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Analysis and Evaluation of Construction Worker Competencies of Kathmandu Valley

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Abstract

In addition to practical abilities, construction workers also need additional socioemotional, cognitive, and technological skills to do their jobs well as literature suggests. Therefore, a study of construction industry professionals in the Kathmandu Valley is conducted for the unskilled and skilled categories of workers respectively and 6 and 15 sets of competencies were identified. For unskilled workers, these qualities are listening, health/physical strength as essential and attitude, aptitude speaking skills and resilience as desirable competencies; for skilled workers, technical skills, working experience, confidence, and problem-solving abilities as essential and memory, writing skills, reading skills, mathematical skills and motivations as desirable competencies. Then, using these identified competencies, a support vector machine model was fitted and trained to assess the overall competency of skilled construction workers. The case study demonstrates that the support vector machine evaluation model has good accuracy and can consistently identify skilled construction workers (carpenter, bartender, and meson) with excellent efficiency with predicting score of 0.93 for Barbendor, 0.92 for carpenter and 0.96 for masonry workers.

Keywords

Support Vector Machine, Competencies, Resilience, Aptitude

1. Introduction

Construction Industry is world one of the oldest industry as we can observe ample historically renowned structures such as Pyramid of Giza, Taj Mahal, Changunarayan temple, Krishna Temple of Patan and various other have paved our way until today all only possible due to human effort. The size and scope of development increased as more people moved into urban areas. Humans created ever-more-advanced permanent structures where they could live, work, and congregate. They also created the infrastructure needed to support sedentary lifestyles. The building business as we know it today started to take shape in the 16th century as the implementation of major projects necessitated the labor of engineers and architects, the coordination of materials, employees on the ground level, as well as laws to direct construction. The rise of modern construction begins alongside with the rise of modern science in the 17th and 18th centuries. Scientific breakthrough enabled to use wide variety of material and with optimization of resources along with 19th century industrial revolution construction industry made a huge advancement.

Construction Industry is Labor Intensive industry [1] with proper implication and uses of Construction Equipment, so progress of work and quantity of work done is influenced by way construction worker preform their work and way they are organized.[2]

Around 1,766 million individuals, or 56 percentage of the global labor force, lived in Asia and the Pacific in 2013. [3]. Worker skills are essential to both the employ-ability of individuals and the productivity and competitiveness of businesses. To make sure that workers' abilities match the demands of the workplace, great effort has been put into improving the relevance of the training programs.

So, researchers have started to pay close attention to the variables that affect the performance of construction workers on-site as a result of this necessity [4]. These variables include the competence of a worker [5], the influence of workmates [6], the working environment [7], the nature of the work [4],peer guidance [6] and material availability [8]. However, the elements determining a worker's performance, except for competence, which refers to a person's capacity to execute on the job [9], are largely dependent on the organizational working culture [6], which can vary substantially depending upon. The organizational working culture, which can vary considerably based on the basic values, ethics, and purpose statement of a particular organization, is a major element influencing a worker's performance. A worker can operate effectively in a range of work settings by having a particular set of linked abilities, commitments, knowledge, and skills, which is referred to as competence. Consequently, a worker's competence can be seen as a necessary component for obtaining a greater degree of performance in any working environment.[10].

It's also critical to realize that as responsibility levels rise, so do the demands for these socioemotional, cognitive, and technical skills therefore to validate and strengthen these claim by answering these questions.

- RQ1: What competencies can impact the performance of Construction worker at Site?
- RQ2: How do these competencies differ across categories of workers, from the unskilled to skilled levels?

2. Literature Review

2.1 Construction Workers Competencies

Core competencies are skills necessary for success in both the workplace and in life. They are transferable, meaning they may be applied to different situations or jobs. Other names for core competencies include key competences, essential skill, transferable competencies, core competencies, employ ability skills, and soft skills [3].

Basic education, including reading and writing, obtaining the technical skills necessary to carry out particular tasks, and developing professional and personal qualities like honesty, dependability, punctuality, attendance, and loyalty are all ways to develop core employ ability abilities. Four main categories can be used to group the skills: learning new things, speaking, cooperating with others, and solving problems [3].

Most research on the topic of labor productivity in the construction industry over the past 20 years has centered on determining the skills needed by construction workers to perform their jobs effectively. For instance,Allmendinger [11] examined the connection between the education system and the requirements for a worker to enter the labor market at the beginning of the 1990s and discovered that the education system played a significant influence in making the entry. The educational systems of West Germany, Norway, and the United States were the subjects of this study. The study demonstrated that the educational system shapes people's career opportunities when they enter the workforce and that these systems have long-term effects.

As per another study, Kaufmann and Weaver[**?**] proposed that carefully choosing the right person for the proper training based on the individual's unique competencies significantly improves the working quality of the workforce. The researchers added that there was no doubt that training would take place. The crucial factor was rather who would receive what training and how much of it. The study came to the conclusion that selecting the correct candidate for the proper training based on particular competencies has a substantial impact on the quality of the training outcome. According to Judy and D'Amico [12], one of the abilities used to assess a worker's performance is their intelligence (aptitude). According to the study, more intellectual workers can perform better and make more money than less intelligent ones. In a different study, Schaufelberger [13] suggested a pre-apprenticeship program to assist students who chose to begin working at construction sites in developing their construction-working skills.

Wang [5] conducted research on the main problems that contribute to the US construction industry's low productivity and subpar quality of work. The efficiency of training facilities in the US was specifically examined in the study. Lack of motivation, or the drive to complete a task, is one of the elements that impacts productivity and raises absenteeism, injuries, and rework on the job site, according to the study. The study concluded that training providers should concentrate on enhancing one of the most crucial competencies, namely the workers' motivation, during training.Tam and Fung [14] looked into the Hong Kong construction industry's required safety training program. The study offered a significant theoretical advance by emphasizing the significance of worker safety training for improving workers' performance on the job site. According to the study, a worker's attitude, demeanor, and communication—including their listening and speaking—skills are crucial characteristics that should be the focus of training. After that, Namian [15] offered several suggestions for enhancing workers' hazard-recognition skills and the results of their safety training. The study assessed how training transfer criteria were used in the construction workers' training program. The researchers found that the workers' common language barrier and their mindset, which can have an impact, may be to blame for the training failure on their site work performance.

Lacking such a vision for competencies, training providers simply concentrate on improving the workers' general practical abilities because they do not consider specific competency development for a certain type of workers as part of the curriculum [2]. As a result, the workers' performance is hindered by the training they received, despite the fact that they might have produced much superior work on the job site. Therefore, it is crucial that while developing and finalizing the training modules, practical skills be combined with instruction aimed at increasing certain competences for each group of workers. This expertise, which will offer insightful data based on a real-time evaluation of competencies, will be beneficial to the research community and be useful for designing the curriculum.

2.2 Support Vector Machine

Based on statistical theory, C. Cortes and V. Vapnik developed the Support Vector Machine method. Small sample data set classification problems can be successfully solved by it. The goal of SVM is to identify the ideal hyper plane—i.e., the hyper plane that is physically farthest from the sample—that divides the various classes of samples. The sample is initially translated from the original space into the high-dimensional space. The following is an expression for the model corresponding to the hyperplane in the feature space

$$f(x) = w^T Ø(x) + b \tag{1}$$

where w and b are hyper plane parameters.

2.3 Research Objective

The objective of study is to find out competencies factor affecting the work progress and their inter-relation among their competencies. Such identified competencies can be incorporated in training curriculum for improving work performance. The specific objectives of the study are as follows:

- To identify competencies increasing work performance and find out how these competencies differ across categories of workers from unskilled to skilled.
- To evaluate skilled construction workers competency based on support vector machine model'

3. Research Methodology

3.1 Study Procedure

This study focuses on finding the skills that both skilled and unskilled construction workers need to acquire therefore can perform well on job sites. For this investigation, a questionnaire survey approach was used. To begin with, a thorough literature analysis was done to determine the different competencies needed by construction personnel. A questionnaire was then distributed to the industry veterans, and trainers including the construction superintendent, experienced supervisor, foreman, project engineer, and manager who worked closely with the valley of Kathmandu's construction workers. The significant

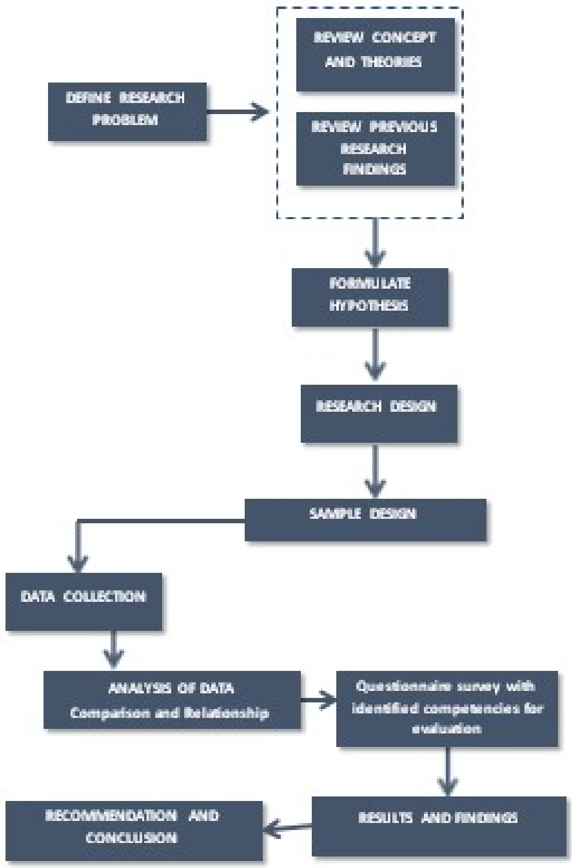

Figure 1: Research Methodology flowchart

competencies for the unskilled and skilled groups of workers were then identified after the responses were gathered and subjected to descriptive statistical analysis. The selected competencies were then divided into desirable and essential competencies for the groups of unskilled and skilled workers by conducting a one-sample t-test.

Then identified competencies are circulated using another questionnaire survey among foremen and supervisors of different building projects in Kathmandu valley for evaluation of workers' competencies. The overall procedure is mentioned in fig 1.

Based on the performance gaps identified at each level and the workers' evaluated scores, the results will assist training providers in effectively training of workers. This will eventually aid in resolving the issue of construction employees' subpar performance on the job site.

3.2 Variables for Research

Fifteen competencies that have an impact on the performance of construction employees on the job site are collected from secondary data sources, such as literature and reports. The list of these qualities was personally discussed in-depth with five specialists who each had more than 15 years of experience in the training system, supervisors, general manager, and human resource manager for construction workers in Kathmandu in order to assess the applicability of the identified competencies. This discussion also served to make sure that no key characteristics related to the workers are missed and with rigorous discussion these competencies were finalized and are given in table no 1.

3.3 Questionnaire Survey

This study used a questionnaire survey approach to identify the essential and desired competencies of workers. This methodology was selected since it was anticipated that the study's findings would be inferential in nature. A five-point Likert scale questionnaire is prepared consisting of demographic information and a second consisting of competencies require self-administered as well as distributed via the goggle form platform to sample population (different questionnaire to different experts of bar bending, construction carpenter, meson (brick and concrete works) to trainers, project managers, engineers foreman, supervisor, HR managers and validation of the questionnaire with experts.

Table 1: List of Competencies and their Sources

Performance Attribute	Source
Aptitude	Johari and Jha [16] Johari and Neeraj Jha [2]
Reading Skills	Schaufelberger [13]
Speaking Skills	Namian [15] Marín and Roelofs [7] Johari and Neeraj Jha[2] Frey [17] Durdyev and Mbachu [4]
Technical Knowledge	Małachowski and Korytkowski [18] Johari and Neeraj Jha [2]
Working Experience	Małachowski and Korytkowski [18]
Writing Skills	Johari and Neeraj Jha [2] Suakanto [19]
Resilience	Chen [20] Brewer [3]
Memory	Johari and Jha [16] Leung [21] McClelland [22]
Attitude	Johari and Jha [23] Johari and Neeraj Jha [2] Judd and Johnson [12] Tam and Fung [14] Namian [15]
Confidence	Johari and Neeraj Jha [2] Marín and Roelofs [7] Johari and Neeraj Jha [2]
Problem Solving skills	Małachowski and Korytkowski [18] Agrawal and Agrawal [10]
Health Physical strength	Johari and Neeraj Jha [2] Chakraborty [24]
Mathmatical skill	Schaufelberger [13]
Motivation	Johari and Jha [25] Kazaz [26] Namian[15]

3.4 Sample size

A 5 percent standard error was maintained. Additionally, the authors increased the test's statistical power by 90percent in order to reduce Type II error. Therefore, a minimal sample size, as indicated by Lieber[27], was determined with the use of Equation-2 in order to maintain the power of the test at 90%.

$$(n) = 2(\sigma/\delta)^2(t\alpha\gamma + t2(1-\rho),\gamma)^2$$

Where n = the sample size, σ = the population standard deviation, δ= the difference that is desired to detect, α= significance level (probability of type I error), ρ = the degrees of freedom, tα , ρ = the t value corresponding to α and γ, and ρ = the desired statistical power. (σ =0.8 & δ=0.5 from previous similar research)

$$\rho = a(n-1)$$

where,
a = number of subgroups
v = degrees of freedom
n = the number of independent
Observations per group gives value of 34.677

Table 2: Sample Size for each trend and class of workers

Trade	Skilled	Unskilled
Barbending	39	39
Carpentory	37	37
Masonary	37	37
Total	113	113

Table 3: Sample Size for each trend and class of workers

	Experience				Total By trade
Trade	<5	5-10	10-15	>15	
Barbendor	8	13	7	11	39
Carpenter	6	11	8	12	37
Meson	10	10	6	11	37
Total	24	34	21	34	113

3.5 Data Analysis

Hypothesis testing

To check level of agreement along all the trend of workers following hypothesis is formulated. 1. Null hypothesis (Ho): There is no statistically significant correlation between any two trades' rankings of the competences. 2. Alternative hypothesis (H1): There is statistically significant correlation between any two trades' rankings of the competences. To test these hypothesis, a Spearman's Rank correlation will be employed at a significance of 95% percent confidence interval.

Significance Test

A significance test was run on the gathered data to identify the essential and desirable competencies. The impact of each ability on a worker's performance was therefore thought to lay between the midpoints of two adjacent scales, as indicated by Tripathi and Jha [28], because results of the descriptive statistical analysis revealed that the responses' mean value was not a whole number. Regarding the mean value () more than and equal to 4.5, the importance of the competencies was deemed to be extremely high in terms of how well the workers performed. The range of mean values 4.5 > 3.5 was similarly considered as high relevance, 3.5 > 2.5 as moderate importance, and 2.5 > handled as very low importance on the performance of worker. The statistical significance of the qualities at a mean value of 3.5 and a confidence interval percentage of 95percent was examined with a one-sample t-test as the study's data is free of outliers and regularly distributed. Table 6 provides the mean, standard deviation, t-value, and p-value from a one-sample t-test for the categories of workers who are unskilled, and skilled. Based on the findings in Table 6, the unskilled, and skilled categories of workers' competencies ranked high for mean value > 3.5 and considered critical.

4. Results

The findings of the hypothesis test demonstrate value less than 0.05 which ultimately reject the null hypothesis and accepts the alternate hypothesis stating significant correlation between the ranks of the skills of two separate trade shown in Table no 4. This indicates that performance of workers belonging to two or more trades within a given category of workers—for example, the unskilled category—was found to depend on the same sets of skills. In other words, for a specific group of workers, the competences required of them at work are independent of their trend of their work and their relative ranking are demonstrated on Table no 5.

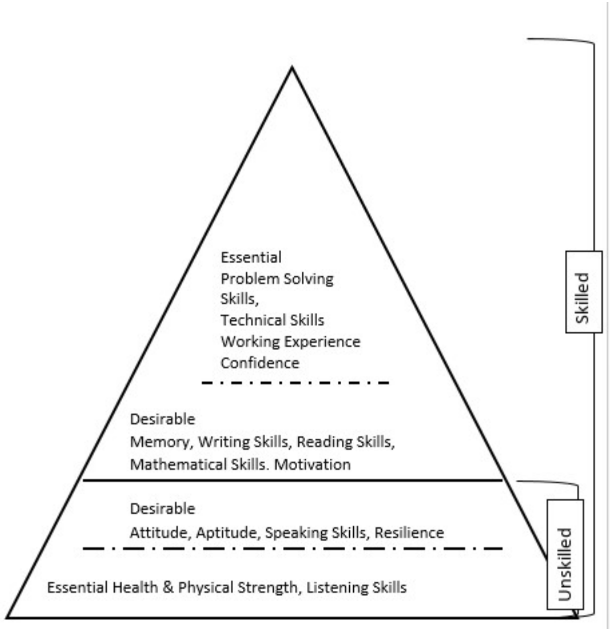

Figure 2: Essential & desirable competencies for skilled and unskilled construction workers

Table 4: Spearman's Rank Correlation Coefficient

Barbendor & carpenter			Barbendor and Meson	
Coefficient (Rs)	0.814		Coefficient (Rs)	0.954
N:	15		N:	15
T: statistics	5.058		T: statistics	11.416
DF	14		Df	14
p value:	0.000		p value:	0.000

Carpenter and Meson	
Coefficient (Rs)	0.871
N:	15
T: statistics	6.405
Df	14
p value:	0.000

*Note: calculated with respect to average mean value of 3.5

In addition, Table no 6 findings demonstrate that while some competencies in two categories of workers—listening skills, Health & Physical Strength are critical in the unskilled category, and problem solving skills, technical skills, working experience, and confidence have mean values greater than 3.5 (critical competencies), and a 95 percent confidence interval reveals that they are significant so essential to workers' whereas memory, writing skills, reading skills mathematical skills motivation found desirable to skilled sets and attitude, Aptitude, speaking skills resilience desirable to unskilled workers.

5. Case Study

The identified 15 competencies are applied to develop questionnaire for measuring competency of Barbendor, carpenter, and meson on running building projects of Kathmandu valley. The questionnaire are distributed to foreman and supervisor of respective projects and given to access the construction worker based on the identified competencies and overall competency with score of 3 for high competency, 2 for medium competency and 1for low competency.

Table 7: SVM model input Data for 5n fold validation

SN	Competency	Barbendor	Carpenter	Meson
1	High Competency	27	27	35
2	Medium Competency	24	26	22
3	Low Competency	23	24	16
	sub-total	74	77	73

*Note High competency Value=3, Medium competency value =2 & low competency value=1 for analysis

A total of 74 data collected for Barbendor, 77 for carpenter and 73 for meson, detail is shown as in table no 7. Then SVM model is implemented, Grid search is applied for obtaining the optimum parameter value of C and G which is found to be C=1 for Barbendor, 0.3 for carpenter and 1 for mason and Gamma g value be set on auto as shown no table no 7. For best efficiency Kernel function is found RBF (radial basis function) on Barbendor and carpenter, linear on Meson. With 5fold validation and average efficiency on each fold with optimum parameter selection best score is 93.3 percent for Barbendor, 92.1 percent for carpenter and 96 percent for Meson also shown on table no.7 Future prediction function also developed on Python on Jupyter Notebook (tool used to develop SVM model for study) with which one can predict whether the worker is highly competent, medium competent or low competency.

Table 5: Performance attribute competencies along with their hierarchy for skilled and unskilled

Serial No.	Competencies	Bar bending		Carpentry		Masonry	
		Unskilled	Skilled	Unskilled	Skilled	Unskilled	Skilled
1	Aptitude	10	5	8	7	9	5
2	Attitude	7	10	1	6	3	7
3	Confidence	6	2	4	5	4	4
4	Health and Physical Strength	1	9	2	12	2	9
5	Listening Skills	2	14	3	11	1	14
6	Mathematical Skills	14	11	3	8	14	11
7	Motivation	4	6	5	4	6	8
8	Problem Solving Skills	9	1	10	1	8	1
9	Memory	11	12	11	14	11	13
10	Reading Skills	15	15	15	15	15	15
11	Speaking Skills	5	8	7	13	7	10
e 12	Technical Skills	13	3	12	2	12	2
13	Work Experience	3	4	6	3	5	3
14	Writing Skills	12	13	14	10	13	12
15	Resilience	8	7	9	9	10	6

Table 6: Result for one sample t-test on identified competencies

Serial No.	Competencies	unskilled (Df=103)				Skilled (Df=103)			
		Mean	SD	t-vale	p-valve	Mean	SD	t-value	p-value
1	Health & Physical Strength	3.699	0.653	3.241	0.002	3.451	0.945	0.548	0.585
2	Listening Skills	3.637	0.483	3.019	0.003	3.283	0.750	3.075	0.003
3	Attitude	3.407	0.650	1.520	0.131	3.575	0.962	0.831	0.408
4	Aptitude	3.018	0.855	5.993	0.000	3.681	0.672	2.871	0.005
5	Speaking Skills	3.212	0.784	3.898	0.000	3.434	0.953	0.740	0.461
6	Resilience	3.000	1.044	5.093	0.000	3.602	0.688	1.571	0.119
7	Memory	2.770	0.707	10.974	0.000	3.283	0.738	3.125	0.002
8	Writing Skills	2.451	0.720	15.493	0.000	3.336	0.820	2.124	0.036
9	Reading Skills	2.301	0.865	14.739	0.000	3.168	0.731	4.828	0.000
10	Mathematical Skills	2.372	0.804	14.919	0.000	3.425	0.854	0.937	0.351
11	Motivation	3.292	0.831	2.660	0.009	3.655	0.864	1.906	0.059
12	Confidence	3.301	0.611	3.466	0.001	3.876	0.734	5.450	0.000
13	Problem Solving Skills	2.991	0.796	6.794	0.000	4.239	0.735	10.683	0.000
14	Technical Skills	2.531	0.768	13.404	0.000	4.071	0.623	9.744	0.000
15	Work Experience	3.345	0.741	2.221	0.028	3.885	0.810	5.051	0.000

*Note: Df= degree of freedom, SD= Standard Deviation Significance competencies (at the 95% confidence interval)

Table 8: Grid Search for Parameter selection, best parameter and best score for prediction of SVM model

	Barbendor			carpenter			Meson		
Serial no.	par_C	par_kernel	mean test score	par_C	par_kernel	mean test score	par_C	par_kernel	mean test score
1	0.3	rbf	0.907	0.3	rbf	0.922	0.3	rbf	0.958
2	0.3	linear	0.919	0.3	linear	0.896	0.3	linear	0.958
3	1	rbf	0.933	1	rbf	0.908	1	rbf	0.958
4	1	linear	0.906	1	linear	0.870	1	linear	0.959
5	2	rbf	0.920	2	rbf	0.908	2	rbf	0.958
6	2	linear	0.906	2	linear	0.858	2	linear	0.959
7	3	rbf	0.907	3	rbf	0.896	3	rbf	0.958
8	3	linear	0.906	3	linear	0.844	3	linear	0.959
		best parameter={'C': 1, 'kernel': 'rbf'}			best parameter='C': 0.3, 'kernel': 'rbf'			best parameter={'C': 1, 'kernel': 'linear'}	
		best Score=0.933			best Score=0.921			best Score=0.959	

*Note: param_kernal= kernel function parameter, rbf= radial basis kernal functio, param_C= parameter C for SVM, g=Gamma parameter at "auto" set

6. Conclusion

This paper has addressed the important aspects of the necessity for worker to develop certain sets of competencies such as technical, socioemotional, and cognitive skills. These abilities complement those of construction workers, and they are just as crucial for productive and efficient work performance on the job site as practical ones. The study examines how these competencies are different as workers varies from being unskilled to being skilled. The study also looks into the issue of whether a particular category of workers' competencies are trade-specific or not. For this, a thorough literature review was performed first. Then, using descriptive analysis on the data gathered from a questionnaire survey, the essential and desirable competences for categories (unskilled and skilled) were determined.

Then SVM model is developed which can be applicable in finding the competency of construction workers of Kathmandu valley with sound accuracy. The benefits of competency evaluation based on Support Vector Machine algorithm are, The SVM evaluation method can learn the nonlinear correlation between indicators, making it more realistic than other evaluation methods.

7. Limitations of research

Research is concerned about two construction worker (Skilled and Un-skilled worker), with proper desirable competencies unskilled could be skilled whereas, skilled gap with other sector is not demonstrated on this study.

Three trends of Construction Worker (Construction form work Carpenter, Barbendor and Meson (Brick work, concrete work) are discussed here where other workers such as scaffold, welder (heat working) category are not discussed.

Although the competences are relevant to construction workers, the study takes its conclusions from the perception of the foreman, supervisor, engineer, project manager, and trainer since it creates perception-based results rather than data from workers.

8. Significance of Study

Policy maker, administrator will have significance while designing the curriculum program for training works for construction workers. Construction worker from lower ranks could achieve the competencies level of higher level worker after correctly assessment of required competency Use of SVM model to evaluate the competency with score which assists while hiring construction workers.

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