The relationship between work environment and labour productivity

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Abstract

The oil palm industry is vital to Malaysia's national output, socio-economic development, and employment. Its significant contribution to national income and export earnings highlights the importance of labour productivity in this sector. Recently, however, a decline in Malaysian oil palm production has been attributed to a shortage of labour, especially foreign workers, due to COVID-19 movement restrictions. With Malaysian oil palm, smallholders are now relying solely on local labour, assessing local labour productivity has become crucial. Understanding how local labour productivity is influenced by leadership productivity and work environment is essential. However, there is a lack of research directly exploring the impact of these factors on local labour productivity. This study seeks to address this gap by investigating the relationship between leadership productivity, work environment, and local labour productivity. Data was collected from oil palm smallholders in Sarawak, Malaysia, and analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicate a strong, positive, and significant relationship between the work environment and local labour productivity. These insights provide practical guidance for oil palm smallholders on strategies to improve local labour productivity.

Keywords: Agriculture, local labour, oil palm, PLS-SEM, productivity, work environment

Introduction

The oil palm industry is a major contributor to Malaysia’s Gross Domestic Product (GDP), representing 37.1% of the agricultural sector’s GDP in 2020 (DOSM, 2021b). This sector plays a crucial role in the Malaysian economy by providing raw materials, food, income, and revenue for both individuals and industries. Additionally, the industry supports approximately one million jobs (MPOC, 2021b). As the world’s second-largest palm oil exporter (Naidu & Moorthy, 2021), Malaysia accounts for 34.3% of global palm oil exports and 25.8% of global production (MPOC, 2021a). The country’s significant production and export activities are essential in meeting the growing global demand for palm oil.

However, the oil palm industry remains highly labour-intensive due to limited mechanization and technology (Abdullah et al., 2016), heavily relying on foreign workers due to persistent labour shortages. Data from the Malaysian Palm Oil Board (MPOB) indicate that in 2010, 69% of plantation workers were foreign (Abdullah et al., 2010), a figure that rose to 76.5% in 2012 (Ismail, 2013) and 78% by 2015 (Ismail et al., 2015). This reliance on foreign labour highlights the lack of local interest in plantation work.

Recent declines in Malaysian oil palm production, such as a 2.1% drop in fresh fruit bunches from 99,065,400 tonnes in 2019 to 96,969,300 tonnes in 2020 (DOSM, 2021b), and a significant slowdown in growth from -3.6% in 2019 to 11.1% in the third quarter of 2021 (DOSM, 2021a), can be partly attributed to labour shortages exacerbated by the COVID-19 pandemic (Neo, 2021). The industry's dependency on foreign labour, particularly from Indonesia (Ismail et al., 2015), was further disrupted by the movement control order implemented on March 18, 2020, which prevented returning foreign workers from re-entering Malaysia. Consequently, many smallholders have faced losses despite stable crude palm oil prices, as they are unable to harvest at previous levels.

During this crisis, smallholders have had to rely solely on local labour, but local workers are often unwilling to take up plantation jobs (Abdullah et al., 2016) or perform tasks typically handled by foreign workers (Crowley, 2020). Research has identified several reasons for this reluctance, including heavy workloads and unattractive working conditions, described as dangerous, dark, and dirty (Abdullah et al., 2016; Kamaruddin et al., 2016; Mohammad Amizi et al., 2014). Improving employee welfare packages and economic profitability could enhance job satisfaction and retention in the sector (Kamaruddin et al., 2016). Recommendations for smallholders include providing better facilities, such as transportation and comfortable housing, and adhering to occupational safety standards to improve the working environment and leadership in oil palm plantations.

To date, there has been no research examining the impact of working environment on local labour productivity. This study aims to fill this gap by exploring the relationships between work environment, and local labour productivity. Specifically, the study seeks to answer research question "Is there a relationship between leadership productivity and local labour productivity"? This paper contributes in two main ways. First, it offers a detailed examination of how the work environment affect local labour productivity. Understanding these relationships is crucial, particularly in the agricultural sector. To our knowledge, this is the first study to directly explore these connections. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), this study identifies significant positive relationships between leadership productivity, work environment, and local labour productivity. This exploration is valuable both theoretically and practically. Second, the study focuses on oil palm smallholders, who manage about half of the world's oil palm land. Improving local labour productivity among these smallholders is vital for enhancing global oil palm yields and benefiting Malaysian and global oil palm smallholders.

Literature review

Labour productivity

Labour productivity is a critical focus for economies as it serves as a key indicator of economic performance, directly influencing competitiveness, economic growth, and living standards. Generally, labour productivity is defined as the total output produced per unit of labour. Various researchers have defined and measured labour productivity in different ways. Day et al. (2018) describe labour productivity as the degree to which workers' effectiveness is compromised during their work. He and Ji (2021) measured it based on the amount of time labourer works such as annual working hours and average working months and their unit wage, represented by the average hourly wage. Other studies have utilized value added per worker as a measure of labour productivity (Lebedinski & Vandenberghe, 2014; Tang, 2014). Some researchers have assessed labour productivity through the logarithm of real sales per number of employees (Avarmaa et al., 2013; Dimelis & Louri, 2002), while others have measured it by output per person employed (Cristea et al., 2020). An increase in labour productivity can enhance the efficiency of agricultural production (Vorontsov, 1978).

In agriculture, labour productivity measures are particularly crucial as they help analyse sector performance where farmers also function as entrepreneurs and suppliers of agro-food products. For instance, Selim (2012) calculated labour productivity by averaging wage rates for cropping seasons of Aus rice, considering daily wages for both female and male workers without meals. Arouna et al. (2021) determined labour productivity as the ratio of grain yield to the total labour days required for cultivating one hectare of rice. Beyond being a measure of efficiency, labour productivity is closely linked to net economic value or return on capital, which significantly affects a firm's investment decisions.

Work environment

The work environment is crucial in any organization, regardless of its location, industry, or size. Key concerns for workers include having a safe environment free from accidents and violence. Ramlall (2003) emphasises that individuals prefer to work and remain in organizations that offer a positive and supportive work environment. Briner (2000) defines the work environment as the overall setting where people perform their tasks. This encompasses job-related aspects (such as task complexity and workload), the physical setting (including tools and equipment), extra-organizational factors (like work-home balance), and broader organismal features (such as company culture) (Briner, 2000). According to Sharavasti and Bhola (2015), the work environment consists of the conditions that either facilitate or hinder workers' performance. Greig et al. (2021) describe the work environment as all elements of work system design and management that affect how workers interact with their workplace.

Research indicates that the environment where workers operate significantly influences their productivity. A positive work environment is linked to higher job satisfaction, which in turn can enhance productivity (Kagan et al., 2021). Similarly, Islam and Shazali (2011) found a connection between a favourable work environment and increased productivity. Essential components of a good work environment, such as access to drinking water, lunch breaks, paid sick and casual leave, and timely wage payments, contribute positively to productivity, particularly in labour-intensive processes.

Karthik and Kameswara Rao (2019) identified working conditions as a crucial factor affecting masonry labour productivity in construction projects in India. Doloi (2007) explored motivational factors influencing worker productivity in the Australian construction industry. Regression analysis revealed that the basic working environment is a major motivator for productivity. Conversely, poor working conditions are associated with lower labour productivity. Li et al. (2016) conducted a regression analysis showing that a negative work environment decreases construction labour productivity, with high temperatures leading to heat stress that impairs productivity. Similarly, Kamaruddin et al. (2018) found that adverse working conditions (such as hazardous, dirty, and strenuous environments) significantly reduce job satisfaction among oil palm plantation workers. Purwanta (2021) also noted that uncomfortable work environments, characterized by high temperatures and limited green space, can diminish productivity in the batik industry.

Method and study area

Participants and data collection procedure

This study focuses on oil palm smallholders in Sarawak, which has the largest oil palm cultivation area in Malaysia (MPIC, 2021). We employed a purposive sampling method to select smallholders in Sarawak who utilise local labour. The total population of these smallholders is 275. Due to factors such as movement control restrictions and the COVID-19 pandemic, and because not all smallholders agreed to participate, the survey was distributed in September 2021 to 80 smallholders. Data collection was conducted through face-to-face surveys at the smallholders' plantations, where they were assisted in completing the questionnaires. Participants were asked to circle their level of agreement for each question. Out of the 80 questionnaires distributed, 56 were usable for analysis. This sample size aligns with the recommendation of Hair Jr et al. (2017), which suggests that the PLS-SEM method is effective with sample sizes under 100. Participants volunteered and were informed about the study's objectives, with assurances that their responses would remain confidential throughout the process.

Although the study focuses on local labour productivity, the primary data was collected from smallholders rather than the workers themselves. This decision is based on several practical and methodological considerations. First, smallholders are the direct supervisors and employers of local labour and are thus well-positioned to evaluate worker productivity based on daily interactions and outcomes. Their perspectives provide valuable operational insights that would be difficult to capture through direct engagement with labourers, who may lack the broader context of performance measurement. Second, due to language barriers, education levels, and logistical challenges in accessing and surveying plantation labourers, collecting reliable data directly from the workers was not feasible within the constraints of the research grant and fieldwork timeframe. As such, the study adopted an indirect assessment approach, which is consistent with prior empirical research where supervisors or managers provide performance evaluations on behalf of their teams. Finally, the focus of this study is not on the psychological or motivational states of labourers but rather on how environmental and managerial factors influence observable productivity outcomes. Therefore, relying on smallholders as key informants remains a valid and effective methodological choice in this research context. This approach is also consistent with previous studies (e.g., Osibanjo et al., 2015; Rahman et al., 2019) that evaluated worker productivity based on the perceptions of supervisors or employers, particularly in informal sectors such as smallholder agriculture.

Measurement instrument

The questionnaire was designed to measure various variables relevant to the study. It assessed the work environment through four constructs: topography, soil types, cleanliness, and distance. Local labour productivity was measured with seven items. The questionnaire was reviewed by an expert to ensure the accuracy of the constructs, and a pilot study with several smallholders ensured clarity and comprehensibility.

Some items (e.g., Da3 for topography and Dc2 for cleanliness) showed standardised factor loadings below the recommended threshold of 0.708, they were retained in the model to preserve conceptual and content validity. According to Hair et al. (2019), items with slightly lower loadings may be acceptable when composite reliability (CR) and average variance extracted (AVE) values are above the required thresholds, which was the case in this study.

Removing additional items risked weakening the theoretical foundation and interpretability of the constructs.

Additionally, the measurement of local labour productivity relied on smallholders' self-assessments of their workers' performance. While these indicators are subjective, they reflect behavioural and psychological productivity components, which are commonly used in management and social science research (Briner, 2000; Osibanjo et al., 2015). Given the constraints on collecting direct output metrics, this approach was considered suitable for capturing perceived productivity levels within the smallholder context.

Data analysis

Data were analysed using the PLS-SEM technique with Smart PLS version 3.2.9 software. This technique is preferred when data distributions are non-normal. The presence of multivariate non-normal distribution was tested using Mardia's multivariate skewness ($p<0.05$) (Loperfido, 2020). The study's research framework employs a hierarchical latent variable model with reflective-formative, Type II model, as illustrated in Figure 2. The analysis proceeded in three stages: first, evaluating the reflective measurement model for lower-order constructs; second, assessing the formative measurement model for higher-order constructs; and third, examining the structural model. The disjoint two-stage approach with Mode B and path weighting scheme, as proposed by Sarstedt et al. (2019), was used for specifying and estimating hierarchical latent variable models. This approach involves two stages: the first stage for reflective measurement model evaluation (internal consistency reliability, convergent validity, and discriminant validity) and the second stage for formative measurement model evaluation (collinearity, outer weight, and statistical significance). The structural model was evaluated for path coefficient significance, relevance, predictive relevance (Q2), and PLSpredict.

Sample size justification

Although the final sample size of 56 smallholders falls short of the 85 recommended by G*Power for detecting medium-sized effects ($f^2 = 0.15$) with four predictors at 80% power ($\alpha = 0.05$), the use of Partial Least Squares Structural Equation Modelling (PLS-SEM) is appropriate for small to medium samples, especially in exploratory research settings. PLS-SEM does not require multivariate normality and has been widely validated for use in contexts with sample sizes below 100 (Hair et al., 2017). Moreover, the observed effect sizes in this study such as for the distance variable ($f^2 = 0.160$) fall within the moderate range, supporting the statistical adequacy of the sample. Given the pandemic-related fieldwork constraints and targeted focus on smallholders in Sarawak, the sample size remains justifiable for the exploratory and theory-building nature of this study.

Results

Local labour involvement in oil palm agriculture

Table 1 illustrates the involvement of local labour in the oil palm industry. It shows that approximately 42.9% of smallholders employ between 4 and 6 local workers, 41.1% employ between 1 and 3 local workers, and the remainder employ more than 6 local workers. The table also indicates that 91.7% of oil palm smallholders prefer hiring labour on a contract basis. Unlike full-time positions, contract labour is employed on an as needed basis.

The study's findings reveal that the primary motivation for oil palm smallholders to hire local labour is to provide employment opportunities for local residents (98.21%). Other reasons include the ease of giving instructions to local workers (75%) and their manageable nature (71.43%). Additional factors include the government's halt on importing foreign workers (64.29%), the relative ease of hiring local workers (64.29%), and lower wages compared to foreign workers (21.43%). This suggests that while the government's restriction on foreign labour is a factor, it is not the main reason smallholders opt for local labour.

Table 1. The involvement of local labour in the oil palm industry

Respondent background	Frequency	Percentage
Number of local labour		
1-3 people	23	41.1%
4-6 people	24	42.9%
7-10 people	8	14.3%
11 people and more	1	1.8%
Hiring labour option		
Contract	44	78.60%
Full-time	4	7.10%
Both (contract and full-time)	8	14.3%
Reason		
Cheap wages	12	21.40%
Easy to obtain	36	64.30%
Provide employment	55	98.20%
Easy to manage	40	71.40%
Easy to accept instructions	42	75.00%
Government factor	36	64.30%
Method of paying worker's wages		
Number of trees	6	10.70%
Contract-based	52	92.90%
Local labour classification		
Family	19	33.90%
Relatives	18	32.10%
Village workers	19	33.9%

Factors affecting the work environment for local labour

Table 2 presents the median, interquartile range, and level of agreement regarding various aspects of the work environment. The results show that most smallholders agree on several cleanliness and soil management practices. Specifically, they report that rotten loose fruits are properly disposed of (Mdn=4, IQR=0.75), frond and leaflet residues are placed in designated garbage areas (Mdn=4, IQR=1), tree bases are cleaned at least twice annually (Mdn=4, IQR=1), impurities from tree base cleaning are not disposed of near water sources (Mdn=4, IQR=2), and peat soils contribute to increased crop productivity (Mdn=4, IQR=1).

However, opinions are more divided regarding the impact of terrain on their work. While a significant number of smallholders (N=21, 37.50%) either strongly disagreed or disagreed with the statement that flat terrain facilitates their work, a similar proportion (N=25, 44.60%) agreed or strongly agreed with it (Mdn=3, IQR=3.75). Similarly, ratings for the productivity benefits of wetlands (Mdn=3, IQR=2) and hilly soils (Mdn=3, IQR=1) were mixed, suggesting that for some smallholders, these terrains do enhance productivity.

Conversely, the findings indicate that hilly farm conditions (Mdn=2, IQR=2) and undulating terrain (Mdn=1.5, IQR=2) are generally seen as problematic. Over 70% of smallholders "strongly disagreed" or "disagreed" that hilly conditions (71.40%) and undulating terrain (73.2%) do not bother them. Additionally, most smallholders agreed that their farms are located far from their homes (Mdn=2, IQR=3), the mill (Mdn=2, IQR=2), and workers' homes (Mdn=2, IQR=2). Approximately 64.30%, 73.20%, and 67.80% of smallholders "strongly disagreed" or "disagreed" that the farm is close to their home, the mill, and workers' homes, respectively. This suggests a consensus among smallholders that topography and distance are significant factors affecting their work environment.

Table 2. Median (*Mdn*), interquartile range (IQR) and level of agreement on work environment

Work environment	*Mdn*	IQR	Level of agreement (percentage)				
			Strongly disagree	Disagree	Not sure	Agree	Strongly agree
Topography							
The hilly farm conditions did not bother me	2	2	48.2%	23.2%	16.1%	8.9%	3.6%
The undulating terrain does not bother me	1.5	2	50.0%	23.2%	12.5%	12.5%	1.8%
The flat terrain facilitates my work	3	3.75	32.1%	5.4%	17.9%	19.6%	25.0%
Type of soils							
Peat soils boost crop productivity	4	1	1.8%	1.8%	19.6%	50.0%	26.8%
Wetlands boost crop productivity	3	2	7.1%	19.6%	28.6%	35.7%	8.9%
Hilly soils boost crop productivity	3	1	1.8%	7.1%	44.6%	35.7%	10.7%
Cleanliness							
The rotten loose fruit is disposed of in appropriate location	4	0.75		14.3%	10.7%	57.1%	17.9%
Frond and leaflet residues are disposed of in the garbage aisle	4	1			17.9%	55.4%	26.8%
Tree bases should be cleaned at least twice a year	4	1		7.1%	19.6%	50.0%	23.2%
Impurities from tree base cleaning will not be disposed of near water sources	4	2		3.6%	26.8%	32.1%	37.5%
Distance							
My house and the farm are not far apart	2	3	30.4%	33.9%	3.6%	19.6%	12.5%
The farm and the mill are not far apart	2	2	32.1%	41.1%	10.7%	12.5%	3.6%

The workers' home and the farm are not far apart	2	2	32.1%	35.7%	16.1%	12.5%	3.6%

This study hypothesises: H1: Topography has a significant relationship with local labour productivity. H2: Soil types have a significant relationship with local labour productivity. H3: Farm cleanliness has a significant relationship with local labour productivity. H4: Distance has a significant relationship with local labour productivity. The Mardia's multivariate skewness and Mardia's multivariate kurtosis were used in order to validate the multivariate non-normal distributions ($p < .05$) (Loperfido, 2020) (Mardia, 1974) as presented in Table 3.

Table 3. Mardia's multivariate skewness and kurtosis

	B	***z***	***p***
Skewness	200.843	1874.531	0.000
Kurtosis	457.241	2.175	0.030

Latent variables model

The research framework in this study represents the latent variables model as depicted in Figure 1. The assessment of latent variables model includes the assessment of measurement model and assessment of structural model (Hair et al., 2017; Hair et al., 2019).

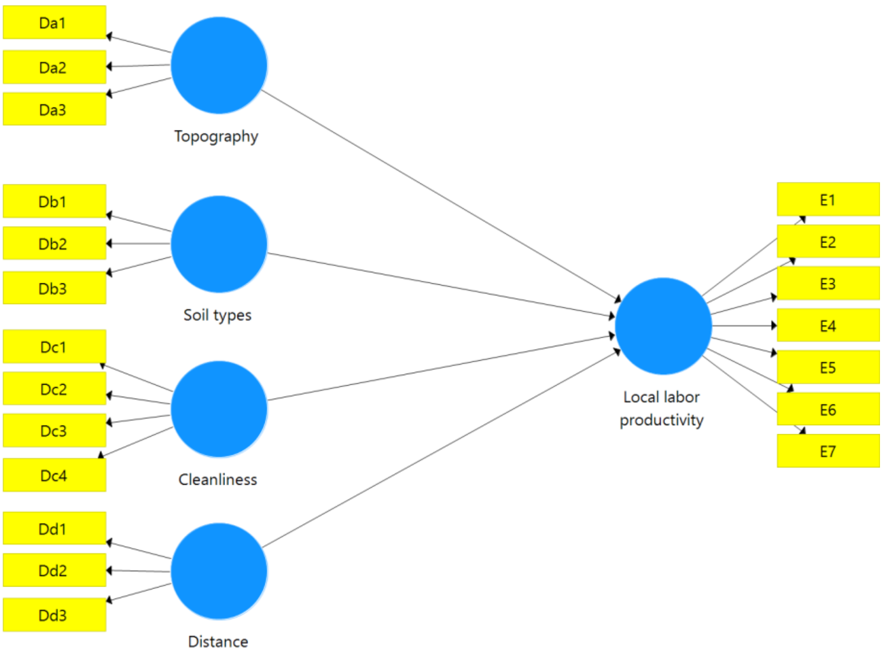

Figure 1. Latent variables model

Assessment of measurement model

The measurement model was evaluated in terms of internal consistency reliability, convergent validity and discriminant validity. Internal consistency reliability was assessed using item loadings, cronbach alpha (CA) and composite reliability (CR), while the convergent validity was assessed using average variance extracted (AVE). The item loadings were all above the standard threshold of 0.708 (Hair et al., 2019) except for E3, E4, E5, E6, E7, Da3, Db1 and Dc2. Meanwhile, the CA and CR of each construct were all above the standard threshold of 0.7 (Hair Jr et al., 2020; Sarstedt et al., 2019) except for type of soils as reported in Table 4. Also, the AVE estimates for all constructs were above the threshold of 0.5 (Hair Jr et al., 2020)(Fornell & Larcker, 1981). It means that the types of soil and local labour productivity constructs do not meet the requirements of internal consistency reliability and convergent validity, so some of the items with the lowest item loading in these constructs must be deleted.

Table 4. Items loadings, CA, CR dan AVE

Construct	Item	Loadings	CA	CR	AVE
Local labour productivity	E1	0.863	0.828	0.871	0.497
	E2	0.821			
	E3	0.635			
	E4	0.641			
	E5	0.630			
	E6	0.610			
	E7	0.687			
Topography	Da1	0.870	0.700	0.831	0.630
	Da2	0.905			
	Da3	0.559			
Types of soil	Db1	-0.433	0.431	0.501	0.513
	Db2	0.802			
	Db3	0.842			
Cleanliness	Dc1	0.770	0.836	0.865	0.625
	Dc2	0.508			
	Dc3	0.917			
	Dc4	0.900			
Distance	Dd1	0.937	0.916	0.947	0.856
	Dd2	0.914			
	Dd3	0.925			

Figure 2 depicts the new latent variables model, and Table 3 reports the values of item loadings, CA, CR and AVE after deletion of items E6 and Db1. Even though the item loadings of E3, E4, E5, E7, Da3, Dc2 were less than 0.708, the CA, CR and AVE values of each construct were greater than the standard threshold, so we kept all these items in this study. This means that the model satisfies the requirements for internal consistency reliability and convergent validity.

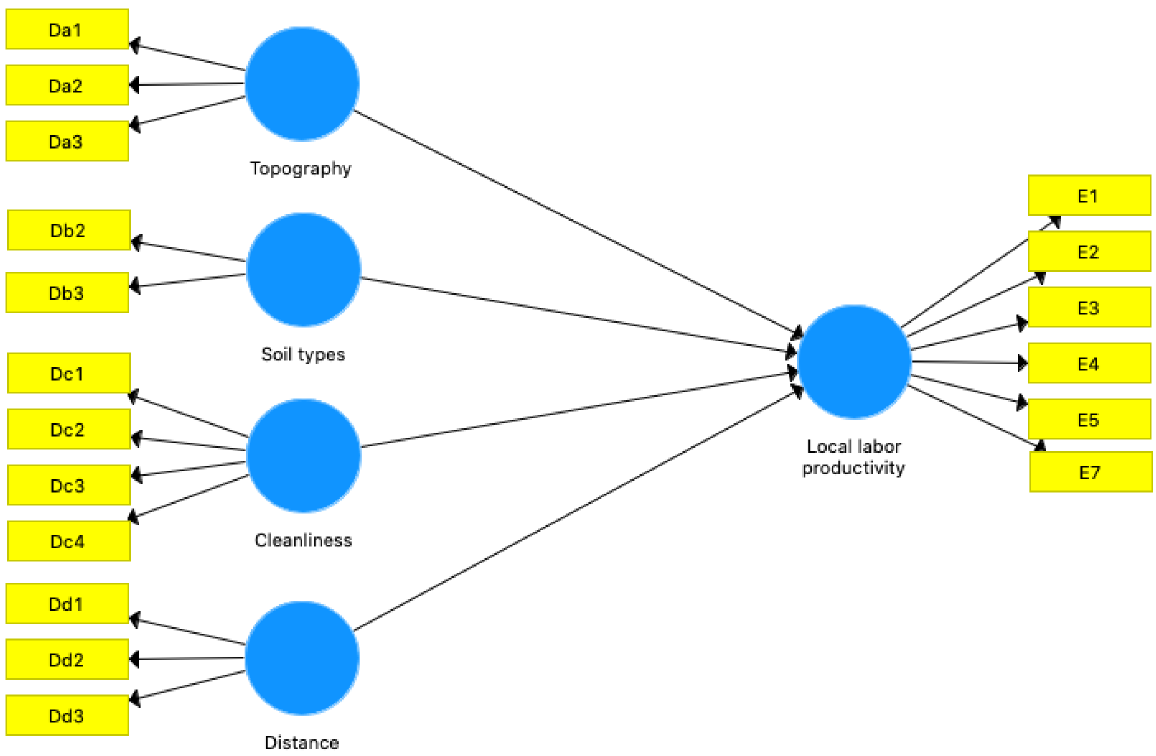

Figure 2. The new latent variables model

Table 5. Item loadings, CA, CR dan AVE after deletion of items E6 and Db1

Construct	Item	Loadings	CA	CR	AVE
Local labour productivity	E1	0.875	0.813	0.866	0.524
	E2	0.820			
	E3	0.647			
	E4	0.681			
	E5	0.600			
	E7	0.682			
Topography	Da1	0.870	0.700	0.831	0.630
	Da2	0.904			
	Da3	0.563			
Types of soil	Db2	0.950	0.785	0.897	0.814
	Db3	0.852			
Cleanliness	Dc1	0.770	0.836	0.865	0.626
	Dc2	0.512			
	Dc3	0.913			
	Dc4	0.903			
Distance	Dd1	0.938	0.916	0.947	0.856
	Dd2	0.914			
	Dd3	0.924			

To assess the model's discriminant validity, the Fornell-Larcker criterion and Heterotrait-Monotrait, HTMT ratio were used (Acquah et al., 2021). The results shown in Table 6 shows that the square root of the AVE of each construct, in bold print, was greater than the correlation with other constructs (Fornell & Larcker, 1981). In addition, as shown in Table 7, the HTMT values for each construct were less than the cut-off of 1 (Garson, 2016). The measurement model can be said to have the discriminant validity requirement based on these criteria.

Table 6. Fornell-Larcker criterion

Construct	Distance	Soil types	Cleanliness	Local labour productivity	Topography
Distance	**0.925**				
Soil types	0.270	**0.902**			
Cleanliness	-0.631	-0.213	**0.791**		
Local labour productivity	0.618	0.422	-0.525	**0.724**	
Topography	0.614	0.132	-0.725	0.471	**0.794**

Table 7. HTMT ratio

Construct	Distance	Soil types	Cleanliness	Local labour productivity	Topography
Distance					
Soil types	0.300				
Cleanliness	0.554	0.192			
Local labour productivity	0.711	0.484	0.486		
Topography	0.772	0.301	0.814	0.603	

Assessment of structural model

The structural model results are summarised in Table 8, where the significance and relevance of path coefficient, effect size (f^2), coefficient of determination (R^2), variance inflation factor (VIF) and predictive relevance (Q^2) are displayed. The VIF values were used to confirm that there is no issue with multicollinearity as the values are less than 5 (Hair Jr et al., 2017). Also, Table 6 demonstrated the findings of hypothesis testing of H_1: Topography → Local labour productivity, H_2: Soil types → Local labour productivity, H_3: Farm cleanliness → Local labour productivity and H_4: Distance → Local labour productivity. The results of hypothesis testing revealed four major outcomes, the first of which was that the farm's topography has no significant relationship with local labour productivity (β = 0.074, t = 0.481, p = 0.603), implying that H_1 was rejected. Second, the type of soil has a significant relationship with local labour productivity (β = 0.271, t = 2.578, p = 0.010), implying that H_2 was accepted. Third, the cleanliness of the farm has no significant relationship with local labour productivity (β = 0.164, t = 1.205, p = 0.228), implying that H_3 was rejected. Lastly, the distance has a significant relationship with local labour productivity (β = 0.396, t = 3.010, p = 0.003), implying that H_4 was accepted. This result suggests that physical proximity plays a crucial role in enhancing labour productivity. Workers who are located closer to project sites may experience less travel fatigue, better punctuality, and more efficient communication, all of which contribute to higher productivity levels. Furthermore, these findings show that distance has the highest influence on local labour productivity, as evidenced by the highest value of β = 0.396 when compared to the types of soil, β = 0.271. After reporting the path coefficient and their significance, the analysis proceeded to assess the predictive ability of the model by evaluating in-sample predictions such as R^2, f^2 and Q^2. The model explains 48% of the variance in local labour productivity ($R^2 = 0.48$); also, the effect size for the relationship between farm's topography and local labour productivity ($f^2 = 0.005$), the relationship between soil types and local labour productivity ($f^2 = 0.129$), the relationship between cleanliness of the farm and local labour productivity ($f^2 = 0.021$) and the relationship between distance and local labour productivity ($f^2 = 0.160$). This indicates that the size of the effect of distance on local labour productivity is moderate. While the size of the effect of types of soil on local labour productivity is small. Moreover, the results of the blindfolding test showed that the Q^2 value was 0.218, which is larger than zero, confirming that the model achieved the relevant prediction (Chin, 1998). The results from the R^2, f^2 and Q^2 suggest that the model has adequate in-sample predictive power (Hair Jr et al., 2020).

Table 8. Structural model results

Hypotheses	Structural path	*β*	*t*-value	*p*-value	Decision	f^2	Decision	VIF
H_1	Topography ➔ Local labour productivity	0.074	0.481	0.630	Not supported	0.005	No effect	2.327
H_2	Soil types ➔ Local labour productivity	0.271	2.578	0.010	Supported	0.129	Small effect	1.091
H_3	Cleanliness ➔ Local labour productivity	-0.164	1.205	0.228	Not supported	0.021	Small effect	2.412
H_4	Distance ➔ Local labour productivity	0.396	3.010	0.003	Supported	0.160	Moderate effect	1.89
			Construct				R^2	**Q^2**
			Local labour productivity				0.480	0.218

Finally, a $PLS_{predict}$ analysis was carried out to determine the out of sample predictive power of the model. The results in Table 7 suggest that the $Q^2_{predict}$ statistics of PLS model outperformed the Linear Regression Model (LM) (Hair Jr et al., 2020)(Shmueli et al., 2019), hence the prediction errors of both models were assessed. The RMSE is the most popular and acceptable prediction statistics used (Hair Jr et al., 2020). The results suggest that all of local labour productivity have RMSE values lower than those obtained by LM values, which means that the model has a higher predictive power (Hair Jr et al., 2020). Hence, the results from the R^2, f^2, Q^2 and $PLS_{predict}$ suggest that the model has sufficiently in-sample predictive power and out of sample predictive power (Hair Jr et al., 2020).

Table 9. $PLS_{predict}$ results

Local labour productivity	RMSE		$Q^2_{predict}$	
	PLS	LM	PLS	LM
E1	0.595	0.609	0.405	0.378

E2	0.592	0.621	0.194	0.114
E3	0.690	0.790	0.134	-0.134
E4	0.754	1.001	0.173	-0.457
E5	0.715	0.765	0.082	-0.053
E7	0.729	0.934	0.148	-0.398

Note: RMSE: *Root Min Square*; PLS: *Partial Least Square*; LM: *Linear Regression Model*

Discussion

This study explored how dimensions of the work environment specifically topography**,** soil types**,** cleanliness**,** and distance influence local labour productivity among oil palm smallholders in Sarawak. The findings confirm that soil types and distance have statistically significant positive relationships with productivity, while topography and cleanliness do not. These results provide both confirmation and contrast with existing literature, adding new contextual insights into labour dynamics within a labour-intensive agricultural setting.

The strong influence of distance on productivity ($\beta = 0.396$) highlights the importance of proximity between workers' residences, plantations, and processing facilities. This finding supports prior work by Kumaraswamy and Dissanayaka (2001) and Rahman et al. (2019), which showed that reduced commuting time and physical fatigue lead to better punctuality, lower absenteeism, and higher output. In the context of oil palm plantations, where the physical burden of tasks is high, travel related exhaustion may significantly hinder performance an insight critical for farm layout and labour planning. Similarly, the positive relationship between soil types and productivity ($\beta = 0.271$) is aligned with agronomic literature suggesting that soil quality and composition directly affect ease of harvesting and crop output (Selim, 2012; Arouna et al., 2021). Peaty and fertile soils require less manual intervention and support higher yields, indirectly reducing labour fatigue and improving work efficiency. This suggests that soil management is not only an agronomic concern but also a labour productivity strategy**.**

By contrast, topography and cleanliness**,** though hypothesised to affect productivity, were not statistically significant. This could be due to adaptive behaviours or long-term acclimatization among local workers to hilly terrains, as well as variations in how cleanliness is defined or implemented across plantations. While prior studies (Kamaruddin et al., 2018; Li et al., 2016) emphasized the adverse effects of uncomfortable and unsafe environments, this study's results suggest that terrain and cleanliness alone may not suffice as predictors without being paired with other structural or motivational factors. Alternatively, these variables may exert indirect or moderating effects**,** which were not captured in this model but warrant future exploration.

From a theoretical perspective, the study supports the argument by Briner (2000) and Ramlall (2003) that work environment variables are multi-dimensional and should be interpreted within their social, physical, and economic context. It contributes to existing models of productivity by applying PLS-SEM to a rural agricultural context, thus offering a replicable framework for future research in similar sectors**.**

Practically, the findings indicate that improving productivity among local labourers in the oil palm sector does not require generalized environmental improvements but rather targeted interventions. Policies that improve accessibility**,** transport infrastructure**,** and housing proximity can yield more immediate and measurable productivity gains than broader terrain modifications or general cleaning protocols. Overall, this study bridges the gap between environmental geography, agricultural economics, and human resource productivity. It demonstrates that in resource-constrained smallholder systems, optimising spatial and physical variables may provide more sustainable productivity improvements than costly technological interventions.

The findings of this study, particularly the significant relationship between work environment (specifically soil type and proximity/distance) and local labour productivity, carry substantial implications for both policy making and practical management in Malaysia's oil palm sector. From a policy perspective**,** the results call for a targeted government response to enhance rural infrastructure and accessibility in oil palm cultivation areas. Distance was found to have the strongest influence on productivity ($\beta = 0.396$), suggesting that reducing the physical distance between farms and essential services such as mills, worker accommodations, and transportation facilities can considerably improve productivity. This aligns with the broader rural development literature, which highlights how infrastructure improvements, such as road networks and public transport, can reduce transaction costs and enhance farm labour efficiency (Fan et al., 2000; Ali & Pernia, 2003). Policymakers should consider subsidising infrastructure development or offering incentives for closer mill-to-farm linkages.

In terms of agricultural extension services and land use policy**,** attention should also be given to land suitability and soil types. Since soil quality is positively correlated with labour productivity ($\beta = 0.271$), efforts should be made to provide smallholders with soil assessments and training on soil management practices. This echoes findings in agronomic research suggesting that knowledge dissemination about soil health and management enhances agricultural productivity (Pretty et al., 2011; Kassie et al., 2015). Thus, institutional support, including training and soil enhancement programs (e.g., compost subsidies or peatland management guidelines), could further empower smallholders.

On the practical level**,** oil palm smallholders and plantation managers should prioritise proximity planning when allocating labour resources. Encouraging the development of on-site or nearby housing for workers may mitigate the productivity loss caused by long commuting times. This recommendation is supported by studies in both agriculture and construction, which show that worker fatigue and tardiness can be reduced through proximity (Kumaraswamy & Dissanayaka, 2001; Rahman et al., 2019). Additionally, although not statistically significant, cleanliness and topography still emerged as relevant contextual elements. Interventions at the farm level, such as terrain stabilisation (e.g., terrace farming on hilly landscapes) and hygiene initiatives (e.g., regular frond removal, organised waste management), could have indirect effects on worker morale and efficiency, resonating with workplace productivity studies (Briner, 2000; Niemelä et al., 2002).

Finally, the study highlights a broader need for a shift in labour policy toward strengthening the local labour supply. Since local labour has demonstrated potential when given conducive conditions, national labour strategies should include campaigns to destigmatise plantation work, skills development programs, and improved contractual conditions (e.g., fair wages, safety regulations, and insurance schemes). This could complement findings from Osibanjo et al. (2015), who argue that a strategic human resource environment significantly enhances public sector productivity. Together, these implications suggest that a multi-stakeholder approach linking federal agricultural policy, infrastructure planning, and local farm-level practices is essential to sustainably improve labour productivity in Malaysia's vital oil palm sector.

Conclusion

This study provides important empirical evidence on how environmental factors shape local labour productivity in Malaysia's oil palm sector, particularly among smallholders in Sarawak. By applying Partial Least Squares Structural Equation Modelling (PLS-SEM), the research demonstrated that distance and soil type significantly influence productivity, while topography and cleanliness were not statistically significant. These results indicate that operational proximity and soil conditions are more critical than terrain or general field hygiene in determining how effectively local labour performs in oil palm cultivation. The study contributes both theoretically and practically. Theoretically, it extends work environment literature by contextualising it within a labour-intensive, agricultural setting. It is among the first to quantify environmental variables such as terrain and distance in relation to productivity using PLS-SEM in the palm oil context. Practically, the findings inform policy and smallholder decision-making, suggesting that investment in infrastructure, soil management, and labour housing proximity may yield better productivity outcomes than purely aesthetic or terrain-level interventions. However, the findings must be interpreted with several limitations in mind. The sample size of 56, while valid for exploratory PLS-SEM, limits generalisability. Regional focus on Sarawak and reliance on smallholder perspectives (excluding workers themselves) further constrain the scope. Despite these limitations, the study opens pathways for future research to integrate objective productivity indicators**,** include worker feedback**,** and expand across different Malaysian regions. Enhancing local labour productivity in Malaysia's palm oil sector requires not just better wages or mechanisation, but smarter design of the physical and managerial environment. This research offers a practical foundation for redesigning labour deployment strategies that align more closely with spatial and environmental realities on the ground.

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