EASR

Engineering and Applied Science Research

https://www.tci-thaijo.org/index.php/easr/index

Published by the Faculty of Engineering, Khon Kaen University, Thailand

Analysis of factors hindering labor productivity in large-scale high-rise building construction projects

Tewakun Chankampom, Preenithi Aksorn and Korb Srinavin*

Department of Civil Engineering, Faculty of Engineering, Khon Kaen University, Khon Kaen 40002, Thailand.

Received 20 March 2025
Revised 25 October 2025
Accepted 30 October 2025

Abstract

Thailand faces persistent challenges in its labor market, notably low and declining labor productivity, labor shortages, and skill mismatches in the construction sector. Over the past decade, national development has focused more on capital investment and labor quantity than on productivity improvement. This study aims to address this gap by developing and validating a Structural Equation Model (SEM) to examine relationships among key labor productivity indicators in Thailand's construction industry, particularly large-scale high-rise projects. Data were collected from 600 construction workers employed in residential projects across Bangkok and surrounding provinces, representing a population of 1,125,400 workers (2013–2019). The SEM incorporated nine latent constructs: Materials, Equipment/Tools, Labor, Safety, Construction Methods, Rework, Weather, Motivation, and Productivity that capture both resource-related and human-factor dimensions. The validated model demonstrated a good fit with empirical data, with all observed variable correlations significant at the 0.05 level. Motivation was identified as the most influential factor on labor productivity (total effect = 0.680), followed by Equipment/Tool performance (0.483), Labor Management (−0.049), and Resource Management/Working Conditions (−0.066). Collectively, these factors explained 92.7% of the variance in productivity. Indirect effects through Motivation accounted for 51.7% of its variation. Findings underscore the crucial role of worker motivation in improving productivity. Housing support had the most substantial positive influence on Motivation, explaining 75.7% of its variance. Construction managers should prioritize motivational strategies, particularly housing support, project-end bonuses, and social insurance, to enhance workforce satisfaction and productivity in Thailand's construction sector.

Keywords: Factors hindering, Labor productivity, Large-scale high-rise building

1. Introduction

The construction industry plays a vital role in the economic development of every country, particularly in developing nations [1]. Almost all industries rely on construction as part of their business investments. The sector contributes approximately 15-20% of a country's Gross Domestic Product (GDP) [2-4]. Given the high investment involved, the construction industry significantly impacts national economies. Consequently, improving productivity in construction remains a critical concern for both developed and developing nations [5]. Developed countries emphasize economic growth and social welfare through cost savings and efficient resource utilization. In contrast, developing nations, facing challenges such as unemployment, inflation, and resource shortages, aim to maximize resource efficiency to drive economic progress and enhance citizens' quality of life [6].

Labor productivity is a key indicator of performance in the construction sector, as this industry is labor-intensive [7, 8]. Labor costs account for approximately 30-50% of total project expenses. Low labor productivity leads to cost overruns and project delays. However, research suggests that productivity growth in construction is lower than in other industries [4, 9]. Additionally, both labor shortages and skill gaps present significant challenges. While advanced technology and efficient management are crucial for improving outputs, they cannot replace the necessity of skilled labor [10, 11]. Ensuring high labor productivity at every project stage is essential for construction success. Despite extensive research on labor productivity, no universal improvement strategies or standardized performance metrics have been established [12, 13]. To enhance productivity, stakeholders must collaborate effectively, including public and private sector entities, contractors, project managers, skilled workers, and laborers.

While prior studies have broadly discussed construction labor productivity [14], this study focuses explicitly on large-scale high-rise building construction projects, which are resource-intensive, complex, and involve unique challenges such as vertical logistics, specialized equipment, and large, diverse workforces that differentiate them from other construction types. Understanding labor productivity in this context requires a tailored investigation of factors that directly affect on-site efficiency and workforce performance [15]. Although many factors influencing labor productivity have been identified globally, a gap remains in empirically validated models for large-scale high-rise projects in Thailand [16]. This study addresses that gap by developing a structural equation model (SEM) to examine the relationships between labor productivity indicators and empirical data within this specific construction context [17], thereby building upon existing knowledge while providing insights tailored to the particular challenges of high-rise construction.

*Corresponding author.
Email address: korbsri@kku.ac.th
https://doi.org/10.64960/easr.2026.261292

This study aims to identify key factors influencing labor productivity in the construction industry, evaluate the validity of the measurement model, and determine the significance of each observed variable on the latent variables affecting labor productivity decline. Structural equation modeling (SEM) is employed to analyze these relationships, offering insights into enhancing workforce efficiency in large-scale, high-rise construction projects.

2. Review of previous studies

Labor is a critical resource in construction projects, both in terms of workforce quantity and associated costs. A project's success heavily depends on worker productivity, making labor efficiency a key factor in a company's competitiveness within the construction industry [18]. However, the declining trend in labor productivity remains a significant concern [19, 20]. Despite extensive research on this topic, there is still no consensus among academics and industry practitioners regarding the definition and measurement of construction effectiveness.

High labor productivity in the construction sector is often reflected through several key characteristics, including strong job security, competitive wage levels, good work discipline, and high job satisfaction among workers. Job security represents a stable employment environment that supports employees' commitment, motivation, and long-term performance focus [21]. Competitive wages indicate an organization's ability to attract and retain skilled labor, thereby reducing turnover and sustaining consistent work quality, consistent with human capital theory and expectancy theory [22]. Likewise, work discipline reflects adherence to established procedures, schedules, and quality standards, which contributes to efficient and error-free performance [23]. Furthermore, high job satisfaction signifies a positive psychological state among workers, leading to greater commitment and reduced absenteeism and turnover conditions that typify productive labor forces, as supported by the Human Relations Movement and Herzberg's Two-Factor Theory [24, 25].

Attar et al. [26] examined factors affecting labor productivity in India and categorized them into 15 groups: design, planning, materials, equipment, labor, health and safety, supervision, working time, project quality, finance, leadership, organization, and external influences. Similarly, Soekiman et al. [27] identified 113 variables impacting construction labor productivity, grouping them into the same 15 categories. Shashank et al. [28] analyzed key factors influencing labor productivity changes in construction projects, categorizing them into eight groups with 34 specific factors. Material-related factors ranked among the top three, aligning with Gerges et al. [29], who studied labor productivity improvement in Egypt's construction sector. Their classification included labor, management, environmental conditions, motivation, materials/equipment, scheduling, safety, and work quality. In Zimbabwe, a study identified the top five factors affecting labor productivity: material availability, delayed salary payments, project suitability, equipment shortages, supervisory capability, and worker skills. These factors were grouped into construction site conditions, equipment, materials, management, labor, motivation, and technical aspects [13].

Over the years, research has identified numerous factors influencing labor productivity, forming the basis for questionnaire development in construction industry studies. These factors apply to both developed countries, such as Canada [30], the UK [31], and New Zealand [32], as well as developing nations like Nigeria [33, 34], Malaysia [35], Palestine [6], Kuwait [36], Sri Lanka [37], Turkey [38], Trinidad and Tobago [39], Yemen [40], Zimbabwe [13], and Uganda [41]. Labor productivity is affected by both external and internal elements, totaling 103 factors classified into 12 categories.

3. Method

3.1 Identifying population and sampling

The population in this research consists of construction workers classified by industry from 2013 to 2019 throughout Thailand, totaling 1,125,400 people [42].

The determination of the sample size for this study was based on Yamane's [43] formula, with additional units reserved to compensate for potential incomplete responses. To ensure statistical rigor, the guidelines proposed by Krejcie and Morgan [44] were also applied, using a 95% confidence level and a 5% margin of error. This calculation yielded an initial required sample size of approximately 400 respondents. However, to strengthen the reliability of the study and address issues related to incorrect or incomplete responses, the sample size was further increased to 600 units [45]. In terms of sampling approach, the distribution of questionnaires initially adopted a non-probability convenience sampling method, which facilitated practical data collection. Following the completion of data collection, purposive sampling was employed to refine and select the final set of usable questionnaires, ensuring that the data aligned with the objectives of the study. The response rate obtained from the survey was 56%, corresponding to 336 valid questionnaires returned. According to Babbie's criterion, a response rate above 50% is deemed acceptable for social research, and thus the achieved response rate in this study was considered suitable for subsequent analysis and interpretation [46].

3.2 Questionnaire design and measurement scales

Prior to field administration, the questionnaires underwent a rigorous development and validation process to ensure their validity, relevance, and reliability. The validity of the instrument was examined through the Index of Item-Objective Congruence (IOC), evaluated by a panel of five experts. The overall IOC score was 0.81, which indicates strong alignment between the questionnaire items and the research objectives. To further confirm the reliability of the instrument, a pilot test was conducted with a group of 30 respondents possessing characteristics similar to those of the target population. The analysis produced a Cronbach's Alpha [47] coefficient of 0.961, significantly exceeding the generally accepted threshold of 0.7, thereby demonstrating excellent internal consistency. The final questionnaire employed an interval-level measurement using a five-point Likert-type rating scale, specifically designed to capture the degree of perceived impact of various factors on labor productivity [48].

3.3 Data collection

Data were collected through questionnaires administered to construction workers engaged in residential housing projects located in Bangkok and its surrounding provinces. These projects were characterized by standardized housing units with uniform or nearly identical design features. The selection of construction workers as respondents was appropriate, as their direct involvement in these projects enables them to reliably assess the practical impact of various factors on labor productivity. Their daily work experience provided the foundation for their perceptions and evaluations of these linkages.

3.4 Variable reduction and analytical procedures

The researcher developed a measurement model to systematically extract and refine relevant variables for analyzing labor productivity factors in construction projects. The process began with a comprehensive literature review, which established the theoretical relationships between observed and latent variables, ensuring that the model was grounded in both empirical evidence and conceptual foundations. To verify the reliability and validity of the constructs, composite reliability (CR) values were required to exceed 0.70, indicating internal consistency, while the average variance extracted (AVE) values were expected to surpass 0.50, confirming adequate convergent validity. Furthermore, individual observed variables were required to demonstrate standardized factor loadings between 0.50 and 1.00, ensuring that each indicator made a significant contribution to its corresponding latent construct [49].

Following this rigorous variable extraction and validation process, nine latent variables were identified and retained, representing key domains influencing construction labor productivity: (1) Materials, (2) Equipment/Tools, (3) Labor, (4) Safety, (5) Construction Methods, (6) Rework, (7) Weather, (8) Motivation, and (9) Productivity. These latent variables serve as the study's foundational theoretical constructs, capturing both resource-related and human-factor dimensions critical to productivity analysis. From the initial pool of factors, 57 observed sub-components were retained, as summarized in Table 1. These observed variables not only satisfied the statistical criteria for inclusion but also aligned with findings from previous studies, thereby reinforcing the theoretical robustness and validity of the measurement model.

Table 1 Compilation of labor productivity factors affecting construction projects

Criteria	Factors	Symbol	Reference
1. Materials	1.1 Materials have not arrived onsite yet	V1b*	[13, 40]
	1.2 Lack of material	V2b	[11, 50, 51]
	1.3 Insufficient or poor material handling	V3b	[13, 52]
	1.4 Unsuitability of materials storage location	V4b	[28, 51]
	1.5 Low quality of raw materials	V5b	[6, 28, 40]
2. Equipment/ Tools	2.1 Lack of proper tools and equipment on-site	V1c*	[6, 11, 51]
	2.2 There are frequent tools/equipment breakdowns due to aging or poor maintenance	V2c	[13, 50]
	2.3 Suitability or adequacy of equipment/tools	V3c	[13, 40]
	2.4 Old and Inefficiency of equipment/tools	V4c	[28, 50, 51]
3. Labor	3.1 High absenteeism of labor	V1d	[18, 28, 51]
	3.2 Working for long periods without holiday	V2d	[13, 53]
	3.3 Lack of manpower skills	V3d	[5, 52, 54]
	3.4 Lack of labor experience	V4d	[55, 56]
	3.5 Inappropriate use of skills	V5d	[13]
	3.6 Crew size inefficiency	V6d	[13]
	3.7 Use of alcohol and drugs	V7d	[27, 41]
	3.8 Worker turnover and changing crewmember	V8d	[54, 56]
	3.9 Labor disloyalty	V9d*	[53, 55]
	3.10 Labour dissatisfaction	V10d	[6, 52]
	3.11 Misunderstanding among labor	V11d	[6, 53]
	3.12 Lack of training	V12d	[28]
4. Safety	4.1 Accidents	V1e*	[28, 41, 55]
	4.2 Violation of safety precautions	V2e*	[6, 28, 55]
	4.3 Management does not support safety planning	V3e*	[50]
	4.4 Lack of site safety resources	V4e*	[56]
	4.5 No safety engineer in site	V5e*	[28]
	4.6 Working at high places	V8e*	[28, 50]
	4.7 Insufficient lighting	V9e*	[28, 41, 50]
	4.8 Bad ventilation	V10e*	[6, 41, 55]
5. Construction method	5.1 The site is slippery or steep imposing terrible conditions	V1f*	[50]
	5.3 Delay in responding to requests for information	V3f*	[39]
	5.4 The extent of variation/change orders during execution	V4f*	[5, 39, 54]
	5.5 Improper construction method	V6f*	[56]
	5.6 Stringent inspection by the engineer	V10f*	[5, 39]
	5.7 Ease of processing and preparation of materials for the work (cutting/ chopping)	V11f*	[40]
	5.8 Quantity of work available every day (daily workloads)	V13f*	[40]
	5.9 Specialized nature of the work	V14f*	[40]
6. Rework	6.1 The work needs to be redone due to the damage after the work was complete	V5g*	[50]
	6.2 The works need to be redone because it fails quality control inspection or testing	V6g*	[50]
	6.3 The work needs to be redone due to changes in design, drawings or specifications	V8g*	[50, 57]
7. Weather	7.1 Cold, Humidity	V1h*	[5, 39, 58]
	7.2 Rain	V2h*	
	7.3 High Temperature	V3h*	

*Factors with eigenvalues less than 1 were eliminated.

Table 1 (continue) Compilation of labor productivity factors affecting construction projects

Criteria	Factors	Symbol	Reference
8. Motivation	8.1 Proportion of labor's salary and responsibility	V1j	[59]
	8.2 Delay in salary payment	V2j	[37, 53, 59]
	8.3 Bonus at the end of project or year	V3j	[13, 36, 40]
	8.4 Social insurance	V4j	[36, 40, 41]
	8.5 Canteen for employee (Good food for free or at a reduced price)	V5j	[6, 37, 53]
	8.6 Medical care (Having a particular hospital to attend in case of illness or subsidizing the cost of hospital bills)	V6j	[13, 37, 40]
	8.7 Accommodation (Provision of physical accommodation)	V7j	[28, 37]
	8.8 Working hours (working 8 hours per day)	V8j	[40]
	8.9 Wages level for labor	V9j	[13, 37, 41]
	8.10 Public holidays	V10j	[40]
9. Productivity	9.1 Job security	V1p	[37, 59]
	9.2 Wages level for labor	V2p	[13, 38, 40]
	9.3 Work discipline	V3p	[38]
	9.4 Work satisfaction	V4p	[38]

*Factors with eigenvalues less than 1 were eliminated.

3.5 Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) was employed as a preliminary and essential step within the Structural Equation Modeling (SEM) framework to validate and refine the theoretical structure of latent variables empirically. By identifying underlying latent constructs from a broad set of observed variables, EFA consolidated a large number of factors into a more parsimonious and theoretically meaningful measurement model. This process ensured that the latent variables incorporated into the SEM were both empirically supported and reflective of the actual relationships in the dataset, thereby establishing a robust foundation for subsequent analyses. In contrast, relying solely on theoretically derived groupings without empirical validation would risk poor model fit and undermine the accuracy of the study's findings. Based on a review of previous research, seven principal components were initially identified: (1) Materials, (2) Equipment/Tools, (3) Labor, (4) Safety, (5) Construction Methods, (6) Rework, and (7) Weather. These components were further decomposed into 43 observed variables [47].

EFA was a critical step in the SEM process, as it provided empirical confirmation and refinement of the theoretical structure established through the literature review. While prior studies offered a foundation for identifying potential latent variables, EFA was necessary to ensure that the observed variables were appropriately grouped and represented distinct underlying constructs within the specific context of this study [60]. Through this process, the researchers were able to determine the appropriate number of latent factors that best explained the variance in the observed variables. This data-driven validation ensured that the latent variables incorporated into the subsequent SEM were empirically supported and reflected the actual relationships present within the dataset. Furthermore, the use of EFA prevented the risk of poor model fit that might arise if theoretically derived latent variables were applied directly without empirical validation [61].

The EFA procedure involved several systematic stages to ensure the validity and reliability of the measurement model. The process comprised the following key steps

3.5.1 Data suitability assessment

Prior to factor extraction, the adequacy of the dataset for factor analysis was evaluated using two statistical tests:

- The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy, where values between 0.6 and 1.0 indicate acceptable sampling adequacy.
- Bartlett's Test of Sphericity, where a significance value ($p < 0.05$) confirms that the observed variables are sufficiently correlated for factor analysis.

3.5.2 Factor extraction

The extraction of factors was performed using the Principal Component Analysis (PCA) technique. The number of factors to be retained was determined based on the following selection criteria:

- Eigenvalues (Kaiser's Criterion): Only factors with eigenvalues greater than 1 were retained, as these explain more variance than a single observed variable.
- Scree Plot Analysis: A scree plot was examined to identify the "elbow point," representing the optimal number of factors before the curve levels off.
- Cumulative Variance: The total variance explained by the extracted factors was considered adequate when exceeding 60%, ensuring sufficient representation of the original dataset.
- Component Validity: Each retained factor was required to include at least three observed variables with significant loadings.

3.5.3 Factor rotation

To facilitate interpretability and ensure that extracted factors remain uncorrelated, Varimax orthogonal rotation was applied. This rotation method simplifies the factor structure by maximizing the variance of squared loadings within each factor, making it easier to identify which observed variables load most strongly on specific factors.

3.5.4 Interpretation and model validation

After rotation, the pattern of factor loadings was examined to ensure conceptual coherence and theoretical consistency among the grouped variables. Observed variables with low loadings (below 0.50) or cross-loadings on multiple factors were eliminated to maintain construct validity. The retained factors were interpreted and labeled according to the theoretical framework derived from the literature review.

Discriminant validity was assessed using the Fornell–Larcker criterion [62] to verify the distinctiveness of the latent constructs in the measurement model. The analysis compared the square root of the Average Variance Extracted for each construct with the inter-construct correlations. The results indicated that the AVE values for each latent construct Resource Management (X1) = 0.816, Labor Management (X2) = 0.629, Equipment/Tool Performance (X3) = 0.651, Motivation (Y1) = 0.625, and Labor Productivity (Y2) = 0.774 were greater than their highest inter-construct correlations, which ranged between 0.001 and 0.609. According to the Fornell–Larcker criterion, discriminant validity is achieved when the AVE of each construct exceeds its correlations with other constructs. The findings, therefore, confirm that all latent constructs are empirically distinct and conceptually independent, indicating that the measurement model possesses satisfactory discriminant validity before structural model analysis.

3.6 Structural Equation Modeling (SEM) process

Structural Equation Modeling (SEM) was employed to examine the structural relationships among latent and observed variables, integrating both the measurement and structural components within a single analytical framework. This method allows simultaneous evaluation of multiple dependency relationships, thereby providing a comprehensive understanding of how latent constructs interact within the proposed theoretical model. The SEM process in this study consisted of three primary stages: model specification, parameter estimation, and model evaluation.

3.6.1 Model specification

Model specification involves developing a conceptual framework that defines the hypothesized relationships between latent and observed variables. This step includes identifying:

- Exogenous variables, which represent independent latent constructs, and
- Endogenous variables, which are dependent constructs influenced by other variables in the model.

Each latent variable was linked to its respective observed indicators based on theoretical foundations and prior empirical studies. The structural relationships among the latent constructs were then represented through directional paths, forming the hypothesized model to be tested.

3.6.2 Measurement model validation

Before testing the structural relationships, Confirmatory Factor Analysis (CFA) was conducted to assess the measurement validity of the latent constructs. CFA evaluates how well the observed variables represent their respective latent variables by examining factor loadings, reliability, and convergent validity. Items with low factor loadings (below 0.50) or significant cross-loadings were considered for elimination to enhance construct validity. To ensure the robustness of the measurement model, a rigorous validation process was applied following established SEM guidelines [17, 61]. The results demonstrated that all retained items exhibited satisfactory standardized factor loadings (> 0.50), composite reliability (CR > 0.70), and average variance extracted (AVE > 0.50), confirming both reliability and convergent validity. This comprehensive validation procedure ensures that each latent construct is measured accurately and consistently, providing a sound empirical foundation for subsequent SEM analysis.

3.6.3 Model identification and parameter estimation

In the model estimation stage, model identification was performed first to ensure the dataset contained sufficient information to estimate all parameters uniquely. Once the model was identified, parameter estimation was conducted using the Maximum Likelihood (ML) and Generalized Least Squares (GLS) methods. These estimation techniques were selected for their robustness in handling large samples and their ability to produce efficient, unbiased parameter estimates. During the estimation process, the model's parameters, including path coefficients, variances, and covariances, were computed to assess the strength and direction of the hypothesized relationships among the latent and observed variables. Non-significant paths or parameters inconsistent with theoretical expectations were subsequently examined and considered for revision in later stages of model refinement.

3.6.4 Model fit evaluation

Model fit was assessed using a combination of absolute, incremental, and parsimonious fit indices, which were explicitly applied as a critical step in evaluating the quality of the proposed SEM. The following criteria were used to ensure the adequacy and overall appropriateness of the model.

- Chi-square (χ^2) and its associated p-value, to test overall model discrepancy;
- Root Mean Square Error of Approximation (RMSEA), with values below 0.08 indicating acceptable fit;
- Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI), where values above 0.90 reflect good model fit; and
- Goodness of Fit Index (GFI) and Adjusted Goodness of Fit Index (AGFI) as complementary measures of model adequacy.

When the model did not meet these fit criteria, modification indices (MIs) were examined to identify potential areas for improvement. Adjustments such as correlating error terms or removing weak indicators were made only when they aligned with theoretical justifications, maintaining the model's conceptual integrity.

3.6.5 Model refinement

To enhance model fit and ensure empirical robustness, a systematic refinement process was conducted. This involved:

- Eliminating low-loading variables (factor loadings < 0.50) to strengthen convergent validity;
- Checking for multicollinearity by identifying observed variables with excessively high intercorrelations (r > 0.85);
- Examining standardized residuals, where residuals beyond ±2.58 indicated poor model-data fit at a 99% confidence level; and
- Reviewing modification indices (MIs) to assess potential misfit relationships and determine whether theoretical adjustments were warranted.

This iterative process ensured that the final model achieved an optimal balance between statistical validity and theoretical coherence.

3.6.6 Interpretation

Once a satisfactory model fit was achieved, the final stage involved interpreting the results through path coefficients, variances, and correlations among latent variables. Statistical significance was evaluated to confirm the hypothesized relationships and to assess the extent to which the empirical findings supported the study's underlying theoretical framework.

4. Research findings and results

4.1 Results of exploratory factor analysis

The analysis was performed using SPSS, employing Principal Component Analysis (PCA) and Varimax rotation. The Kaiser-Meyer-Olkin (KMO) measure yielded a value of 0.910, indicating the appropriate sample size. Additionally, Bartlett's test of sphericity produced a significance value (Sig.) < 0.05, verifying the data's suitability for EFA. For the seven principal components Materials, Equipment/Tools, Safety, Construction Methods, Labor, Rework, and Weather Conditions the following quality assessment criteria were applied:

- Eigenvalues: Factors with eigenvalues less than 1 were excluded. Three components met the selection criteria, with the lowest eigenvalue at 1.100.
- Cumulative Variance: The variance explained reached 64.41%, exceeding the 60% threshold.
- Scree Test: Used to confirm the number of components influencing labor productivity.
- Component Validity: Each component required at least 3 observed variables.

Through Exploratory Factor Analysis (EFA), three principal components were extracted based on eigenvalues greater than 1, representing the key influences on construction labor productivity. These components correspond to Resource Management (X1), Labor Management (X2), and Equipment/Tool Performance (X3), which serve as the independent latent variables in the model and play critical roles in large-scale high-rise construction projects. (1) Within Resource Management (X1), challenges such as material handling, storage locations, and raw material quality are exacerbated by vertical transportation requirements and limited on-site space. Inadequate material supply and the use of low-quality materials were identified as significant determinants of efficiency in high-rise projects. (2) Labor Management (X2) encompasses factors including workforce skill levels, worker turnover, and crew changes elements that are particularly vital given the large and diverse labor forces required for vertical construction tasks. The study highlights that maintaining high labor productivity at every stage of a construction project is essential to ensure overall project success. Finally, Equipment/Tool Performance (X3) in terms of suitability, adequacy, and maintenance was found to be of paramount importance in high-rise construction, where specialized, heavy machinery is indispensable for lifting, hoisting, and working at considerable heights. Together, these three components provide a comprehensive framework for understanding and enhancing labor productivity in the complex environment of high-rise building projects, as detailed in Table 2.

Table 2 Result on total variance explained

	Criteria	No. of items	Extraction Sums of Squared Loading		
			Total	**Variance %**	**Cumulative %**
1	Resource Management and Working Conditions (X1)	9	7.727	48.635	48.635
2	Labor Management (X2)	6	2.218	21.096	69.731
3	Equipment/Tool Performance (X3)	3	1.479	7.397	77.128
	Total	18	11.424	77.128	77.128

The Exploratory Factor Analysis (EFA) resulted in the extraction of three principal components, each representing distinct latent constructs relevant to construction labor productivity.

Component 1, named Resource Management and Working Conditions (X1), has an Eigenvalue of 7.727, explaining 48.635% of the total variance. This component comprises nine observed variables, with factor loadings ranging from 0.529 to 0.850. The variable with the highest factor loading is Low-quality materials (V5b), while the variable with the lowest loading is Misunderstanding among labor (V11d). These variables can be ranked in descending order according to their factor loadings, reflecting their relative contributions to the construct of resource management and working conditions.

Component 2, named Labor Management (X2), has an Eigenvalue of 2.218, accounting for 21.096% of the variance. This component consists of six observed variables, with factor loadings ranging from 0.509 to 0.789. The variable with the highest factor loading is Labor turnover and replacement (V8d), while the lowest is Labor dissatisfaction (V10d). As with Component 1, the variables in this component can be systematically ranked in descending order of factor loadings, indicating their relative significance in shaping the latent construct of labor management.

Component 3, named Equipment/Tool Performance (X3), has an Eigenvalue of 1.479, explaining 7.397% of the variance. This component comprises three observed variables, with factor loadings ranging from 0.582 to 0.699. The variable with the highest loading is Suitability or adequacy of equipment/tool (V3c), while the lowest loading is associated with Frequent tools/equipment breakdowns due to aging or poor maintenance (V2c). These variables may also be arranged in descending order of factor loadings to demonstrate their relative contributions to the construct of equipment and tool performance, as shown in Table 3.

Each group of variables derived from the review of relevant past research and analyzed through exploratory factor analysis will be used to develop measurement models for the continuous linear relationship between latent and observed variables. These indicators reflect different aspects or dimensions of the primary construct, consisting of a total of 5 models. Then, the relationships are drawn as a path diagram based on the proposed hypotheses, as shown in Figure 1.

Table 3 The analysis resulted in the extraction of three principal components.

Component	Factor	Symbol	Factor loading
Resource Management and Working Conditions (X1)	Low quality of raw materials	V5b	0.850
	Lack of labour experience	V4d	0.849
	Lack of material	V2b	0.724
	Insufficient or poor material handling	V3b	0.716
	High absenteeism of labors	V1d	0.701
	Use of alcohol and drugs	V7d	0.618
	Unsuitability of materials storage location	V4b	0.575
	Lack of training	V12d	0.569
	Misunderstanding among labor	V11d	0.529
Labor Management (X2)	Worker turnover and changing crewmember	V8d	0.789
	Working for long periods without holiday	V2d	0.696
	Crew size inefficiency	V6d	0.614
	Lack of manpower skills	V3d	0.533
	Inappropriate use of skills	V5d	0.526
	Labor dissatisfaction	V10d	0.509
Equipment/Tool Performance (X3)	Suitability or adequacy of equipment/tool	V3c	0.699
	Old and Inefficiency of equipment/tool	V4c	0.691
	There are frequent tools/equipment breakdowns due to aging or poor maintenance	V2c	0.582

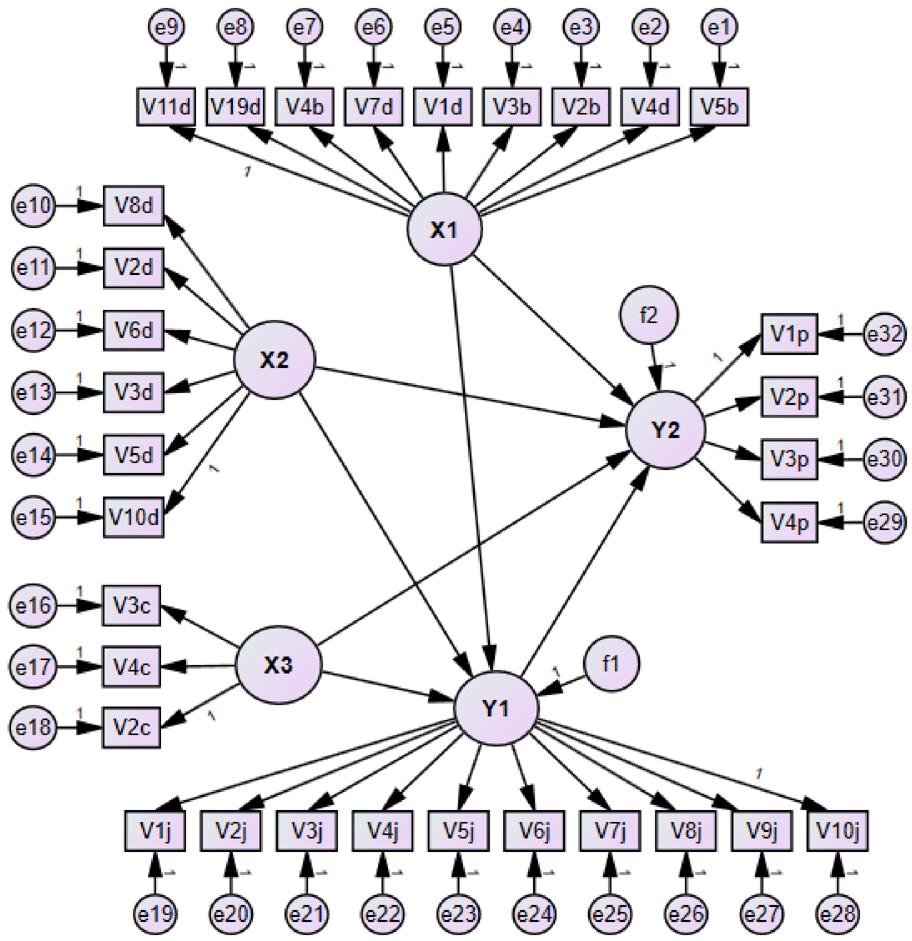

Figure 1 The structural equation model was generated using the AMOS software

4.2 Measurement model results

Enhancing model fit in Structural Equation Modeling (SEM) requires a systematic and rigorous evaluation process. This section outlines the step by step refinement of the measurement model, focusing on the elimination of variables that failed to meet established statistical criteria. Such refinement ensures that the final model is both theoretically meaningful and empirically robust. This study applied the following refinement principles:

4.2.1 Evaluating factor loadings

According to Hair et al. [17], observed variables with factor loadings below 0.50 should be removed, as they indicate weak relationships with latent variables and reduce convergent validity. Based on this criterion, 6 variables were eliminated: V5j (0.327), V10j (0.424), V8j (0.439), V2p (0.202), V2c (0.485), and V4d (0.478).

4.2.2 Checking correlation between observed variables

Observed variables with excessively high correlations (above 0.85) can impact model reliability, causing issues such as:
- Regression Weight Instability.
- Fluctuations in regression coefficients or non-significant parameters.
- Inconsistent Relationship Directions - Empirical results may not align with theoretical expectations.
- Increased Standard Errors - Lowering confidence in parameter estimates.
- Poor Model Fit - Reducing overall model accuracy.
- Difficult Impact Differentiation
- This makes it challenging to distinguish individual variable effects, leading to misinterpretation [63].

Based on this analysis, 5 variables were removed: V1j (0.891), V1d (0.917), V4b (0.869), V11d (0.907), and V5d (0.924).

4.2.3 Identifying high residuals

Variables with residuals greater than ±2.58 indicate poor model-data fit at a 99% confidence level. Standardized Residual Covariances were examined, and variables with high residuals were considered for elimination [61]. 10 variables were removed due to high residuals: V19d (2.611), V2j (3.039), V6j (3.204), V9j (3.208), V4p (3.692), V5b (3.055), V7d (2.880), V8d (2.663), V6d (3.668), and V10d (2.783).

4.2.4 Modification Indices (MI) analysis

Modification Indices (MI) were used to assess whether eliminating or adding relationships between specific variables could enhance model fit. High MI values indicate potential misfit relationships, and removing such variables helps: Reduce residual errors and improve overall model fit.

4.3 Structural model results

The SEM analysis was conducted to evaluate the appropriateness and accuracy of the structural equation model. The model was refined by eliminating variables using the Modification Indices method to enhance completeness and ensure statistical values met acceptable criteria. Further evaluation was performed by analyzing factor loadings and R^2 values and examining the covariance among indicators to validate the model's reliability. The results are summarized in Table 4, while Table 5 presents the analysis of relationships between the variables within the model.

From the standardized score regression coefficients of independent variables, which indicate the influence of variables with statistical significance at the 0.05 level, the test results are summarized by aspect as follows:

4.3.1 Resource management and working conditions

The test results indicate that insufficient/improper material handling has the most significant direct positive influence on the structural equation model of labor productivity, with a standardized weight of 0.864, explaining 62.7% of the changes in resource management and working conditions. There is one direct influence and one indirect influence, as follows:

- Resource management and working conditions directly influence labor productivity, with a regression coefficient of -0.066, a t-value of -0.580, and a Sig. value of 0.562 (> 0.001).
- Resource management and working conditions indirectly positively influence labor productivity through motivation creation, with a total regression coefficient of 0.191 (0.282*0.680).

4.3.2 Labor management

The test results indicate that lack of manpower skills has the most significant direct positive influence on the structural equation model of labor productivity, with a standardized weight of 0.943, explaining 88.90% of the changes in Labor Management. There is one direct influence and one indirect influence, as follows:

- Labor Management directly influences labor productivity, with a regression coefficient weight of -0.049, a t-value of -0.288, and a Sig. value of 0.773 (> 0.05).
- Labor Management indirectly positively influences labor productivity through motivation creation, with a total regression coefficient of 0.273 (0.401*0.680).

4.3.3 Equipment/Tool performance

The test results indicate that Suitability or adequacy of equipment/tool has the most significant direct positive influence on the structural equation model of labor productivity, with a standardized weight of 0.753, explaining 56.70% of the changes in labor management. There is one direct influence and one indirect influence, as follows:

- Equipment/Tool Performance directly influences labor productivity, with a regression coefficient weight of 0.483, a t-value of 2.452, and a Sig. value of 0.014 (< 0.05).
- Equipment/Tool Performance indirectly positively influences labor productivity through motivation creation, with a total regression coefficient of 0.081 (0.119*0.680).

Table 4 Results of relationship analysis using regression coefficient

	Factor	Factor Loading		R^2
		β_i	S.E.	
Independent Variable	Resource Management and Working Conditions (X1)			
	V2b - Lack of material	0.792	-	0.746
	V3b - Insufficient or poor material handling	0.864	0.075	0.627
	Labor Management (X2)			
	V2d - Working for long periods without holiday	0.602	0.093	0.363
	V3d - Lack of manpower skills	0.943	-	0.889
	Equipment/Tool Performance (X3)			
	V3c - Suitability or adequacy of equipment/tool	0.753	0.133	0.567
	V4c - Old and Inefficiency of equipment/tool	0.658	-	0.432
Dependent Variable	Motivation (Y1)			
	V3j - Bonus at the end of project or year	0.869	0.048	0.754
	V4j - Social insurance	0.795	0.046	0.632
	V7j - Accommodation	0.904	-	0.757
	Labor Productivity (Y2)			
	V1p - Work discipline	0.904	-	0.817
	V3p - Work satisfaction	0.751	0.051	0.564
Chi-Square = 9.781 df = 9 Relative Chi-Square = 1.087 p-value = 0.368 RMSEA = 0.016 RMR = 0.009 GFI = 0.995 NFI = 0.996 TLI = 0.998 CFI = 1.000				

Table 5 The relationship between the influence of variables

Dependent Variable	R^2	Influence	Independent Variable			Dependent Variable
			X1	X2	X3	Y1
Y1	0.517	DE	0.282**	0.401**	0.119	0.000
		IE	0.000	0.000	0.000	0.000
		TE	0.282**	0.401**	0.119	0.000
Y2	0.927	DE	-0.066	-0.049	0.483	0.680**
		IE	0.191	0.273	0.081	0.000
		TE	0.125	0.224	0.564	0.680**

Note: DE = Direct effect, IE = Indirect effect, TE = Total effect
** indicates P-Value ≤ 0.05

4.3.4 Motivation in work

This aspect consists of three sub-variables: Bonus at the end of project or year, social security, and housing support (providing accommodation or a rental subsidy for apartments). Their regression coefficient weights range from 0.795 to 0.904, with multiple correlation coefficients between 63.20% and 75.70%. The test results indicate that housing support (providing accommodation or rental subsidy) has the most significant direct positive influence on the structural equation model of labor productivity, with a standardized weight of 0.904, explaining 75.70% of the changes in motivation in work.

4.3.5 Labor productivity as a dependent variable in the structural model

In this study, Labor Productivity (Y2) was conceptualized as a latent construct reflecting both behavioral and psychological dimensions of individual performance in construction projects. It was measured by four observed indicators: Job Security (V1p), Wages Level for Labor (V2p), Work Discipline (V3p), and Work Satisfaction (V4p). The selection of these indicators was theoretically grounded. Job Security represents stability of employment, which encourages workers to maintain consistent performance and reduce turnover intentions [24, 64]. Wage level denotes the degree to which compensation meets workers' expectations, a key extrinsic motivator that enhances productivity [65]. Work Discipline captures punctuality, adherence to safety and quality standards, and self-regulation, core behavioral aspects of productive work [24]. Finally, Work Satisfaction reflects intrinsic contentment and morale, which have been consistently linked to higher labor productivity in the construction sector [66].

Labor Productivity (Y2) is conceptualized as a latent dependent variable representing the overall efficiency and performance of skilled construction workers in achieving desired outputs relative to input resources. In this study, it is measured by two observed indicators: work discipline (V1p) and job satisfaction (V3p). Work discipline (0.904) reflects an employee's adherence to organizational rules, punctuality, and consistent engagement in task execution. It captures the behavioral dimension of productivity, emphasizing structured, reliable, and goal-oriented work performance. Job satisfaction (0.751), on the other hand, represents the attitudinal dimension of productivity, reflecting how employees' sense of fulfillment and positive perceptions of their job environment contribute to enhanced performance. High satisfaction often leads to increased commitment, lower turnover intentions, and sustained productivity.

Empirically, both indicators demonstrated strong factor loadings, confirming their robust reflection of the underlying latent construct. Furthermore, both loadings were statistically significant at the 0.05 level, providing evidence of measurement validity and supporting their suitability as key indicators of labor productivity. Together, these two measures provide a comprehensive representation of labor productivity, integrating both behavioral and psychological aspects of worker performance.

The structural equation model demonstrates an excellent fit to the data, with all key indices meeting accepted criteria. Specifically, it states: relative Chi-square = 1.087 (<2), RMSEA = 0.016, RMR = 0.009 (<0.05), GFI = 0.995, NFI = 0.996, and CFI = 1.000 (>0.95), confirming the model's validity and robustness [67].

5. Discussion

Exploratory Factor Analysis (EFA) and SEM ensured the validity and robustness of your findings. EFA was crucial for empirically confirming and refining the theoretical structure of latent variables, preventing poor model fit that could arise from relying solely on theoretical groupings. The SEM model demonstrated an excellent fit to the data, with all key indices meeting the accepted criteria for model fit.

5.1 Impact of motivation on labor productivity

The analysis revealed that Motivation was the most influential factor affecting labor productivity, with an overall influence coefficient of 0.680, followed by Equipment/Tool Performance (0.483), Labor Management (-0.049), and Resource Management and Working Conditions (-0.066). Collectively, these variables accounted for 92.7% ($R^2 = 0.927$) of the variations in Labor Productivity (Y2). Furthermore, the R^2 value for Motivation (Y1) was 0.517, indicating that the independent variables included in the model explained 51.7% of the variance in Motivation. This suggests that, while Motivation was the most significant predictor of labor productivity, it was itself moderately explained by the antecedent factors incorporated into the model. Motivation, treated as a latent construct within the SEM framework, was measured through a set of observed variables representing inherently positive motivational attributes. These included a Bonus at the end of the project or year (V3j), with a regression coefficient of 0.869 and an R^2 of 75.4% for Motivation, representing a direct financial incentive. Social Insurance (V4j) was another key factor, with a regression coefficient of 0.795, explaining 63.2% of the variance, highlighting the role of security and welfare in sustaining worker motivation. Accommodation (V7j), representing housing support, exerted the most potent positive effect on Motivation, with a standardized weight of 0.904 and accounting for 75.7% of the variance. The provision of housing support was shown to significantly enhance morale and efficiency, aligning with Herzberg's Two-Factor Theory [24], which posits that hygiene factors such as welfare and job security play a crucial role in fostering positive Motivation.

Research by Jarkas and Bitar [36] found that appropriate welfare support, including housing assistance, positively impacts job satisfaction and work engagement among construction workers in developing countries. This, in turn, helps reduce turnover rates and enhances productivity. Similarly, Dai and Goodrum [68] emphasized that worker well-being, such as providing accommodation near construction sites or housing subsidies, helps reduce commuting fatigue and promotes efficient work performance. Therefore, project managers and stakeholders should prioritize housing support as a key motivational strategy to improve construction project labor productivity and job satisfaction.

5.2 Overall labor productivity outcomes

The findings indicate that the latent variable Labor Productivity is strongly reflected by its observed indicators, work discipline, and job satisfaction, with high factor loadings (0.904 and 0.751, respectively). These indicators highlight that structured work behavior and employee satisfaction are central to efficient performance. This finding is consistent with prior research. Organ [67] emphasized that positive workplace behaviors, such as discipline and responsibility, are essential for improving organizational productivity, while Judge et al. [66] demonstrated that job satisfaction is directly correlated with work efficiency. Accordingly, this study reinforces the view that discipline and job satisfaction are critical determinants of labor productivity in large-scale high-rise construction projects. Project managers should therefore foster workplace discipline and create conditions that enhance job satisfaction to improve productivity and ensure project success.

However, these findings differ from some prior studies. For example, Podsakoff et al. [69] argued that job satisfaction primarily impacts productivity in specific contexts, such as creative or collaborative work, rather than in structured, task-oriented construction work. Additionally, Pinder [70] noted that excessive workplace discipline in rigid environments may reduce flexibility and motivation. Given these insights, the effects of discipline and job satisfaction should be carefully assessed based on the nature of the construction project and the specific tasks involved.

6. Conclusions

6.1 Direct influences on labor productivity (Y2)

6.1.1 Resource management and working conditions (X1)

The study found that Resource Management and Working Conditions (X1) directly influence labor productivity with a regression coefficient of -0.066. The negative coefficient indicates that when workers perceive greater adverse impacts or deficiencies in X1 such as low-quality raw materials or insufficient workforce skills labor productivity decreases accordingly.

6.1.2 Labor management (X2)

Labor Management (X2) also directly influences labor productivity, with a regression coefficient of -0.049. Similar to X1, the negative coefficient suggests that inefficiencies in labor management such as inadequate skill levels or frequent workforce turnover negatively affect overall efficiency.

6.1.3 Equipment/Tool performance (X3)

Equipment/Tool Performance (X3) has a positive direct influence on labor productivity, with a regression coefficient of 0.483. This positive relationship highlights that well-maintained, high-performing equipment and tools significantly enhance labor efficiency.

6.1.4 Motivation (Y1)

Motivation (Y1) emerges as the most influential determinant of labor productivity, with a direct regression coefficient of 0.680. This underscores the crucial role of worker motivation in improving performance and mitigating negative effects from other factors.

6.2 Indirect influences on labor productivity (Y2) via motivation (Y1)

6.2.1 Resource management and working conditions (X1)

X1 indirectly influences labor productivity through motivation, with a total regression coefficient of 0.191 (0.282 × 0.680). This implies that improvements in resource management positively enhance workforce motivation, which in turn increases productivity.

6.2.2 Labor management (X2)

X2 indirectly influences labor productivity through motivation, with a total regression coefficient of 0.273 (calculated as 0.401 × 0.680). This suggests that effective labor management practices, such as workforce training, crew scheduling, and retaining skilled workers, strengthen motivation and, consequently, improve productivity.

6.2.3 Equipment/Tool performance (X3)

X3 indirectly influences labor productivity through motivation, with a total regression coefficient of 0.081 (0.119 × 0.680). This indicates that appropriate and well-functioning equipment can enhance worker motivation, thereby indirectly improving productivity.

6.3 Summary of combined effects

The structural equation for labor productivity (Y2) can be expressed as: $Y2 = (-0.066X1) + (-0.049X2) + (0.483X3) + (0.680Y1)$

This equation illustrates the combined effects of Resource Management and Working Conditions (X1), Labor Management (X2), Equipment/Tool Performance (X3), and Motivation (Y1) on Labor Productivity (Y2). The negative coefficients of X1 and X2 indicate that adverse conditions in these areas reduce efficiency, whereas the positive coefficients of X3 and Y1 emphasize their significant contributions to productivity improvement.

7. References

[1] Zhang D, Hassan N, Carl TH. Development of an internal benchmarking and metrics model for industrial construction enterprises for productivity improvement. Can J Civ Eng. 2017;44(7):518-29.

[2] Chia FC, Skitmore M, Runeson G, Bridge A. Economic development and construction productivity in Malaysia. Constr Manag Econ. 2014;32(9):874-87.

[3] Gerges M, Ahiakwo O, Aziz R, Kapogiannis G, Saidani M, Saraireh D. Investigating and ranking labor productivity factors in the Egyptian construction industry. J Archit. 2016;5(1):44-52.

[4] Sherekar V, Tatikonda M. Impact of factor affecting on labour productivity in construction projects by AHP method. Int J Eng Sci Comput. 2016;6(6):6771-5.

[5] Hafez SM, Aziz RF, Morgan ES, Abdullah MM, Ahmed EK. Critical factors affecting construction labor productivity in Egypt. Am J Cvi Eng. 2014;2(2):35-40.

[6] Enshassi A, Sherif M, Ziad AM, Peter EM. Factors affecting labour productivity in building projects in the Gaza Strip. J Civ Eng Manag. 2007;13(4):245-254.

[7] Olomolaiye A, Egbu C. Training needs in the management of human resources for knowledge management. In: Stephenson P, Greenwood D, editors. ARCOM Doctoral Workshop on Skills, Training and Development in the Construction Industry; 2005 Nov 30; Northumbria University, United Kingdom. p. 12-7.

[8] Jarkas AM. Critical investigation into the applicability of the learning curve theory to rebar fixing labor productivity. J Constr Eng Manag. 2010;136(12):1279-88.

[9] Fayek AR. Fuzzy hybrid computing in construction engineering and management: theory and applications. Emerald; 2018.

[10] Karunarathna DMTGNM, Siriwardana CSA. A tool to assess construction worker productivity. 2018 Moratuwa Engineering Research Conference (MERCon); 2018 May 30 - Jun 1; Moratuwa, Sri Lanka. USA: IEEE; 2018. p. 577-82.

[11] Muhammad NZ, Sani A, Muhammad A, Balubaid S, Ituma EE, Suleiman JH. Evaluation of factors affecting labour productivity in construction industry: a case study. Jurnal Teknologi. 2015;77(12):87-91.

[12] Hasan A, Bassam B, Abbas E, Raufdeen R. Factors affecting construction productivity: a 30 year systematic review. Eng Constr Archit Manag. 2018;25(7):916-37.

[13] Chigara B, Moyo T. Factors affecting labor productivity on building projects in Zimbabwe. Int J Arch Eng Constr. 2014;3(1):57-65.

[14] Hwang BG, Ng WJ. Project management knowledge and skills for green construction: overcoming challenges. Int J Proj Manag. 2013;31(2):272-84.

[15] Thomas HR, Horman MJ. Fundamental principles of workforce management. J Constr Eng Manage. 2006;132(1):97-104.

[16] Shan M, Li YS, Hwang BG, Chua JE. Productivity metrics and its implementations in construction projects: A case study of Singapore. Sustainability. 2021;13(21):12132.

[17] Hair JF, Black WC, Babin BJ, Anderson RE. Multivariate data analysis. 8th ed. UK: Cengage Learning; 2019.

[18] Mojahed S. A project improvement system for effective management of construction projects [dissertation]. Louisiana: Louisiana University; 2005.

[19] Umoru D, Yaqub JO. Private and public health capital expenditures in Nigeria: an empirical test of the relationship. Amer Acad Scholarly Res J. 2013;5(1):83-105.

[20] Soham M, Rajiv B. Critical factors affecting labour productivity in construction projects: case study of south Gujarat region of India. Int J Eng Adv Technol. 2013;2(4):583-91.

[21] Mowday RT, Porter LW, Steers RM. Employee–organization linkages: the psychology of commitment, absenteeism, and turnover. New York: Academic Press; 1982.

[22] Vroom VH. Work and motivation. New York: Wiley; 1964.

[23] Robbins SP, Judge TA. Organizational behavior. 18th ed. London: Pearson; 2019.

[24] Herzberg F. Work, and the nature of man. New York: World Publishing Company; 1968.

[25] Mayo E. The human problems of an industrial civilization. New York: Macmillan; 1933.

[26] Attar AA, Gupta AK, Desai DB. A study of various factors affecting labour productivity and methods to improve it. IOSR J Mech Civ Eng. 2012;1(3):11-4.

[27] Soekiman A, Pribadi KS, Soemardi BW, Wirahadikusumah RD. Factors relating to labor productivity affecting the project schedule performance in Indonesia. Procedia Eng. 2011;14:865-73.

[28] Shashank K, Hazra S, Pal KN. Analysis of key factors affecting the variation of labour productivity in construction projects. Int J Emerg Technol Adv Eng. 2014;4(5):152-60.

[29] Gerges M, Ahiakwo O, Aziz R, Kapogiannis G, Saidani M., Saraireh D. Investigating and ranking labor productivity factors in the Egyptian Construction Industry. J Archit. 2011;5(1):44-52.

[30] Jergeas G. Improving construction productivity on Alberta oil and gas capital projects. A report submitted to Alberta Finance and Enterprise. Alberta: University of Calgary; 2009.

[31] Chan P. Factors affecting labour productivity in the construction industry. In: Greenwood, editor. Proceedings of the 18th annual ARCOM conference; 2002 Sep 2-4; University of Northumbria, United Kingdom. p. 771-80.

[32] Durdyev S, Mbachu J. On-site labour productivity of New Zealand construction industry: key constraints and improvement measures. AJCEB. 2011;11(3):18-33.

[33] Ameh OJ, Osegbo EE. Study of relationship between time overrun and productivity on construction sites. IJCSCM. 2011;1(1):56-67.

[34] Adamu NB, Adamu JY, Mohammed D. Prevalence of helminth parasites found on vegetables sold in Maiduguri, Northeastern Nigeria. Food control. 2012;25(1):23-6.

[35] Kadir MRA, Lee WP, Jaafar MS, Sapuan SM, Ali AAA. Factors affecting construction labour productivity for Malaysian residential projects. Struct Surv. 2005;23(1):42-54.

[36] Jarkas AM, Bitar CG. Factors affecting construction labor productivity in Kuwait. J Constr Eng Manage. 2012;138(7):811-20.

[37] Halwatura RU. Critical factors which govern labour productivity in building construction industry in Sri Lanka. PM World J. 2015;4(4):1-13.

[38] Kazaz A, Manisali E, Ulubeyli S. Effect of basic motivational factors on construction workforce productivity in Turkey. J Civ Eng Manage. 2008;14(2):95-106.

[39] Hickson BG, Ellis LA. Factors affecting construction labour productivity in Trinidad and Tobago. JAPETT. 2014;42(1):4-11.

[40] Alaghbari W, Al-Sakkaf AA, Sultan B. Factors affecting construction labour productivity in Yemen. Int J Construct Manage. 2019;19(1):79-91.

[41] Alinaitwe HM, Mwakali JA, Hansson B. Factors affecting the productivity of building craftsmen-studies of Uganda. J Civ Eng Manage. 2007;13(3):169-76.

[42] Office of Permanent Secretary for Ministry of Labour. Labour statistics yearbook 2019 [Internet]. 2019 [cited 2020 Sep 12]. Available from: https://www.mol.go.th/wp-content/uploads/sites/2/2021/01/สถิติแรงงานประจำปี-2562-ฉบับเพิ่ม-ISBN.pdf. (In Thai)

[43] Yamane T. Statistic: an introductory analysis. 3rd ed. New York: Harper and Row; 1973.

[44] Krejcie RV, Morgan DW. Determining sample size for research activities. Educational and psychological measurement. 1970;30(3):607610.

[45] Neuman WL, Nardi PM, Berg BL, Jackson W, Varberg N, Neuman L, et al. Research methods in communication. Pearson: Canada; 2011.

[46] Babbie ER. The practice of social research. 5th ed. Belmont: Wadsworth; 1989.

[47] Cronbach LJ. Essentials of psychological testing. 3rd ed. New York: Harper Collins; 1970.

[48] Li Q. A novel Likert scale based on fuzzy sets theory. Expert Syst Appl. 2013;40(5):1609-18.

[49] Hai J, Black W, Babin B, Anderson R, Tatham R. Multivariate data analysis. Upper Saddle River: Pearson Prentice Hall; 2006.

[50] Ghoddousi P, Poorafshar O, Chileshe N, Hosseini MR. Labour productivity in Iranian construction projects: perceptions of chief executive officers. Int J Prod Perform Manag. 2015;64(6):811-30.

[51] Bekr GA. Study of significant factors affecting labor productivity at construction sites in Jordan: site survey. J Eng Technol. 2016;4(1):92-7.

[52] Malisiovas A. Construction productivity: from measurement to improvement. Advancing project management for the 21st century concepts, tools & techniques for managing successful projects; 2010 May 29-31; Heraklion, Greece. p. 1-8.

[53] Sandbhor S, Botre R. Applying total interpretive structural modeling to study factors affecting construction labour productivity. AJCEB. 2014;14(1):20-31.

[54] Hashem YM, Ali SM, Dokhan SA. Factors affecting labor productivity in building projects in Great Cairo [Internet]. 2010 [cited 2020 Sep 12]. Available from: http://www.researchgate.net/publication/258100086.

[55] Gundecha MM. Study of factors affecting labor productivity at a building construction project in the USA: web survey [master thesis]. North Dakota: North Dakota State University; 2012.

[56] Mahamid I. Contractors perspective toward factors affecting labor productivity in building construction. Eng Constr Archit Manag. 2013;20(5):446-60.

[57] Makulsawatudom A, Emsley M, Sinthawanarong K. Critical factors influencing construction productivity in Thailand. J KMITNB. 2004;14(3):1-6.

[58] Srinavin K, Mohamed S. Thermal environment, and construction workers' productivity: some evidence from Thailand. Build Environ. 2003;38(2):339-45.

[59] Nasirzadeh F, Nojedehi P. Dynamic modeling of labor productivity in construction projects. Int J Project Manage. 2013;31(6):903-11.

[60] Fabrigar LR, Wegener DT. Exploratory factor analysis. Oxford: Oxford University; 2011.

[61] Kline RB. Principles and practice of structural equation modeling. New York: Guilford; 2016.
[62] Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. J Mark Res. 1981;18(1):39-50.
[63] Byrne BM. Structural equation modeling with AMOS: basic concepts, applications, and programming. 3rd ed. New York: Routledge; 2016.
[64] Locke EA. The nature and causes of job satisfaction. Handbook of Industrial and Organizational Psychology. 1976;1:1297-349.
[65] Jayaweera T. Impact of work environmental factors on job performance, mediating role of work motivation: a study of hotel sector in England. IJBM. 2015;10(3):271-78.
[66] Judge TA, Thoresen CJ, Bono JE, Patton GK. The job satisfaction–job performance relationship: a qualitative and quantitative review. Psychol Bull. 2001;127(3):376-407.
[67] Organ DW, Podsakoff PM, MacKenzie SB. Organizational citizenship behavior: its nature, antecedents, and consequences. Thousand Oaks: Sage; 2005.
[68] Dai J, Goodrum PM. Differences in perspectives regarding labor productivity between Spanish- and English-speaking craft workers. J Constr Eng Manage. 2011;137(9):689-97.
[69] Podsakoff PM, MacKenzie SB, Paine JB, Bachrach DG. Organizational citizenship behaviors: A critical review of the theoretical and empirical literature and suggestions for future research. J Manag. 2000;26(3):513-63.
[70] Pinder CC. Work motivation in organizational behavior. Upper Saddle River: Prentice Hall; 1998.