Kalpa Publications in Computing
Volume 22, 2025, Pages 453–463
Proceedings of The Sixth International Conference on Civil and Building Engineering Informatics

Assessment of Automation Potential for On-Site Construction Tasks

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Abstract

In the context of "machine substitution", advanced automation technologies, such as construction robots, are anticipated to mitigate future labor shortages in the construction industry. However, the feasibility and urgency of automating various construction tasks vary significantly, indicating that not all tasks are suitable for automation. This study focuses on construction task attributes and proposes a method for assessing the automation potential of construction tasks. By comparing and analyzing 45 key construction tasks in terms of safety and technology dimensions, it is found that: decoration and furnishing construction tasks have a higher potential for automation than the main structure construction tasks; the rebar cage welding task has the lowest potential for automation and the floor skimming task has the highest automation potential; curtain wall installer has the highest automation potential, followed by painter. This study would provide valuable insights for investment decisions in construction robots and the future strategic allocation of construction tasks between human workers and robots.

1 Introduction

The construction industry is facing severe low productivity and skilled labor shortages [1,2]. Automation technologies such as construction robotics are expected to be an effective means of increasing productivity and improving safety and health in the construction industry [3-5]. However, the adoption of robotics in the construction industry is not optimistic, especially in on-site construction [6]. ABB's global survey results show that only 55% of construction companies use robots, much lower than the 84% in the automotive industry and 79% in the manufacturing industry [5]. One of the main reasons is that construction activities are complex, decentralized, highly nonlinear, and unpredictable, compared with the streamlined, standardized, and forward-lagging production of other industries [7]. Therefore, not all construction tasks can be and are suitable for automation. Only with a full understanding of the construction task and a determination of whether construction robots are of sufficient value will cost-sensitive construction companies be willing to invest in and adopt construction robots [8]. Similarly, it is more profitable for construction robot manufacturers to analyze the needs of

I. Hkust, J. Cheng and Y. Yantao (eds.), ICCBEI 2025 (Kalpa Publications in Computing, vol. 22), pp. 453–463

construction companies and develop construction robots with more market potential.

There are existing studies that assess the risk of automation and the degree of replacement of workers from a competency perspective. Paolillo, et al. [9] calculated the risk of automation for nearly 1,000 existing occupations by quantitatively assessing the extent to which robotics and AI capabilities could replace the human capabilities required for these jobs. Ma, et al. [7] determined the degree to which construction robots can replace construction workers by analyzing four competency dimensions: perceptual, analytical, decision-making, and executive skills. However, the comparison of robot and human capabilities ignores the fact that robots may far outperform workers in specific tasks in the future. Additionally, using occupation as a level of assessment is not suitable for construction robots. Because a type of workers may perform multiple tasks, whereas the currently prevalent construction robots are often single-task. Malik and Bilberg [10] identified the automation potential of a gear assembly task based on the physical characteristics of the part and its task description. However, their method is clearly not applicable to construction tasks.

On this basis, the aim of this study is to propose a model for evaluating the automation potential of construction tasks based on the construction task characterization perspective and to explore the automation potential of key construction tasks with a view to providing useful insights for the development of construction robots.

2 Methodology

2.1 Research Framework

The purpose of this study is to analyze construction task characteristics, quantify construction task automation potential, and rank automation priorities for construction tasks. In this study, automation potential refers to the extent to which a task or an activity can be performed or replaced by automated technologies, mainly construction robots. First, this study constructs a model for assessing the automation potential of construction tasks from the safety dimension and the technology dimension. The safety dimension reflects the urgency of these tasks to be robotized in terms of two metrics: ergonomic risk and safety risk. The technology dimension reflects the feasibility of construction tasks being robotized from two perspectives: complexity and environmental difficulty. Then, the proposed model is utilized to assess the automation potential of 45 key on-site construction tasks. Based on the evaluation results, recommendations are provided for research and development decisions of construction robot manufacturers and investment decisions of construction contractors.

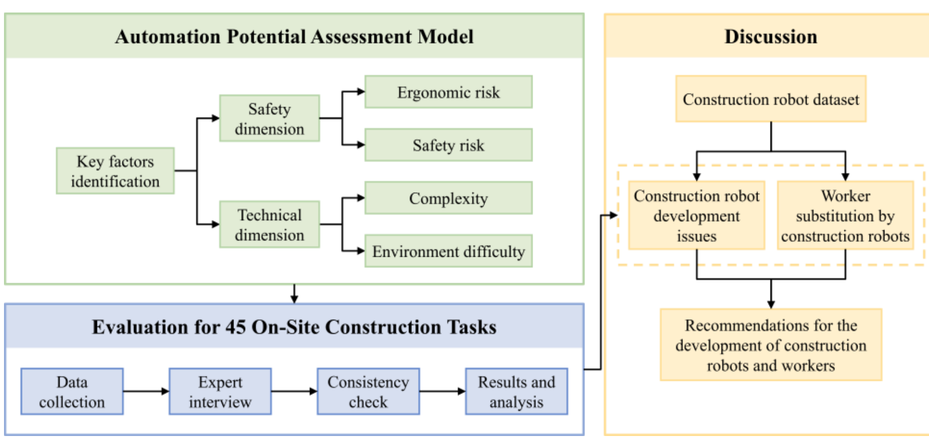

Figure 1: Research Framework

2.2 Automation Potential Assessment Model

(1) Ergonomic Risk

Construction workers, who often perform long, repetitive, and physically demanding manual tasks in the workplace, are exposed to significant ergonomic risks [11]. The current ergonomic assessment methods can be categorized into manual assessment (e.g., self-reporting and systematic observation) and automated assessment using intelligent devices (e.g., computer vision, wearable sensors, and multimodal fusion-based methods) [12,13]. Expert observation and quantification using ergonomic scales is the most widely recognized and proven technique for assessing ergonomic risk. This study utilizes the Rapid Entire Body Assessment (REBA) to assess the ergonomic risk of construction workers performing various construction tasks. The assessment should contain at least one complete action cycle when videoed or observed on-site. After fully understanding the REBA method, each expert selects multiple representative postures from the videos of the construction tasks for ergonomic risk assessment. The maximum of all posture scores is selected as the result of one expert's assessment for a construction task.

(2) Safety Risk

According to ABB's report, the most important anticipated advantages that construction robots will provide are bettering the working environment for workers to prevent them from engaging in risky tasks and enhancing their safety and health [5]. This study uses the British Standards Institution's risk matrix, which divides construction tasks into three risk levels by combining the likelihood of injury with its potential severity [14]. Based on the difference in research objectives, different risk types have different criteria. Tables 1 and 2 present the assessment criteria for this study, which focuses on the safety risk that workers face while completing each construction task [15].

Assignment	Rating category	Description
1	Insignificant	No loss of working hours and requiring first aid
2	Minor	No loss of working days, requiring outpatient treatment without a lasting impact and requiring first aid
3	Moderate	Minor injury, requiring inpatient treatment
4	Major	Major injury, requiring long-term treatment and therapy, occupational disease
5	Catastrophic	Death, permanent total disability

Table 1: Assessment criteria for severity of consequences [15]

Assignment	Rating category	Description
1	Rare	Hardly ever
2	Unlikely	Remote (once a year), only in abnormal conditions
3	Possible	Occasional (a few events in a year)
4	Likely	Frequent (monthly)
5	Almost certain	Very frequent (once a week, every day), under normal working conditions

Table 2: Assessment criteria for the possibility [15]

Likelihood multiplied by severity	Risk level	Score
1-6	Low	0
8-15	Medium	0.5
16-25	High	1

Table 3: Safety risk scoring criteria

(3) Complexity

Highly complex tasks have high uncertainty and failure probability [16]. More advanced perceptual and manipulative control are needed for intricate coordinated movements, precise grasping, or hand control, which may not be compatible with the current state of robotic autonomy. [17]. In addition, increased task complexity requires robots to have more skills [18]. Whereas, current popular single-task robots have limited skills, which makes it difficult to solve high-complexity tasks. Although multi-robot systems can simplify a task overall, the programming effort required can be greatly increased due to their requirement for precise coordination and teamwork [18]. The complexity assessment equations for construction tasks oriented to human-robot collaboration are suggested based on the information entropy theory and complexity models in previous studies.

An action primitive library for construction robots is constructed by analyzing the action primitives, motion primitives, and therbligs proposed in the recent literature related to construction and manufacturing tasks and robots. Based on the action primitive, this study measures the action scale of construction tasks by analyzing the number of action primitives that can add value to each construction task [19]. Equation (1) shows the method for calculating the scale of construction tasks.

$$H(x) = \ln A \tag{1}$$

Where $H(x)$ is the action scale of the construction activity, and x is the construction activity analyzed, A is the number of action primitives.

Due to their specialized end-effectors, construction robots are less able to adapt to various situations and objects [20]. But it is easier for them to manage standardized materials with pre-programming [21]. For fragile or highly sensitive materials, robots require precise force control or specialized end-effectors capable of evenly distributing pressure. In addition, Furthermore, different construction tasks demand varying levels of precision, with complexity influenced by factors such as configuration, accuracy, and other specific task requirements [18]. Therefore, task difficulty is assessed from the degree of standardization and sensitivity of construction materials, and placement or connection requirements of the process (as shown in Table 4).

Category	Indicator	Attribute	Score
Material	Degree of standardization	Standardized	0
		Semi-standardized	0.5
		Non-standardized	1
	Sensitivity	Robust	0
		Damage at high force	0.25
		Damage in light force	0.75
		Highly sensitive	1
Process	Placement or connection requirements	Not required	0
		Release of an object at a known predefined position, but the final orientation of the object is not required	0.25
		Placed in a predefined position with a fixed orientation	0.75
		Placed in a predefined position with a fixed orientation and required to be aligned with existing objects	1

Table 4: Task difficulty scoring criteria

The equation for calculating the material difficulty of a construction activity is:

$$O(x) = \frac{\sum_1^M \sum_1^N O_{m,n}}{MN} \tag{2}$$

Where $O(x)$ is the material difficulty of the construction activity x, and $O_{m,n}$ denotes the value of the n-th material attribute of the m-th material in the construction task, M is the total number of materials involved in the construction task, and N is the total number of material attributes evaluated.

The process difficulty is calculated as:

$$P(x) = \frac{\sum_1^L \sum_1^K P_{l,k}}{LK} \tag{3}$$

Where $P(x)$ is the process difficulty of the construction activity, $P_{l,k}$ denotes the value of the k-th process attribute at the l-th step of the construction task, L is the number of processes included in the construction task, and K is the total number of process attributes evaluated.

The difficulty of the construction task x is then a weighted average of the material difficulty and the process difficulty:

$$K(x) = \frac{O(x)\sum_1^M \sum_1^N O_{m,n} + P(x)\sum_1^L \sum_1^K P_{l,k}}{\sum_1^M \sum_1^N O_{m,n} + \sum_1^L \sum_1^K P_{l,k}} \tag{4}$$

Construction activities are quasi-repetitive. For example, each brick on the same brick wall is in a different location but in the same orientation, whereas each concrete molding installed may be in a different orientation and location. This necessitates the parametrization of motions which increases the difficulties to explore solutions through methods like reinforcement learning [22]. Therefore, the diversity is assessed by counting the number of features that can lead to internal differences in construction activities, such as orientation, location, and material types (as shown in Equation 5).

$$D(x) = -p \cdot \ln p \tag{5}$$

Among them $p = \frac{1}{q}$, q is the number of difference characteristics of the construction task.

Then the complexity is calculated by the formula:

$$C(x) = K(x)(1 + D(x))H(x) \tag{6}$$

(4) Environment Difficulty

Construction robots frequently interact with their surrounding environment. As the complexity of the environment increases, the robot's level of autonomy decreases, which can consequently impact its overall performance [23]. In this study, the construction environment difficulty is evaluated in terms of two dimensions: lighting and ground conditions. The environmental difficulty score was the average of the lighting score and the ground condition score.

Category	Attribute	Score
Lighting	Poor	0
	Good	1
Ground condition	Poor	0
	Good	1

Table 5: Environment difficulty scoring criteria

(5) Automation Potential Score

The four metrics were normalized using the Min-Max Normalization method and summed to obtain the automation potential score for each construction task.

3 Evaluation of Automation Potential for On-Site Construction Tasks

3.1 Data Collection

Through conducting interviews with experts with rich working experience in on-site construction, this study identifies 45 key construction tasks based on importance, repetition, duration, and frequency of occurrence. The 45 construction tasks extracted were relatively comprehensive, covering two scenarios and eight types of work. Two experts in the field of construction were invited to evaluate the ergonomic risks, and two mid-level engineers from construction companies with many years of experience were invited to evaluate the environmental difficulties of each construction task, respectively. The complexity is evaluated based on the proposed action primitive library and information entropy model. The results of the two experts and two engineers were each tested for consistency and their average scores were taken as the final score.

Scenario	Construction task	Abbreviation	Construction task	Abbreviation
Main Structure	Concrete Floor Pouring	CFP	ALC Wall Panel Installation	AWPI
	Concrete Floor Leveling	CFL	ALC Wall Panel Fixing	AWPF
	Concrete Floor Smoothing	CFS	ALC Wall Panel Interconnection	AWPIT
	Concrete Floor Troweling	CFT	Vertical Rebar Installation	VRI
	Concrete Floor Grinding	CFG	Vertical Rebar Welding	VRW
	Concrete Floor Cutting	CFCT	Rebar Cage Welding	RCW
	Concrete Wall Grinding	CWG	Rebar Cage Tying	RCT
	Concrete Wall Cutting	CWC	Slab Rebar Tying	SRT
	Concrete Ceiling Grinding	CCG	Concrete Formwork Installation	CFIS
	Brick Wall Masonry	BWM	Concrete Formwork Connection	CFCN
Decoration and Finishing	Wall Spraying	WSP	Wall Tiling	WT
	Wall Rolling	WR	Roof Tile Laying	RTL
	Wall Grinding	WSD	Glass Curtain Wall Installation	GCWI
	Wall Wallpapering	WW	Glass Curtain Wall Connection	GCWC
	Ceiling Spraying	CSP	Ceiling Frame Installation	CFI
	Ceiling Rolling	CR	Ceiling Frame Connection	CFC
	Ceiling Grinding	CS	Ceiling Gypsum Board Installation	CGBI
	Floor Spraying	FSP	Ceiling Gypsum Board Connection	CGBC
	Floor Skimming	FSK	Wall Frame Installation	WFI
	Floor Rolling	FR	Wall Frame Connection	WFC
	Wall Plastering	WP	Wall Gypsum Board Installation	WGBI
	Ceiling Plastering	CP	Wall Gypsum Board Connection	WGBC
	Floor Tiling	FT		

Table 6: 45 key construction tasks in on-site construction

3.2 Results and Analysis

(1) Comparison of Automation Potential for Decoration and Furnishing and Main Structure Construction Tasks

The average automation potential for the decoration and furnishing tasks was 2.3080, while the average value for the main structure construction was below 1.8857, which is lower than the average automation potential of 2.1203 for the 45 construction tasks. The main reason may be that the decoration and furnishing tasks are usually indoor, with the floors having been leveled and hardened. Moreover, the main structure construction tasks are usually outdoors at night, relying on searchlights on tower cranes that are far away from the workers and have poor lighting conditions. Decoration and furnishing tasks, on the other hand, can utilize temporary lighting systems indoors to ensure adequate lighting of the work area.

(2) Differences in Automation Potential Across Construction Tasks

The construction task with the highest potential for automation is floor skimming, at 2.8954. It is technically feasible because the construction steps and objects are simple, single, and performed indoors. It also has a high ergonomic risk due to the fact that the worker has to crouch on the floor and swing his arms considerably, with an unstable center of gravity of the body. Next is the connection and installation of glass curtain walls. Because they need the workers to work outdoors or even at height, and glass curtain walls are usually heavy leading to workers' high ergonomic and safety risks. Robots, on the other hand, are very good at solving such problems. A wide range of curtain wall installation robots such as the Hephaestus are already available. The lowest potential for automation is for rebar cage welding at 0.9964, followed by vertical rebar installation at 1.0199. Although welding robotic arms have been very well developed in industry, when fabricating steel cages at construction sites, the ground is usually not hardened and is still a dirt floor that is not easy for robots to walk around. Floor tiling has the third lowest automation potential. Tiling is a complex task that involves not only two easily damaged materials, ceramic tile, and mortar, but also a number of actions, including picking up a tile, taking adhesive, applying adhesive, positioning the tile, apply pressure to the tiles.

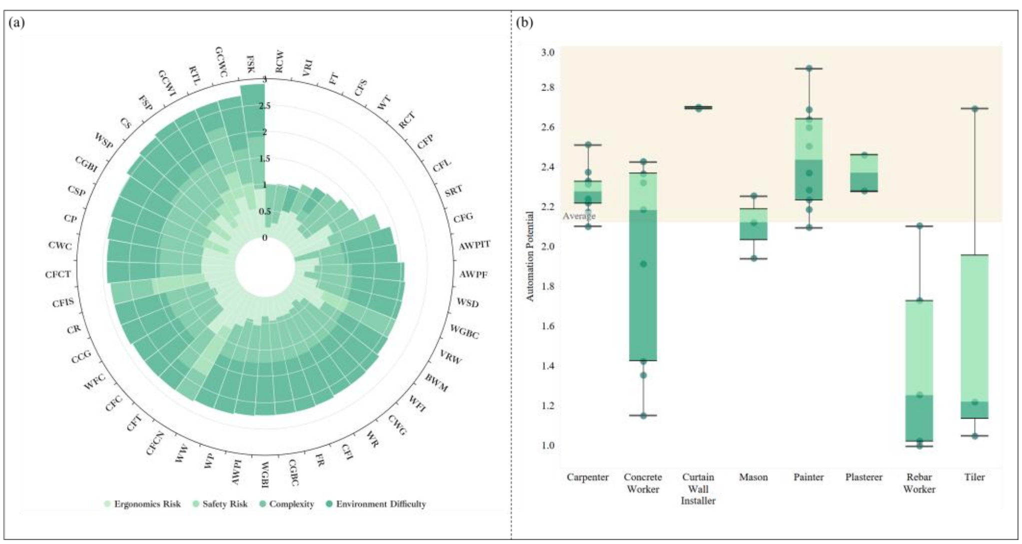

Figure 2: Results of automation potential assessment (a) automation potential for each construction task (b) automation potential for each construction worker type

(3) Differences in Automation Potential by Construction Worker Types

The type of construction worker most likely to be replaced by robots and with the highest potential for automation is the curtain wall installer with a mean of 2.6964, followed by the painter with a mean of 2.4353. Most of the construction tasks undertaken by the carpenter, painter, and plasterer have higher than average automation potential. Concrete workers, masons, rebar workers, and tilers are responsible for construction tasks that vary widely in automation potential. Especially for tilers, the difference between tile laying and floor tiling is 1.6475.

4 Discussion

4.1 Construction Robotics Companies Prefer to Develop Robots with High Technical Feasibility

101 construction robots that can be applied to on-site construction in China currently available on the market are collected and they are matched with 45 construction tasks and 8 construction worker types. Scatter plots are drawn based on the safety index (sum of ergonomics score and safety risk score) and technology index (sum of complexity score and environmental difficulty score) of the construction tasks (as shown in Figure 3a). The automation potential was categorized into four quadrants using the mean values of the technology index and safety index as boundaries: quadrant I (high urgency, high feasibility), quadrant II (low urgency, high feasibility), quadrant III (low urgency, low feasibility) and quadrant IV (high urgency, low feasibility).

Overall, the development of construction robots is on a reasonable path, taking into account both urgency and feasibility. 58.6207% of highly feasible construction tasks and 55.0000% of highly urgent construction tasks are already being progressively automated with robots. Quadrant II has the highest number of robotic products at 53, accounting for 52.4752%. On the contrary, quadrant III has the lowest number of robots, at only 11.8812%. Only half of the construction tasks in quadrant IV are starting to be substituted by robots. This is consistent with the results of our enterprise survey, i.e., enterprises are more inclined to develop construction robots whose necessary hardware and software have been mature in order to capture the market for construction robots and obtain policy incentives.

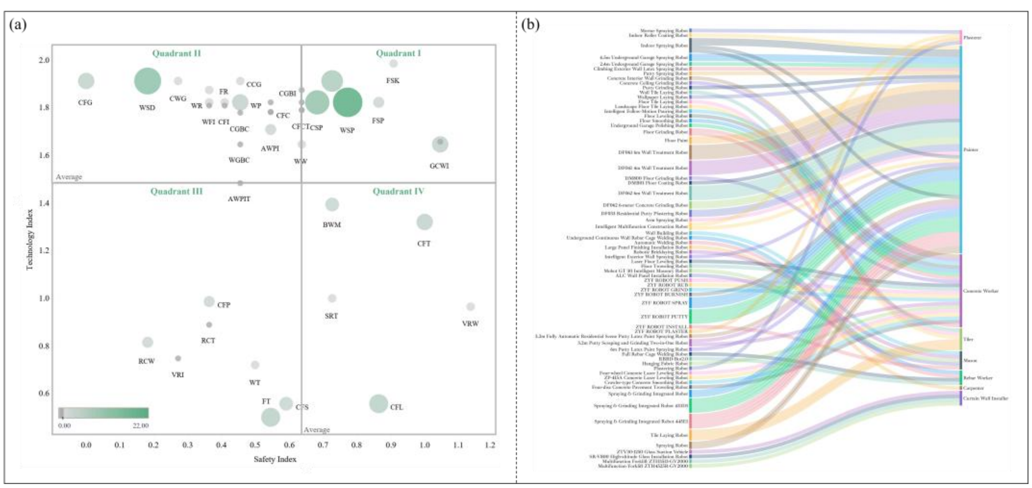

Figure 3: Current development of construction robots in China (a) distribution of construction robot products in 4 quadrants (b) mapping of construction robot products to construction worker types

4.2 Painters Are the Jobs Most Likely to Be Replaced by Robots

Figure 3b shows the current status of “machine substitution” for various types of construction workers. The highest potential for replacement by construction robots is for painters. Construction robots can currently spray paint and putty and other coatings on columns, walls, floors, and ceilings. The concrete worker ranks second. Nowadays, construction workers and robots can collaborate easily when constructing concrete floors by using a group of robots that can pour concrete, level floors, smooth floors, and polish underground garages. The carpenter is the hardest of the eight worker types to replace. Only a small number of companies are currently developing large panel finishing installation robots. Therefore, it is recommended that when training new workers, construction companies should, not only gradually develop workers’ skills in using automated tools such as robots, but purposefully train for worker types that are more difficult to replace by automation and have a larger labor gap in the future.

5 Conclusions

There is a trend towards the gradual automation of construction tasks. Ranking the automation potential of construction tasks can, to a certain extent, guide the development of automation technologies such as construction robots and predict labor changes on construction sites. To fill the gap in current research, this study proposes a model for assessing the automation potential of construction tasks and evaluates the automation potential of 45 key construction tasks. This study analyzes from three dimensions: construction scenario, task type, and worker type, and draws the following conclusions: the automation potential of decoration and finishing tasks is higher than that of main structure construction tasks; the automation potential of rebar cage welding is the lowest, and the automation potential of floor skimming is the highest; and the automation potential of curtain wall installers is the highest, followed by painters. Combining the results with the construction robot products currently available in the Chinese market, the analysis found that: the current development of robots in the construction field takes both urgency and feasibility into account, but robot manufacturers prefer to develop products with high technological feasibility; painters are the worker type most likely to be replaced by robots. This study not only provides suggestions for the development of construction robots but also serves as a basis for human-robot task allocation in the construction field.

Acknowledgments

This study was supported by the National Natural Science Foundation of China (Grant No. 72471039 and 72201229), the Humanities and Social Science Fund of Ministry of Education of China (Grant No. 24YJA630064), the Natural Science Foundation of Chongqing (Grant No. CSTB2022NSCQ-MSX1622), and the Research Grants Council of the Hong Kong Special Administrative Region, China (Grant No. 25211722).

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