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OPTIMISATION OF LABOUR-INTENSIVE PRODUCTIVITY FOR CONSTRUCTION PROJECTS IN GHANA

RESEARCH ARTICLE[1]

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ABSTRACT

The construction industry in Ghana is labour-intensive and relies heavily on the skills of its workforce. No coordinated policy framework has been implemented or developed to guide and mainstream the application of labour-intensive methods in Ghana's development process. The aim of this article is to develop a framework for optimising labour-intensive productivity for construction work. The article adopted a quantitative research design, using a questionnaire survey to determine the factors influencing labour-intensive productivity in the Ghanaian construction industry. Records available at the Ghana Social Opportunity Project (GSOP) indicate that there are 920 professionals involved in labour-intensive works on road infrastructure. A purposive sampling technique was used to select 40 districts that were into road construction projects; from these, 560 respondents were considered. Descriptive statistics and inferential statistics were used for the data analysis. Principal axis factor analysis revealed six components in the three labour-productivity categories with eigenvalues above 1 that may influence the optimisation of labour-intensive productivity for construction projects in Ghana. These comprise equipment and

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tools, material and temperature. Optimising labour-intensive productivity in construction works requires the involvement of all stakeholders, including project managers, workers, suppliers, and subcontractors. By implementing the six components in the proposed labour productivity framework, construction projects can achieve increased productivity, cost savings, and improved outcomes. The framework may help policymakers in the construction industry review the existing national policies that are geared towards helping indigenous firms in improving productivity in the construction industry.

ABSTRAK

Die konstruksiebedryf in Ghana is arbeidsintensief en maak staat op die vaardighede van sy arbeidsmag. Geen gekoördineerde beleidsraamwerk is geïmplementeer of ontwikkel om die toepassing van arbeidsintensiewe metodes in Ghana se ontwikkelingsproses te lei nie. Die doel van hierdie artikel is om ’n raamwerk te ontwikkel vir die optimalisering van arbeidsintensiewe produktiwiteit vir konstruksiewerk. Die artikel het ’n kwantitatiewe navorsingsontwerp aangeneem wat ’n vraelysopname gebruik het om die faktore te bepaal wat arbeidsintensiewe produktiwiteit in die Ghanese konstruksiebedryf beïnvloed. Rekords beskikbaar by die Ghana Social Opportunity Project (GSOP) dui aan dat 920 professionele persone betrokke was by arbeidsintensiewe werke aan padinfrastruktuur. ’n Doelgerigte steekproeftegniek is gebruik om 40 distrikte te selekteer wat in padbouprojekte betrokke was; hieruit is 560 respondente oorweeg. Beskrywende en inferensiële statistiek is vir die data-analise gebruik. Hoofasfaktoranalise het ses komponente in die drie arbeidsproduktiwiteitskategorieë met eiewaardes bo 1 aan die lig gebring wat die optimalisering van arbeidsintensiewe produktiwiteit vir konstruksieprojekte in Ghana kan beïnvloed. Dit bestaan uit toerusting en gereedskap, materiaal en temperatuur. Die optimalisering van arbeidsintensiewe produktiwiteit in konstruksiewerke vereis die betrokkenheid van alle belanghebbendes, insluitend projekbestuurders, werkers, verskaffers en subkontrakteurs. Deur die ses komponente in die voorgestelde arbeidsproduktiwiteitsraamwerk te implementeer, kan konstruksieprojekte verhoogde produktiwiteit, kostebesparings en verbeterde uitkomste behaal. Die raamwerk kan beleidmakers in die konstruksiebedryf help om die bestaande nasionale beleid te hersien wat daarop gemik is om inheemse firmas te help om produktiwiteit in die konstruksiebedryf te verbeter.

1. INTRODUCTION

The labour-intensive public works (LIPW) programme in Ghana has been designed to facilitate and promote the local economic development agenda through the provision of local employment opportunities and the use of local resources (Bamfo-Agyei, Thwala & Aigbavboa, 2022a: 2). The cardinal principles of labour-intensive public works include equal opportunities for men and women willing to work; equal pay for equal work, emphasising local resource mobilisation, ensuring cost-effectiveness, value for money, quality output, and environmental sustainability (Bamfo-Agyei *et al*., 2022b: 120).

Labour-intensive works coverage currently includes 60 district assemblies in Ghana. The selection of beneficiary district assemblies is based on the extent of poverty and deprivation as well as ensuring regional balance. Nearly 71.7% of the beneficiary district assemblies can be found in the Savannah region of the country (GSOP, 2017).

Bamfo-Agyei *et al*. (2022b: 3) argued that labour-intensive techniques such as stone pitching, earth compacting, and digging trenches have been applied in various stages of the development process in Ghana during the pre- and post-independence era of construction. Based on the earlier submission in 2016, the government of Ghana designed a labour-intensive public works policy that addresses the following specific issues: Inadequate employable skills; weak institutional training for persons who wish to make a career in the application of labour-intensive techniques; the high cost of public infrastructure, and physical assets produced through capital-intensive methods (GSOP, 2017). Despite the national benefits derived from using labour-intensive methods in the past, the technique could not be sustained because of the absence of national policy and guidelines to regulate and sustain its application, where feasible.

There is also evidence that Ghanaians' approach to government work is poor, due to cultural orientation inherited from the colonial era when public sector work was perceived as belonging to the 'Whiteman'; hence, this could be handled haphazardly (Damoah & Akwei, 2017: 33). The cultural design poses a significant influence on the Ghanaian government's construction project performance. Partisanship politics could influence the failure of Ghanaian government construction projects (Dick-Sagoe *et al*., 2023: 2).

Despite the success of labour-intensive projects in the past, no coordinated policy framework has been implemented/developed to guide and mainstream the application of labour-intensive methods in Ghana's development process. It is, therefore, important to develop a holistic construction labour-intensive productivity framework that would be available to project managers. This will guide and estimate optimal labour productivity as well as evaluate the efficiency of their construction operations. This article determines the factors influencing the optimisation of labour productivity that is needed to develop a framework for estimating the optimal construction labour productivity for labour-intensive work in the Ghanaian construction industry.

2. LITERATURE REVIEW

This literature review aims to provide an overview of the key concepts, theories, and practices related to labour-intensive construction work.

2.1 Labour-intensive construction work

Labour-intensive construction work is a construction method that relies heavily on manual labour instead of heavy machinery and equipment. It is often used in developing countries, where access to modern technology and equipment is limited. There are several definitions for labour-intensive construction work, each emphasising different aspects.

According to Nag and Gite (2020: 308), labour-intensive construction work involves the use of “simple hand tools, human muscle power and minimal mechanical equipment to execute construction works”. This construction method requires a large number of workers and can involve tasks such as excavation, mixing, transporting of materials, and manual installation of components (Wang *et al*., 2021: 84).

The International Labour Organization (ILO) (2020: 5) defined labour-intensive construction work as “a set of techniques which combine labour, local resources and low-cost materials to provide basic infrastructure and services, such as housing, water supply, sanitation, and access roads, particularly in rural and peri-urban areas”. This definition emphasises the use of local resources and low-cost materials, in addition to manual labour.

According to Hilson and Hu (2022: 95), labour-intensive construction work is often associated with small-scale projects such as building homes, schools, and community centres. This definition highlights the focus on community-based projects that aim to improve the quality of life for local communities.

McCutcheon (2008: 5) defined labour-intensive road construction as the economically efficient employment of as great a proportion of labour as is technically feasible to produce as high a standard of the road as demanded by the specification and allowed by the funding available.

Thwala (2011: 6014) defined labour-intensive work as the combination of labour and appropriate equipment, which is generally light equipment. Thwala (2011: 6018) indicates that optimal use is made of labour as the predominant resource in infrastructure projects, while ensuring cost-effectiveness and safeguarding quality. It also means ensuring that labour-intensive projects do not degenerate into ‘make-work’ projects, in which cost and quality aspects are ignored.

For this article, the definition provided by the ILO, emphasising the use of local resources and low-cost materials in addition to manual labour, is adopted.

There are six theories related to labour-intensive construction work that need introduction. To explain the development of the proposed labour-productivity optimisation framework only two (the Resource Dependency Theory and the Capability Approach Theory) were adopted.

The Institutional Theory supports that institutions, or the formal and informal rules that shape social behaviour, play a critical role in shaping economic outcomes (Gao-Zeller *et al*., 2019: 1942). In the context of labour-intensive construction work, institutions such as labour laws, government regulations, and social norms influence the way in which construction projects are carried out and the outcomes produced.

The Transaction Cost Theory argues that the cost of transactions between different elements in the market affects the behaviour of firms and their decision-making processes (Govindan, Shaw & Majumdar, 2021: 5). In the context of labour-intensive construction work, transaction costs can be high, due to the complexity of coordinating labour, materials, and financing across multiple elements in the market.

The Social Learning Theory suggests that people learn from their social environment through observation, imitation, and modelling (Broto & Dewberry, 2016: 3020). This theory can be applied to labour-intensive construction work by encouraging workers to learn from one another through peer-to-peer training, mentorship, and collective problem-solving.

The Social Capital Theory highlights the importance of social networks, relationships, and trust in promoting economic and social development (Teshome, De Graaff & Kessler, 2016: 220). In the context of labour-intensive construction work, social capital can be developed by building trust between workers, contractors, and local communities, and by involving local communities in the construction process (Clarke & Gholamshahi, 2018: 252).

The Resource Dependency Theory suggests that organisations depend on external resources to function effectively and efficiently (Govindan *et al.*, 2021: 5). In the context of labour-intensive construction work, organisations depend on the availability of skilled labour, raw materials, and financing to carry out their projects effectively. Without access to skilled labour, construction projects may be delayed, inefficient, and produce poor outcomes. By understanding the resource dependencies of organisations involved in labour-intensive construction work, strategies can be developed to address the challenges they face and to improve the outcomes of construction projects.

The Capability Approach Theory, developed by economist Amartya Sen (1999), emphasises the importance of human development and individual capabilities, rather than solely focusing on economic growth (Andreoni, Chang & Estevez, 2021: 191). The Capability Approach Theory recognises that each person has a unique set of capabilities, including knowledge, skills, and agency, which are essential for their overall well-being. In the context of labour-intensive construction work, the Capability Approach Theory can be applied by providing workers with opportunities to learn and develop new skills, thus empowering them to take on more responsibility and decision-making roles in the construction process, and recognising the value of their work beyond their economic output. The Capability Approach

Theory recognises the value of individual workers and their capabilities. This is important in labour-intensive construction work that relies heavily on manual labour. By empowering workers with the skills and knowledge to take on more responsibility and decision-making roles, workers are more likely to contribute to the overall success of the construction project.

2.2 Construction labour productivity

Construction labour productivity is a measure of the efficiency and effectiveness of construction workers in completing their tasks (Manoharan *et al*., 2023: 144). Productivity is crucial to the success of construction projects, and understanding the factors that impact productivity is essential (Durdyev & Mbachu, 2018: 388). Weng *et al*. (2020: 2) found that construction labour productivity can be influenced by a wide range of factors, including project management practices, the availability and quality of tools, equipment and materials, worker skills, experience and motivation, work-based conditions, as well as environmental factors. These factors affect the productivity of construction workers and can have a significant impact on project success. The study also found that improving productivity requires a holistic approach that considers all of these factors and that effective project management is crucial to achieving high levels of productivity.

Management factors refer to the practices and strategies adopted by project managers to optimise productivity. These may affect labour productivity (Bender *et al*., 2018: 380; Nguyen & Watanabe, 2017: 781). Weng *et al*. (2020: 3) found that project management practices such as effective communication, coordination, and planning can significantly improve productivity levels. Similarly, Zhang *et al*. (2018: 298) found that the use of lean construction practices such as just-in-time delivery and waste reduction can improve productivity levels, by reducing waste, improving communication, and increasing efficiency.

Tools and equipment factors refer to the availability and quality of tools and equipment used in construction projects (Sheikh, Lakshmipath & Prakash, 2016: 5668; Cheng, Tran & Hoang, 2017: 120). Bogue (2018: 4) found that the use of advanced technology such as drones and robotics can improve productivity, by reducing manual labour and increasing accuracy of the project.

Material factors refer to the availability and quality of materials used in construction projects (Ghanem *et al*., 2018: 18). Liu and Lu (2018: 3) found that the timely and efficient delivery of materials is essential for maintaining high levels of productivity. Similarly, Liao, Teo and Low (2018: 22) found that the use of Building Information Modeling (BIM) technology can improve material management and reduce waste, leading to increased productivity.

Worker factors refer to the skills, experience, motivation, as well as physical and mental well-being of construction workers (Dixit *et al*., 2019: 557; Khosrowpour, Niebles & Golparvar-Fard, 2014: 79). Research has shown that these worker-related factors can significantly impact on productivity. For example, Weng *et al*. (2020: 2) found that training programmes that improve workers' skills and knowledge can lead to higher productivity rates. Zhang *et al*. (2018: 300) found that providing workers with a safe and healthy work environment can improve their motivation and overall well-being, leading to increased productivity.

Work-based conditions, including workspace design, refer to the physical conditions in which construction work takes place (Udris & Nibel, 2017: 79). Wang *et al*. (2018: 663) found that optimising work-based conditions such as reducing noise and improving lighting can lead to significant increases in productivity.

Environmental factors such as temperature also play a significant role in construction labour productivity. Li and Lu (2018: 325) found that extreme temperatures can significantly impact on workers' physical and mental well-being, leading to lower productivity rates. Other researchers also concluded that the weather can negatively disrupt the activities of the project (Ghoddousi & Hosseini, 2012: 102; Lessing *et al*., 2017: 69). Similarly, Chou *et al*. (2019: 12) found that regulations related to safety and environmental protection can impact on productivity, and that careful planning and management can help mitigate their effects.

2.3 Optimisation and productivity

Momade *et al*. (2022: 1930) explored strategies for optimising construction labour productivity in labour-intensive projects. The study found that effective project planning and scheduling are critical to achieving high levels of productivity. This includes identifying and prioritising critical tasks and allocating resources accordingly. The ability to accomplish deadlines on time and on a budget is the most important skill in optimisation. Strategies such as the fuzzy-based simulation annealing method are used to study the optimisation problem in terms of time and cost (Haque & Hasin, 2016: 1475). The fuzzy-based simulation annealing method works by first defining the problem and identifying the input parameters such as the type of labour-intensive technique used, the number of workers, and the amount of time required to complete the task (Rahmanniyay & Yu, 2019: 233).

Next, fuzzy logic is used to create a set of rules that represent the relationship between the input parameters and the output, which is the labour-intensive productivity. These rules are based on expert knowledge and experience and are used to make decisions about the optimal combination of input parameters to maximise the output (Tsehayae & Fayek, 2016: 210).

Simulated annealing is then used to search for the optimal solution within the fuzzy rule-based system. This involves randomly generating a solution and calculating its suitability, which is a measure of how well it meets the objective function. The solution is then subjected to a set of perturbations or changes to explore the search space and find a better solution. This process continues until the optimal solution is found (Rahmanniyay & Yu, 2019: 235).

The fuzzy-based simulation annealing method has been applied in various construction projects, including road construction, building construction, and infrastructure development. Its advantages include its ability to handle uncertainty and vagueness in the input parameters, and to find the global optimum solution rather than getting trapped in local optima. Its limitations include the need for expert knowledge and experience to create the fuzzy rule-based system and the computational complexity of the simulated annealing algorithm (Haque & Hasin, 2016: 1475).

Numerous construction-related fields have employed optimisation approaches such as the critical path method, linear programming (Kumar, Wilfred & Sridevi, 2017); non-dominated genetic algorithm (Taheri Amiri *et al*., 2018: 3745); fuzzy logic with genetic algorithm (Acar Yildirim & Akcay, 2019: 560), and learning curve methods (Abdelkhalek, Refaie & Aziz, 2020: 1075) for managing multiple construction projects simultaneously. Lin and Lai (2020:124) proposed a time-cost trade-off model to reduce project duration that used a genetic algorithm to evaluate productivity.

Durdyev, Omarov and Ismail (2017: 10) found that communication and coordination among project team members can improve labour-intensive productivity, which can be facilitated by using tools such as project management software. Providing workers with appropriate training and support is another strategy for optimising labour-intensive productivity in projects. Hewitt *et al*. (2015:948) presented a model that allocates assignments to workers with various ability levels, using mixed-integer non-linear programming.

For optimising work-based conditions, Jin *et al*. (2020: 635) suggested a multi-objective workspace-based optimisation approach to generate the most effective scaffolding resource allocation and space-planning decisions.

3. RESEARCH METHODOLOGY

3.1 Research design

Factors affecting the labour productivity of labour-intensive works were investigated using a quantitative research design, with data being collected through a questionnaire-based descriptive survey. Quantitative surveys collect data that can be analysed to reveal trends, averages, and frequencies (Bless, Higson-Smith & Sithole, 2018: 16; Fellows & Liu, 2008: 222; Dixon *et al.*, 2020: 742). A quantitative design allows researchers to extrapolate their results to a larger population (Creswell, 2014: 11; Bryman, 2016: 232; Newman , 2020:648). In the survey, 26 factors were chosen as the benchmarks that would evaluate labour-intensive productivity. In order to distil a large number of measured variables into a manageable set, Principal Component Analysis (PCA) was used. According to Rossoni *et al*. (2016: 201), PCA can be used to extract factors, which can be used to summarise the data into a manageable number of factors based on the highest eigenvalues. The framework for optimising labour productivity was developed with the aid of regression analysis.

3.2 Population, sampling, and response rate

Contractors, site engineers, facilitators, timekeepers, district engineers, and GSOP desk officers in Ghana, who are engaged in heavy labour-intensive construction work, form the population for this study. According to data collected by the GSOP, 920 professionals engaged in manual labour activities were eligible for inclusion in the study. The GSOP has regional offices in Bolgatanga, Wa, Temale, Kumasi, and Accra. An equitable distribution of survey responses across the various administrative regions was achieved, using a stratified sample technique, due to the demographic variety of the country's population. Bolgatanga has 12 district offices; Wa has 10; Temale has 11; Kumasi has 14, and Accra has 13 district offices, totalling 60 district offices for all the zonal offices.

Due to the fact that not all districts were involved in heavy labour-intensive construction projects, 40 districts were chosen, using the purposive sampling method. Specifically, one district engineer and one GSOP desk officer were chosen at random from each of the 40 districts, resulting in a total of 80 respondents. Three locations were selected from each of the 40 districts, totalling 120 sites. Each of the 120 sites had one facilitator, one timekeeper, one site engineer, and one contractor. The investigation comprised a total of 560 individuals, of whom only 543 returned valid responses, resulting in a 97% response rate. Krejcie and Morgan's (1970: 608) table suggests a sample size of 175 for a population of 950. For a total population of 920, this recommendation verifies that a sample size of 560 is sufficient.

3.3 Data collection

From November 2016 to August 2017, 560 questionnaires were distributed through drop-and-collect and e-mailed to potential respondents who perform heavy labour-intensive work on construction projects in Ghana. The researchers compiled a questionnaire consisting of two sections. The first section contains questions on the demographic data of the respondents, including age, gender, occupation, level of education, years of experience, and region. Taken from reviews of the relevant literature, the second section set 26 statements on the construct 'factors critical for labour productivity' in three categories, namely 'Equipment and tools', 'Materials', and 'Temperature'. Using a 5-point Likert scale, respondents were asked to rate the importance of these statements in optimising the productivity of firms in Ghana that rely heavily on manual labour. The items used on the Likert scale for the descriptive analysis and the variables for the inferential statistics that examined the validity and reliability of the factors were derived from these measurements. Section two's closed-ended questions were favoured to reduce respondent bias (Harlacher, 2016: 9-10). Cronbach's *alpha* was calculated in accordance with Taber (2018: 1273) to assess the items' internal consistency. It has been established that values between 0.70 and 0.95 for Cronbach's *alpha* are considered adequate (Tavakol & Dennick, 2011: 54-55); hence, a threshold of 0.70 was used in this study.

3.4 Method of analysis and interpretation of the data

All of the tabular and graphical displays are the results of an SPSS 24.0 analysis of the data (Pallant, 2013: 134). Descriptive statistics were used to analyse the respondents' demographics. Frequencies and percentages were calculated and reported.

Using a five-point Likert scale, the 26 items that could optimise the performance of labour productivity were ranked, based on mean scores. Opinions can be measured with the help of Likert-type or rating scales that use fixed choice response formats (Singh, 2006: 202). Mean scores were measured, using a scale where 1 = Very poor (≥1.00 and ≤1.80); 2 = Poor (≥1.81 and ≤2.60); 3 = Good (≥2.61 and ≤3.40); 4 = Very good (≥3.41 and ≤4.20), and 5 = Excellent (≥4.21 and ≤5.00).

Data appropriateness for factor analysis was validated, using the Meyer-Olkin (KMO) (Lorenzo-Seva, Timmerman & Kiers, 2011) and the Bartlett's Test of Sphericity (Hair *et al.*, 2014: 110). Considering that the KMO test scores can be anywhere from 0 to 1, it was determined that EFA could only be used if the values were greater than 0.7 (Hair *et al.*, 2014). In order to proceed with the study, the variables must show sufficient correlation, as indicated by a statistically significant Bartlett test (p=0.05) (Pallant, 2013: 190). This study adopted the assertion made by Hair *et al*.'s (2014) assertion in selecting eigenvalues criterion to determine the maximum number of factors to retain in the model.

Using a PCA criterion of initial eigenvalues greater than 1, the Oblimin rotation with Kaiser normalisation and factor loading of 0.4 was considered to be good, as it had 30% overlapping variance (Rossoni, Engelbert & Bellegard, 2016: 102). A range from 0.2 to 0.4 is the optimal inter-item correlations mean (factor loading) for the factor to be reliable (Pallant, 2013: 134).

4. FINDINGS

4.1 Demographic profile of the respondents

Table 1 shows that the majority of the respondents (87%) are male, aged between 26 and 35 (51.1%) years. Most of the respondents are almost equally employed as contractors, timekeepers, and facilitators (22.1%) each, and supervisors (21.9%). Over half of the participants have post-secondary education, with the majority of them (66.6%) holding either a bachelor's degree (36%) or a technical certificate (30.6%), and the remaining 16.9% having completed high school.

While nearly half of the respondents (47%) have two to five years' experience, just over half (53.1%) have six years' experience or more. This shows that the respondents have the necessary skills and expertise to provide data that could be used to draw conclusions about parameters optimising labour-intensive productivity. The geographic distribution of respondents was nearly even: 20.6% were from Bolgatanga; 20.6% from Wa; 20.3% from Tamale, 20.1% from Kumasi, and 18.4% from Accra. However, the majority of the respondents (61.5%) are employed in the three northern regions of Ghana: Bolgatanga, Wa, and Tamale.

Table1: Demographic profile of the respondents

Demographic	*Characteristic*	*Frequency (N=543)*	*%*
Gender	Male	472	87
	Female	71	13
Age	Under 25	78	14.4
	26-35 years	277	51.0
	36-45 years	179	32.9
	Over 45 years	9	1.7

Demographic	*Characteristic*	*Frequency (N=543)*	*%*
Professional background	Contractors	120	22.1
	Site supervisors	119	21.9
	Timekeepers	120	22.1
	Facilitators	120	22.1
	Project desk officers	32	5.9
	District engineers	32	5.9
Work experience	Less than 5 years	255	47.0
	5-10 years	202	37.2
	10-15 years	51	9.4
	Over 15 years	35	6.4
Geographical location	Bolgatanga	112	20.6
	Wa	112	20.6
	Tamale	110	20.3
	Kumasi	109	20.1
	Accra	100	18.4

4.2 Ranking of productivity factors

In Table 2, average MS of 3.76, 3.93, and 4.09, respectively, for the three productivity optimising categories shows that respondents rated all 26 factors as good to have an influence on the optimisation of labour-intensive productivity of the firms involved in heavy labour-intensive construction works in Ghana. With MS above 4.20 'Use of equipment for a suitable time' (MS=4.26), 'The degree to which material is appropriate for the purpose' (MS=4.21), and 'Quality of soil condition' (MS=4.26) were rated the top three and perceived by respondents as excellent factors that influence the optimising of productivity in heavy labour-intensive construction work. The Cronbach's *alpha* values for each factor were greater than 0.70, indicating acceptable internal reliability, as recommended by Hair *et al*. (2014).

Table 2: Ranking of productivity optimising factors

Factors (N=543) 1 = very poor … 5 = excellent	*MS*	*Cronbach's alpha*	*Rank*
Equipment and tools (Average score = 3.76)			
Use of equipment for a suitable time	4.26	0.768	1
Advanced planning to manage the use of equipment	4.09	0.788	2
Appropriateness of tools to be used for the tasks	4.08	0.750	3
Keeping the same crew and operator on the same piece of equipment	4.06	0.872	4
Availability of tools	4.02	0.705	5
How well operators are assigned to specific tools	3.88	0.751	6
Maintenance of tools	3.74	0.734	7

Factors (N=543) 1 = very poor … 5 = excellent	*MS*	*Cronbach's alpha*	*Rank*
Equipment and tools (Average score = 3.76)			
Frequency of reports provided by tool room supervisors	3.72	0.736	8
Keeping of a record of all toolkit assignments, as well as tools not included in the kits	3.66	0.720	9
Frequency of equipment usage reports	3.64	0.778	10
Issuing of tool kits based on trade	3.54	0.793	11
Storage of non-permanently used tools in storerooms	3.50	0.876	12
Quality of scheduling of equipment use	3.48	0.874	13
Frequency of site inventories to control loss, theft, and breakage	3.43	0.701	14
The degree to which each person is held accountable for a tool kit	3.28	0.777	15
Materials (Average score = 3.93)			
The degree to which material is appropriate for the purpose	4.21	0.871	1
The condition of materials	4.14	0.771	2
Quality of transportation of the material to the site	4.14	0.744	3
The quantity of material	3.98	0.745	4
Quality of storage for material	3.72	0.752	5
The degree to which material is procured on time	3.42	0.741	6
Temperature (Average score = 4.06)			
Quality of soil condition	4.26	0.814	1
Planning for inclement weather	4.12	0.727	2
Suitability of temperature for working	4.08	0.785	3
Quality of site conditions	4.02	0.676	4
Access to appropriate rain gear	3.85	0.744	5

In the category 'Equipment and tools', with mean score ratings above 4, 'Use of equipment for suitable time' (MS=4.26), 'Advanced planning to manage the use of equipment' (MS=4.09), 'Appropriateness of tools to be used for the tasks' (MS=4.08), 'Keeping the same crew and operator on the same piece of equipment' (MS=4.06), and 'Availability of tools' (MS=4.02) were ranked the top five factors that influence optimisation of the performance of labour productivity in heavy labour-intensive construction work.

The factors 'Degree to which material is appropriate for purpose' (MS=2.21), 'The condition of materials' (MS=4.14), and 'Quality of transportation of the material to the site' (MS=4.14) were ranked the top three factors that have an influence on optimising productivity in the 'Materials' category for heavy labour-intensive construction work.

In the category 'Temperature', with mean score ratings above 4, 'Quality of soil condition' (MS=4.26), 'Planning for inclement weather' (MS= 4.12), and 'Suitability of temperature for working' (MS= 4.08) were ranked the top three factors influencing optimisation of the labour productivity performance in heavy labour-intensive construction work.

4.3 Principal component analysis

The 26 factors in the three categories that have an influence on optimising labour productivity of labour-intensive construction work were subjected to PCA to assess their validity and reliability. The results report the suitability of the data to be analysed, factor extraction and rotation, and interpretation.

4.3.1 Equipment and tools category

As shown in Table 3, the KMO measure of sampling adequacy achieved a value of 0.920, exceeding the recommended minimum value of 0.7. Bartlett's test of sphericity was also statistically significant ($p<0.05$), thus supporting the factorability of the correlation matrix for the equipment and tools component.

Table 3: KMO and Bartlett's test for equipment and tools category

KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.920
Bartlett's test of sphericity	Approx. *chi*-square	9192.335
	df	15
	Sig.	.000

The pattern matrix in Table 4 shows that, out of the initial 15 variables, PCA extracted 15 variables in three components with factor loadings above 0.4, with the potential to influence the optimisation of labour productivity of heavy labour-intensive construction work in Ghana.

Table 4: Pattern matrix for equipment and tools category

Variables	*Component*		
	1	*2*	*3*
ETC6 Frequency of site inventories to control loss, theft, and breakage	0.909	-0.188	-0.04
ETC8 Appropriateness of tools to be used for the tasks	0.869	0.298	-0.109
ETC9 Maintenance of tools	0.847	0.092	0.098
ETC7 Availability of tools	0.830	-0.18	0.095
ETC12 Advanced planning to manage the use of equipment	0.655	0.487	-0.088
ETC11 Use of equipment for suitable time	0.640	0.281	0.149
ETC1 Storage of non-permanently used tools in tool rooms	-0.192	0.221	0.809

Variables	*Component*		
	1	*2*	*3*
ETC2 Frequency of reports provided by tool room supervisors	0.220	0.340	0.668
ETC10 How well operators are assigned to specific tools	0.412	0.609	0.246
ETC3 Issuing of toolkits based on trade	-0.305	0.17	0.958
ETC14 Frequency of equipment usage reports	0	-0.05	0.947
ETC13 Keeping the same crew and operator on the same piece of equipment	0.118	0.012	0.797
ETC5 Keeping record of all toolkit assignments, as well as tools not included in the kits	0.363	0.706	-0.506
ETC4 Degree to which each person is held accountable for a toolkit	0.488	-0.315	0.594
ETC15 Quality of scheduling of equipment use	0.51	-0.237	0.569

Extraction method: PCA; rotation method: Oblimin with Kaiser normalisation

Table 5 shows that, after rotation, three components, with eigenvalues exceeding 1.0, were extracted and are meaningful to retain. Factor one explains 50.56% of the total variance; factor two, 17.97%, and factor three, 10.00%. Thus, the final statistics of the PCA shows that three extracted factors explain a cumulative variance of approximately 78.53%.

Table 5: Total variance explained for equipment and tools category

Component	*Initial eigenvalues*			*Extraction sums of squared loadings*			*Rotation sums of squared loadings*
	Total	*% of variance*	*Cumulative %*	*Total*	*% of variance*	*Cumulative %*	*Total*
1	7.584	50.559	50.559	7.584	50.559	50.559	6.389
2	2.696	17.974	68.533	2.696	17.974	68.533	2.363
3	1.500	10.002	78.535	1.500	10.002	78.535	5.533
4	.791	5.272	83.807				
5	.645	4.302	88.109				
6	.412	2.743	90.852				
7	.336	2.238	93.090				
8	.265	1.767	94.857				
9	.203	1.353	96.210				
10	.178	1.190	97.400				
11	.128	.854	98.254				
12	.094	.630	98.884				
13	.080	.531	99.415				
14	.055	.369	99.785				
15	.032	.215	100.000				

Table 6 reveals the correlation of variables based on their factor loadings after rotation in PCA. Three principal components with eigenvalues above 1 (see Table 5) were examined on the inherent relationships among the variables. Variables with the highest loadings (values of 0.4 and above) in a component are most strongly correlated with that component. Component 1 was labelled Appropriate tools (AT); Component 2, Participants' knowledge of tools (PKT), and Component 3, Recording of tools (RT). The names given were derived from a close examination of the variables within each of the components.

Table 6: Rotated matrix for equipment and tools category

Variables	*Component*		
	1	*2*	*3*
	AT	*PKT*	*RT*
ETC6 Frequency of site inventories to control loss, theft, and breakage	0.909		
ETC8 Appropriateness of tools to be used for the tasks	0.869		
ETC9 Maintenance of tools	0.847		
ETC7 Availability of tools	0.830		
ETC11 Use of equipment for a suitable time	0.640		
ETC12 Advanced planning to manage the use of equipment	0.655		
ETC10 How well operators are assigned to specific tools		0.609	
ETC13 Keeping the same crew and operator on the same piece of equipment		0.797	
ETC1 Storage of non-permanently used tools in tool rooms			0.809
ETC2 Frequency of reports provided by tool room supervisors			0.668
ETC3 Issuing of toolkits based on trade			0.958
ETC14 Frequency of equipment usage reports			0.947
ETC5 Keeping record of all toolkit assignments, as well as tools not included in the kits			0.706
ETC4 Degree to which each person is held accountable for a toolkit			0.594
ETC15 Quality of scheduling of equipment use			0.569

Extraction method: PCA; rotation method: Oblimin with Kaiser normalisation

Component 1 Appropriate tools explained 50.6% of the total variance and have six correlated variable loadings, frequency of site inventories to control loss, theft, and breakage (0.909), appropriateness of tools to be used for the tasks (0.869), maintenance of tools (0.847), availability of tools (0.830), use of equipment for a suitable time (0.640), and advanced planning to manage the use of equipment (0.655).

Component 2 Participants' knowledge of tools explained 18% of the total variance and had two variable loadings, how well operators are assigned to specific tools (0.509), and keeping the same crew and operator on the same piece of equipment (0.797).

Component 3: Recording of tools, explained 10% of the variance and had seven variable loadings, storage of non-permanently used tools in tool rooms (0.809), frequency of reports provided by tool room supervisors (0.668), issuing of toolkits based on trade (0.958), frequency of equipment usage reports (0.947), keeping record of all toolkit assignments, as well as tools not included in the kits (0.706), degree to which each person is held accountable for toolkit (0.594), and quality of scheduling of equipment use (0.569).

4.3.2 Material category

Table 7 reveals that the KMO measure of sampling adequacy achieved a value of 0.889, exceeding the recommended minimum value of 0.7. Bartlett's test of sphericity was also statistically significant ($p<0.05$), supporting that the data is suitable for factor analysis.

Table 7: KMO and Bartlett's test for material category

KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.889
Bartlett's test of sphericity	Approx. chi-square	2505.671
	df	15
	Sig.	.000

The pattern matrix from the PCA in Table 8 shows all 6 initial variables, in two components with factor loadings above 0.4 with the potential to influence labour productivity optimisation of heavy labour-intensive construction work in Ghana.

Table 8: Pattern matrix for material category

Variables	*Component*	
	1	*2*
MC3 The degree to which material is procured on time	0.956	-0.089
MC4 Quality of transportation of the material to the site	0.915	-0.011
MC6 Quality of storage for material	0.794	0.11
MC2 The quantity of material	-0.196	1.031
MC1 The condition of materials	0.413	0.674
MC5 Degree to which material is appropriate for the purpose	0.404	0.674

Extraction method: PCA; rotation method: Oblimin with Kaiser normalisation

Table 9 shows that, after rotation, two components with eigenvalues exceeding 1.0 cumulatively explained approximately 83.59% of the total variations and should retain. Component one explains 63.94% of the total variance and factor two, 19.66%.

Table 9: Total variance explained for material category

Component	*Initial eigenvalues*			*Extraction sums of squared loadings*			*Rotation sums of squared loadings*
	Total	*% of variance*	*Cumulative %*	*Total*	*% of variance*	*Cumulative %*	*Total*
1	3.836	63.939	63.939	3.836	63.939	63.939	3.337
2	1.179	19.656	83.594	1.179	19.656	83.594	2.696
3	.413	6.876	90.471				
4	.307	5.121	95.592				
5	.160	2.668	98.259				
6	.104	1.741	100.000				

Extraction method: PCA; rotation method: Oblimin with Kaiser normalisation

Table 10 reveals the correlation of variables based on their loadings after rotation in PCA. Two components with eigenvalues above 1 (see Table 4) were examined on the inherent relationships among the variables. Variables with the highest loadings (values of 0.4 and above) in one component are most strongly correlated with that component. Component 1 was labelled Management of material (MM), and Component 2 Suitability of material (SM). The names given were derived from a close examination of the variables within each of the components.

Table 10: Rotated factor matrix for material category

Code	*Variable*	*Component*	
		1	*2*
		MM	*SM*
MC3	The degree to which material is procured on time	0.956	
MC4	Quality of transportation of the material to the site	0.915	
MC6	Quality of storage for material	0.794	
MC2	The quantity of material		1.031
MC1	The condition of materials		0.674
MC5	The degree to which material is appropriate for the purpose		0.674

Extraction method: PCA; rotation method: Oblimin with Kaiser normalisation

Component 1: Management of material, explained 63.9% of the total variance and had three correlated variable loadings, the degree to which material is procured on time is estimated (0.956), quality of transportation of the material to the site (0.915), and quality of storage for material (0.794).

Component 2: Suitability of material, had three correlated variable loadings, quantity of material (1.031), condition of materials (0.674), degree to which material is appropriate for the purpose (0.674), and accounted for 19.7% of the total variance.

4.3.3 Temperature category

The KMO measure of sampling adequacy achieved a value of 0.801, exceeding the recommended minimum value of 0.7. Bartlett's test of sphericity was also statistically significant ($p<0.05$), supporting that the data is suitable for factor analysis.

Table 11: KMO and Bartlett's test for temperature category

KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.801
Bartlett's test of sphericity	Approx. chi-square	2803.103
	df	10
	Sig.	.000

Table 12 shows that, after rotation, one component with eigenvalues exceeding 1.0 was extracted. This component explains 67.10% of the total variance and is meaningful to retain.

Table 12: Total variance explained for temperature category

Component	*Initial eigenvalues*			*Extraction sums of squared loadings*			*Rotation sums of squared loadings*
	Total	*% of variance*	*Cumulative %*	*Total*	*% of variance*	*Cumulative %*	*Total*
1	3.355	67.101	67.101	3.355	67.101	67.101	3.355
2	.912	18.241	85.342				
3	.561	11.211	96.553				
4	.151	3.019	99.572				
5	.021	.428	100.000				

The pattern matrix in Table 13 shows that, out of the initial 5 variables, PCA extracted 5 variables in one component with factor loadings above 0.4, with the potential to influence optimisation of labour productivity in heavy labour-intensive construction in Ghana.

Table 13: Pattern factor matrix for temperature category

Variables	*Component*
	1
	Isohyperthermic impact
TC3 Planning for inclement weather	0.910
TC2 Access to appropriate rain gear	0.874
TC1 Suitability of temperature for working	0.856
TC4 Quality of site conditions	0.806
TC5 Quality of soil condition	0.616

Based on the examination of the inherent relationships among the variables, Component 1 was termed isohyperthermic impact and explained 67.1% of the variance. Component 1 had five correlated variable loadings, planning for inclement weather is estimated (0.91), access to appropriate rain gear (0.874), suitability of temperature for working (0.856), quality of site conditions (0.806), and quality of soil condition (0.616).

5. PROPOSED LABOUR PRODUCTIVITY OPTIMISATION FRAMEWORK

The productivity of public works that rely heavily on human labour can now be evaluated using frameworks developed from studies of labour productivity that take into account both objective and subjective factors. Figure 1 shows a proposed framework that could optimise labour productivity for heavy labour-intensive construction work. The six components derived from the three labour-optimisation categories in this article form the elements included in the framework.

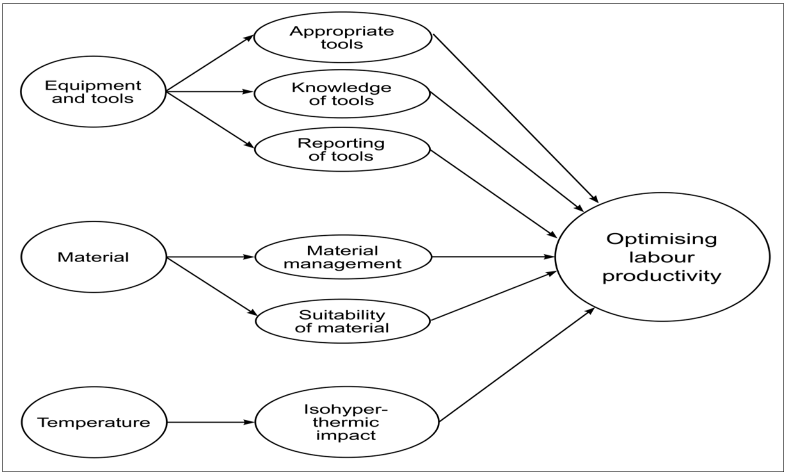

Figure 1: Proposed labour productivity framework

5.1 Equipment and tools

Three main factors were identified to influence the equipment and tools category in optimising labour productivity of heavy labour-intensive construction work. These included appropriate tools, participants' knowledge of tools, and recording of tools that influenced labour productivity.

Appropriate tools play a crucial role in increasing efficiency and reducing the time required for a task. As stated by Yeom *et al*. (2022: 5), the use of advanced and appropriate tools such as cranes, bulldozers, and excavators helped improve labour productivity in the construction industry. Rane, Potdar and Rane (2021: 1470) emphasised that construction companies need to establish a systematic approach to inventory management, including implementing inventory tracking systems, conducting frequent inspections, and implementing security measures to minimise losses. Construction companies should establish maintenance schedules and protocols to inspect, clean, repair, and replace tools as needed. The service and maintenance of tools that need to be fixed could help avoid incidents or accidents, due to faulty equipment and tools on projects (Bamfo-Agyei *et al*. (2022c: 12). Construction companies should carefully plan and schedule the use of equipment, considering factors such as project timelines, task dependencies, and equipment availability. They should engage in comprehensive project planning, considering factors such as equipment requirements, task sequencing, and resource allocation. This can provide guidance on equipment-scheduling techniques, resource-allocation models, and project-planning methodologies to optimise equipment usage.

Even if appropriate tools are available, if the workers lack knowledge of how to use them correctly, their effectiveness may be reduced. Zhang *et al*. (2020: 6) argued that enhancing workers' knowledge, workers can work more efficiently, avoid mistakes, and make informed decisions regarding tool selection and operation. Assigning operators to tools based on their skills, experience, and familiarity with the task requirements can optimise productivity. By keeping the same crew and operator on the same piece of equipment, construction companies can reduce the time needed for adaptation, enhance operational efficiency, minimise errors, and promote effective teamwork (Li, Teng & Yuan, 2018: 160).

Construction companies should establish efficient systems for tool management and storage. Tsai *et al*. (2020: 15) suggested that accurate tool recording when implemented in construction projects will ensure that equipment is available when needed. Accountability for toolkits means that the industry should establish clear protocols and expectations regarding the responsibility of individuals for the tools assigned to them (Albert, Shakantu & Ibrahim, 2021: 152). This can provide guidance on tool-tracking systems, inventory-management practices, and tool-room organisation to optimise labour-intensive productivity. By properly recording and storing tools, companies can ensure easy access, minimise loss or theft, and improve overall efficiency on construction sites. In addition, it can offer insights into accountability frameworks, tool check-out/check-in procedures, and performance-evaluation mechanisms that need to be carried out at the site.

Reporting mechanisms, communication channels, and reporting intervals to ensure effective information flow between tool-room supervisors and project teams is important. Timely and accurate reports can aid in decision-making and proactive management of tools.

5.2 Material

Materials management and material appropriateness are two elements that can improve the efficiency of labour in labour-intensive projects. According to Liu and Lu (2018: 325), the use of effective material-management systems helps ensure that materials are available when needed, thus increasing productivity in the construction industry. Material management provides insights into inventory-management techniques, procurement strategies, and forecasting methods to optimise the availability of materials. Proper management of material involves accurately estimating the required quantities of materials for construction projects. It helps reduce waste and delays, by making sure that the appropriate resources are accessible at the right time and in the right quantity (Liu, Yi & Wang, 2020). Timely procurement is crucial to avoid delays, disruptions, and additional costs (Omopariola *et al*., 2020: 312). Efficient transportation of materials to the construction site ensures that the materials are delivered on time and in good condition. Appropriate storage facilities and practices are essential to preserve the quality and integrity of materials. By adhering to best practices for material storage, construction industries can minimise material damage, improve inventory control, and streamline access to materials, thus leading to increased labour-intensive productivity.

The suitability of materials used can also impact on labour productivity. Santos *et al*. (2019: 135) emphasised that the construction industry needs to carefully assess and determine the appropriate quantity of materials required for each project phase. Pornthepkasemsant and Charoenpornpattana (2019: 852) stated that using high-quality materials can reduce maintenance time and increase productivity. Making use of quality management and material inspection can offer insights into best practices for quality control, quality assurance, and material testing. Implementing these quality practices ensures that the right amount of materials is available, thus minimising waste, reducing costs, avoiding rework and delays (Sibande & Agumba, 2018: 525), and enhancing labour-intensive productivity (Hasan *et al*., 2018: 920). Material selection, specifications, and performance criteria can provide guidance on identifying suitable materials for various construction tasks.

5.3 Temperature

In the construction industry, measures should be taken to ensure that workers work in a comfortable environment, which increases productivity. Morris *et al*. (2021: 292) emphasised the importance of proactive planning for inclement weather conditions in construction projects. This implies that construction companies should consider potential weather disruptions and incorporate contingency plans into their project scheduling and management. Weather-risk management and construction-project planning can provide insights into strategies for weather forecasting, scheduling adjustments, and resource allocation to mitigate the impact of adverse weather conditions.

Construction companies can enable workers to continue working efficiently, even during inclement weather, by providing suitable rain gear and implementing safety protocols on sites.

Temperature and humidity levels can also impact on labour productivity, as stated by Bamfo-Agyei *et al*. (2021: 170); the isohyperthermic impact on workers can reduce efficiency and increase the risk of heat-related illnesses. Mahyuddin *et al*. (2022: 40) argued that the workforce functions most efficiently at an ambient temperature of 15°C to 22°C, with moderate 40% to 70% humidity. Management should consider the expected daily temperatures when deciding when to begin the project or when to carry it out, in order to maximise the efficiency of their workforce.

Several reports have mentioned how poor weather can lead to disruptions, damage, and subsequent delays in projects (Hurlimann, Warren-Myers & Browne, 2019: 130; Zhao *et al*., 2022: 1760). Construction sites should be properly prepared, organised, and maintained to facilitate efficient workflow and minimise disruptions.

Dhakal and Kattel (2019: 670) claimed that soil properties such as stability, compaction, and drainage can significantly influence construction activities. Because of the low quality of the soil, the workers would need extra time to complete a given task. Considering soil conditions and implementing suitable soil-management practices, construction companies can optimise labour-intensive productivity by minimising delays, improving excavation and foundation works, and ensuring stable and safe construction processes.

6. CONCLUSION AND RECOMMENDATION

Construction labour productivity is a complex and multifaceted issue that requires a comprehensive understanding of the factors that impact on productivity. In order to maximise labour productivity in the construction industry, a comprehensive strategy that takes into account a variety of productivity-affecting elements is necessary. These factors include worker skills and motivation, project-management techniques, work base conditions, as well as the availability and quality of materials and tools. The proposed labour productivity optimisation framework contains elements of how these factors can be effectively implemented to increase productivity. The six critical components that need to be considered are appropriate tools, workers' knowledge of tools, recording of tools, material management, suitability of material, and isohyperthermic impact. It can be concluded that the six-component framework represents an adequate description of labour productivity optimisation for heavy labour-intensive public construction work in Ghana. By incorporating these components, construction projects can be completed more efficiently, resulting in cost savings and improved project completion time.

Optimising labour productivity in Ghanian construction works requires the involvement of all stakeholders, including project managers, workers, suppliers, and subcontractors. In practice, labour-intensive construction work often involves the use of participatory approaches, which involve local communities in Ghana for the decision-making process and the implementation of construction projects.

Implementation and use of the proposed framework relies on the willingness of contractors or owners of construction firms relative to understand the importance of such a framework. It is, therefore, recommended that the interrelated 'tools', 'materials' and 'isohyperthermic impact' included in the framework are of utmost importance. These include engaging skilled workers, or organsations that proffer the encouragement of contractors or owners of construction firms to take ownership in an attempt to introduce and implement this proposed labour productivity optimisation framework to their firms. It could guide contractors to ensure that all elements necessary for achieving high labour productivity of construction firms are in place and help them make decisions that impact on the labour productivity of their firms.

The framework may help the Ghana Social Opportunity project, which supervises the implementation of labour-intensive public, in providing relevant training programmes that aim at developing the capacity of indigenous firms to enhance their productivity. The framework may help policymakers in the construction industry to review the existing national policies that are geared towards helping indigenous firms improve productivity in the construction industry.

Optimising labour productivity in construction works is a continuous process that requires ongoing monitoring, evaluation, and improvement. By prioritising productivity and implementing best practices, construction projects can be completed more efficiently, resulting in cost savings and improved outcomes.

This article does not consider the framework as a complete resolve to the plight of the labour-intensive methods in the construction industry and the relationship to good productivity. Further research is needed to improve the framework developed in this article and possibly refine indicator variables to suit specific environments. Further research is also needed, in order to develop an instrument to measure the level of contractors or owners of construction firm's productivity, specifically for heavy labour-intensive construction work, to optimise their productivity.

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