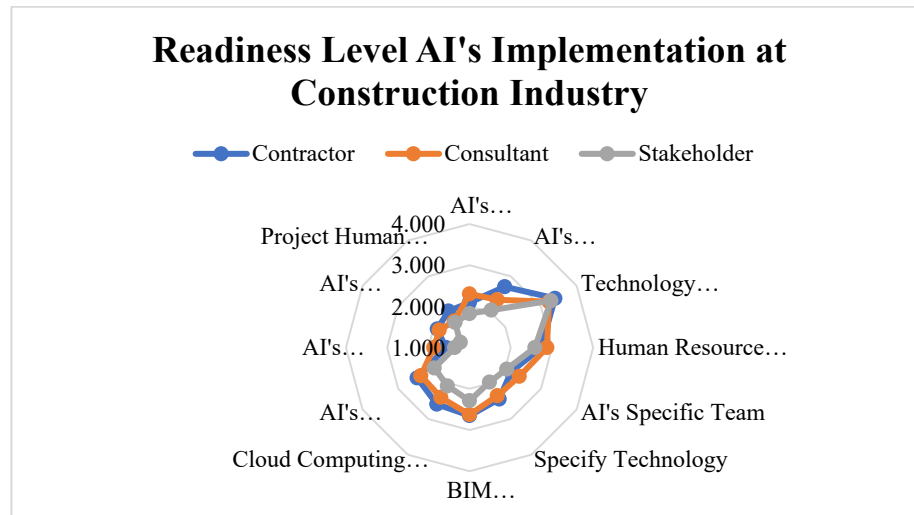


Figure 4: Readiness Level of AI's Implementation at Construction Industry

One of the obstacles faced by construction projects is the ability of the human resources in the project. This can be seen from the results of the questionnaire evaluation, which showed a value of 1.824. The human resource development policy has been implemented to help improve the skills of construction workers through training and certification, although this has not been done comprehensively. The implementation of AI in construction projects is still carried out at the pre-construction stage, where AI is used for survey, investigation, design, and prediction activities. Meanwhile, the party that is more advanced in implementing AI is the contractor with an average value of 2.396, while the consultant is 2.361. Referring to the evaluation of the Spider Web method, both contractors and consultants are still in the medium readiness stage, which is still in the early stage of implementing AI on construction projects. The detailed result is shown in Table 3.

Table 3: Indicator Variable for AI's Implementation in the Construction Project

Code	Dimension	Indicator	Result
A1	Government Policy Pillars		2.092
A2.1	AI's Implementation Vision	Availability of strategic plan documents	2.342
A2.2	AI's Implementation	Data security protection policy	2.461
A2.3	Policy	Data storage procurement policy	2.461

Code	Dimension	Indicator	Result
A2.4	Technology Infrastructure	Data formatting input quality policy	2.421
A2.5		Data outline policy	2.526
A2.6		Data accountability policy	2.026
A3.1		Specific budgeting policy for AI implementation	3.145
A3.2		Hardware (Computer, VR, Laser Scan, Drone, etc.)	3.289
A3.2		Software (BIM Software, CAD, Project Management Software, Coding Software)	3.303
A3.3	Human Resources Competency Improvement	Cloud Computing	3.539
A4.1		Connectivity (WiFi, Router, LAN)	2.789
A4.2		Digital training (BIM, AI, Machine Learning)	2.737
A5.1		Certification (Drone Pilot, BIM, Data Analyst)	2.250
A5.2		Ethics Team (Data privacy, Data security)	2.211
B.1.1		Development Team (UI/UX Designer, Product Manager)	2.605
B.1.2	Construction Project Pillars		
B.1.3	Specific Technology	BIM (3D, 4D, 5D, 6D)	2.474
B.1.4		Internet Of Things (IoT)	1.684
B.2.1		Cloud Computing	2.579
B.2.2		Artificial Intelligence (AI) & Machine Learning (ML)	2.618
B.2.3		Pre-Construction Phase (Planning and Design)	2.421
B.3.1		Construction Implementation Phase	2.461
B.3.2	BIM Implementation Level	Post Construction Phase (Evaluation and Monitoring)	2.276
B.3.3	Cloud Computing Collaboration	Data storage	2.368
B.4.1		Data analysis	1.987
B.4.2		Collaboration between teams	2.737
B.4.3	Pre-Construction Phase AI Implementation	Tenders and contracts	2.447
B.4.4		Use of drones for field surveys	2.224
B.4.5		Use of lidar for field surveys	2.342
B.4.6		Project delay prediction	2.171
B.4.7		Project cost estimation	2.171
B.5.1		Material procurement	1.526
B.5.2	AI Implementation Construction Phase	Risk management	1.658
B.5.3		Utilization of AI for monitoring PPE discipline	1.566
B.5.4		Use of sensors in projects	1.684
B.5.5		Utilizing AI for construction worker productivity monitoring	1.592
B.5.6		Leveraging AI for heavy equipment monitoring	1.803

Code	Dimension	Indicator	Result
B.5.7	Implementation of AI in the Post-Construction Stage	Utilizing AI for construction material monitoring	1.711
B.6.1		Utilizing AI for field condition monitoring	1.605
B.6.2		Utilizing AI to Accelerate Work	1.829
B.6.3		Utilizing AI for cross-checking work handovers	1.711
B.7.1		Utilization of AI for building energy sensors (lights, AC, water flow)	1.895
B.7.2	Project HR Capability	Leveraging AI for maintenance	1.763
A1		Data Analyst Expertise Certification	2.461
A2.1		Coding and Algorithm Skills	2.461

Source: Research Result, 2024

One of the biggest challenges in implementing AI in construction projects is budget. The use of cutting-edge technology is inseparable from the increase in budget in its implementation. Implementing AI requires quite a large initial funding. However, if it can be implemented, AI will be a catalyst for every job in the construction project. This hinders the implementation of AI in construction projects, especially if it is applied in medium-scale projects. Medium-scale projects can be risky, which is why contractors and consultants must think twice if they want to add an AI implementation budget to their projects. Contractors will prefer to use manual methods rather than automating their projects. In addition, human resource capability in applying AI is still limited. Not many of them in construction projects can process coding algorithms or perform data analysis processing because this field is not the main focus of civil engineering. As a consequence, civil engineers will need to relearn programming languages or coding to be able to implement AI in construction projects. The research outcome also can used by government to plan the construction industry vision for 2025-2030 that can improve the lowest indicator to be a mature AI's implementation in Indonesia.

CONCLUSION

The results of this study revealed that the implementation of AI in construction projects in Indonesia is still in the medium readiness stage. This is reflected in the readiness of parties involved in construction projects, such as contractors, consultants, and stakeholders in the field of public works, who are still in the process of preparing for the implementation of AI into construction projects. The technological infrastructures used in construction projects are quite up-to-date, including hardware, software, cloud computing, and connectivity, but the human resources that support them are still insufficient. In addition, government policies to improve the implementation of AI have been reflected in the policies that have been prepared along with the skills improvement programs provided. However,

internal project funding has not been able to improve the ability to process data automatically in construction projects. Automation of construction work is still limited to large-scale infrastructure projects and national strategic projects. The limitations of the civil engineering field in studying algorithmic materials and programming languages are also an obstacle to the unpreparedness of the application of AI in construction projects. This study only focused on evaluation of AI's implementation in Indonesia with government policy and construction site pillars, the future research can be enhanced to discuss related to human resource readiness level for understand AI's implementation in construction. Comparing the development country for evaluation also another opportunity for the future research.

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