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Program evaluation and review technique – Data envelopment analysis in benchmarking sustainable supply chain management of the potato chips industry

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KEYWORDS

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Benchmarking

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ABSTRACT

Supply chain benchmarking of agroindustry can be done by emphasizing the perspective of sustainability. This paper aimed to analyze the efficiency of Sustainable Supply Chain Management (SSCM) in Micro, Small, and Medium Enterprises (MSMEs) and provided a prospective benchmark with the potato chips industry as a study case. Program Evaluation and Review Technique (PERT) estimated future input and output values to obtain prospective benchmarks and be added to the DEA formula later. Analytical Hierarchy Process (AHP) and Data Envelopment Analysis (DEA) methods were used to measure SSCM performance. The results showed that 17 of 20 Decision-Making Units (DMUs) were efficient (score 1). The other 3 DMUs were classified and got an efficiency score of 0.965, 0.955, and 0.995. In future estimates calculation, the efficiency score of one of the inefficient DMUs has changed to 1, while the other two got the scores of 0.996 and 0.980. The limitation of this research mainly comes from the scope of assessment, which is limited to the supply chain's downstream sector and assesses only a limited number of MSMEs in a particular region. SSCM efficiency measurement variables were adjusted to be assessed and applied to MSMEs. PERT was also beneficial to gain future estimates of the assessment scope.

Introduction

The agricultural and horticultural sectors have significantly contributed to the Indonesian national economy through their high diversity and production. Vegetable horticultural crop production reached 16 million tonnes in 2020 (Statistics Indonesia, 2020). One of Indonesia's horticultural commodities with the highest production is the potato. In 2019, potato production in East Java, Indonesia, had the highest output of 38 thousand tonnes. One of the largest potato-producing areas was the city of Malang and Batu (Statistics Indonesia of East Java, 2022). Based on those cases, potato commodity is opening up great opportunities for its utilization (Maulidah et al., 2018).

Nationally, the majority of potato productions are utilized by the potato-based processing industry. One type of processed potato product that is widely marketed is in the form of chips. The high output of potato commodities encourages the growth of the potato chips processing industry, which is dominated by Micro, Small, and Medium Enterprises (MSMEs) (Maulidah et al., 2018; Rahmatin et al., 2018). The central government of Indonesia is supporting the growth of potato-based agroindustry through its sustainable agricultural development program, as stated in the strategic plan of the Ministry of Agriculture in 2010-2014 (Indonesian Ministry of Agriculture, 2012). Potato chips agroindustry actors, including MSMEs, are encouraged to have competitive capabilities, which are viewed from several aspects such as cost, quality, time, and dimensions of flexibility (Krajewski et al., 2010). In achieving competitive advantage, the agroindustry needs to determine

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priority goals; thus, all activities in the agroindustry should be carried out to achieve customer satisfaction both now and in the future. Good supply chain performance is one of the efforts to achieve this goal (Bag et al., 2020). Supply chain management (SCM) is one of the six pillars of developing national horticultural commodities (Indonesian Ministry of Agriculture, 2012).

The dominance of MSMEs in the potato chips agroindustry is still inseparable from various sustainability problems. Potential problems can come from the potato product supply chain's environmental, economic, and social aspects (Verma and Nema, 2019). In the environmental aspect, various problems arise related to increased environmental pollution due to production activities. CO_2 emissions are a by-product of the production and distribution of potato chips that should be minimized. MSMEs account for 99% of all business entities worldwide, contributing 60-70% of global industrial pollution, which is dominated by carbon dioxide gas (Ernst et al., 2021). In the economic aspect, there is a decrease in the productivity of potato chips business actors. Social problems arise due to the lack of institutional relations and cooperation between potato chips business actors. This series of problems encourages industries to continue improving supply chain performance to achieve effective and efficient operating processes, thus saving high costs and enhancing customer satisfaction (Bag et al., 2020).

Sustainability plays an essential role in the long-term achievement of supply chain management, where the development of the SCM framework is not only based on economic aspects but also on social and environmental aspects (Rashidi and Saen, 2015). The sustainability framework is based on three main dimensions called the triple bottom line: environment, economy, and social. The need for sustainable practices is getting more robust due to several issues, such as the depletion of natural resources, attention to wealth inequality, and the importance of corporate social responsibility (Kahi et al., 2017; Tajbakhsh and Hassini, 2015). These problems led to the formation of Sustainable Supply Chain Management (SSCM), which can provide a competitive advantage for the company by creating opportunities to differentiate from competitors. SSCM is applied by using sufficient natural resources, trying not to damage the environment, being socially responsible for human resources, and working economically throughout the supply chain network (Khodakarami et al., 2015).

Data Envelopment Analysis (DEA) is a method that is widely used to calculate the efficiency score of the Decision-Making Unit (DMU) (Kahi et al., 2017; Khodakarami et al., 2015; Shabani and Saen, 2015; Dania et al., 2019). One of the main goals of the DEA is to provide benchmarks for inefficient DMUs, with the implication that these benchmarks serve as targets to be achieved by DMUs (Mirhedayatian et al., 2014). In the standard DEA model, the inefficient DMU benchmark uses only historical data, so it does not consider future planning (Shabani and Saen, 2015). Using the DEA method, all input and output factors are considered to have the same level of importance. However, in actual implementation, these factors can have different priority weights. AHP is the most suitable method for this study because it gives priority weights independent of each criterion that does not have a linear relationship (Kumar and Banerjee, 2014). It is necessary to apply a method to estimate the value of DEA inputs and outputs in the future to support long-term planning. Program Evaluation and Review Technique (PERT) is a method that is widely used in operations research to quantify/estimate the uncertainty of activity over a certain period, which is expressed in terms of “most likely”, “optimistic” and “pessimistic” (Shabani and Saen, 2015). Combining all those methods, this paper aimed to analyze the SSCM efficiency in potato chips industry MSMEs and provided a prospective benchmark among the DMUs.

Research Methods

Identification and definition of input and output variables

The variables used in this study were related to the input and output of each potato chips MSMEs based on the SSCM perspective. These variables were included in a questionnaire given to decision-makers in each DMU. Inputs and outputs were divided into three main aspects following the triple bottom line (TBL), shown in Table 1.

Table 1. Inputs and outputs used in research

TBL aspect	Sub Criteria	Unit	Category	Operational definition
Environment	Energy Consumption	kg	Input	Total energy used for production and distribution activities, consisting of electricity, gas and fuel in one year
	Solid Waste Volume	kg	Input	The total volume of solid waste generated during the production and distribution process in one year
	CO_2 emissions	kg	Output	Total CO_2 emissions generated during production and distribution activities, from electricity, gas and fuel in one year
Economy	Raw Material Cost	USD	Input	Total costs incurred for purchasing raw material (potato) to suppliers in one year
	Production Volume	kg	Input	The total volume of products that can be produced in one year
	Total Sales	USD	Output	The total revenue earned from product sales in one year
Social	Local Employment Rate (LER)	%	Input	Percentage of workers who come from the surrounding ward in one year
	Collaboration with Other Business Units	Unit	Input	Number of other business units involved in collaborative efforts in one year
	Labor Welfare Improvement	Likert	Output	Changes in the workforce's level of social welfare after working in the related MSMEs in one year

All input and output data were obtained within one year (2021 to 2022). Based on Table 1, some inputs and outputs data can be obtained directly from the DMU, and some have to be obtained through calculations and linguistic conversion using a Likert scale. The level of CO_2 emissions was obtained with supporting data, such as energy use and emission factors, through the following guideline from (Ministry of Environment, 2012):

$$E_{CO_2} = EC \,.\, EF \text{...} (1)$$

Where E_{CO_2} was total CO_2 emissions [kg CO_2 /year], EC was energy consumption [TJ/year], and EF was the emission factor for certain types of energy or fuel used for CO_2 pollutant types [kg/TJ or kg/kWh]. According to the Intergovernmental Panel on Climate Change (IPCC), emission factors were, by default, expressed in kg Greenhouse Gases (GHG) per Terra Joule (TJ) or kg GHG per TJ. Most energy consumption data was available in physical units (such as tonnes of coal, liters of fuel, and kilograms of LPG). Therefore, energy consumption data needed to be converted into TJ units with the guideline using Eq. 2 (Ministry of Environment, 2012), as follows:

$$EC\ (TJ) = \text{Raw Energy Cons} \,.\, NCV \text{ ....} (2)$$

Where raw energy consumption was in the form of physical units. The emission level from the LPG energy source was calculated by Eq. 1, where the net calorific value (NCV) of the LPG cylinder energy source was 47.3 x 10^{-6} TJ/kg, while the CO_2 emission factor from that energy source was 63.100 kgCO_2/kWh (Ministry of Environment, 2012). The total emission for running (non-stationary) energy sources in the form of transportation mode fuel was calculated by Eq. 1 but multiplied by the distance traveled in kilometers, using the following formula (Ministry of Environment, 2012):

$$E_{CO_2} = \textstyle\sum_a EC_a \,.\, d_a \,.\, EF_a \text{.................................} (3)$$

Where a was the type of fuel (premium, diesel) and d was the distance traveled. NCV from premium fuel and diesel energy sources were 33 x 10^{-6} TJ/liter and 36 x 10^{-6} TJ/liter, while the CO_2 emission factors were 69.300 kg/TJ and 74.100 kg/TJ (Ministry of Environment, 2012). Total emissions from electrical energy sources were also calculated using Eq. 1, with the emission factor adjusted to the electricity emission factor baseline, which was 0.725 kgCO_2/kWh for the Java-Madura-Bali area (Zacky et al., 2014).

The Local Employment Rate (LER) was obtained through the equation below:

$$\text{LER} = \frac{\text{labor from the surrounding ward}}{\text{total number of labor}} \,.\, 100 \quad (4)$$

Where those labor data came from each MSMEs. The workforce's welfare perception level was measured by distributing Likert scale questionnaires to several workers to change the linguistic perception of the changes felt after working at DMU or related MSMEs. The questionnaire results were averaged and used as data on the output: improving labor welfare.

Determination of population and sample

In this study, the population was the MSMEs involved in producing processed potatoes regardless of their size, while the samples used and studied were 20 potato chips MSMEs in the Greater Malang area. The sampling technique used in this research was purposive sampling, where the sample or object of research was determined based on specific criteria tailored to the researcher's needs (Etikan, 2016). In this study, experts were also involved in assessing the weight of each input and output variable used. They are 3 DMUs with the highest production capacity, indicating their ability to produce maximum output. It was also assumed that MSMEs with bigger production capacity would better manage resources in their operations (Verma and Nema, 2019). The characteristics of the DMU were analyzed based on several criteria, including the number of workers, production volume, supply chain reach, type of business entity, and how long the business has been operating. With some of these criteria, the characteristics and conditions of DMUs can be described clearly; thus, the research objectives can be achieved precisely.

Weighting input and output variables using AHP

The first step that has to be done in AHP calculation was compiling a pairwise comparison matrix filled with expert judgments on the level of importance between variables, which the structure refers to Table 2. The diagonal part of the matrix shows a value of 1, indicating the variables' equal importance. There were two forms of value in the pairwise comparison matrix. The notation a_{ij} (a_{ij} {1,3,...,9}) in cell (i,j) illustrates that the variable in row i was more important by a_{ij} times than the variable in column j, while the remaining cells (j,i) in the table were filled with the notation $1/a_{ij}$ ($1/a_{ij}$ {1/1.1/3,...,1/9}) (Kumar and Banerjee, 2014).

The data obtained from the pairwise comparison matrix was used to calculate the priority weights of each variable. The first step in calculating the variable's weight was to add the values in each column of the pairwise comparison matrix. Then, the values in each row were normalized by dividing each value by the number of each column. The weight of each variable was obtained by summing each row in the normalized pairwise comparison matrix. Mathematically, the calculation or synthesis of weights can be described through the following equations (Singh et al., 2016):

$$\text{Normalize } a_{ij} = \left\{\frac{a_{ij}}{\text{total of the j−th column}}\right\} \quad (5)$$

$$\text{or } b_{ij} = \left\{\frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}}\right\} \quad (6)$$

$$w_i = \left\{\frac{\text{total value of the i−th row}}{n}\right\} \quad (7)$$

$$\text{or } w_i = \left\{\frac{\sum_{i=1}^{n} b_{ij}}{n}\right\} \quad (8)$$

Where b_{ij} was the normalized matrix value, w_i was the weight of the variable, and n was the number of observed variables.

Table 2. Pairwise comparison matrix structure

Input

Variable	***Input*1**	***Input*2**	***Input*3**	***Input*4**	***Input*5**	***Input*6**
*Input*1	1	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}
*Input*2	$1/a_{12}$	1	a_{23}	a_{24}	a_{25}	a_{26}
*Input*3	$1/a_{13}$	$1/a_{23}$	1	a_{34}	a_{35}	a_{36}
*Input*4	$1/a_{14}$	$1/a_{24}$	$1/a_{34}$	1	a_{45}	a_{46}
*Input*5	$1/a_{15}$	$1/a_{25}$	$1/a_{35}$	$1/a_{45}$	1	a_{56}
*Input*6	$1/a_{16}$	$1/a_{26}$	$1/a_{36}$	$1/a_{46}$	$1/a_{56}$	1

Output

Variable	***Output*1**	***Output*2**	***Output*3**
*Output*1	1	a_{12}	a_{13}
*Output*2	$1/a_{12}$	1	a_{23}
*Output*3	$1/a_{13}$	$1/a_{23}$	1

The results of the weighting through the AHP method were calculated for consistency. The acquisition of expert opinion between one factor and another was independent, which can lead to incompetence in expert responses. The inconsistency of respondents' answers can affect the quality of decision-making from the AHP method (Pachemska et al., 2014; Zuraidi et al., 2018). Mathematically, if a_{ij} describes the importance of variable *i* to variable *j* and describes the importance of variable *j* to variable k so that the decision becomes consistent, the importance of factor i to factor k must be described by the consistency equation $a_{ij} .a_{jk} = a_{ik}$ for all *i, j, k* (Singh et al., 2016). The consistency of AHP was seen from the Consistency Ratio (CR) value, which should not be more than 0.1, indicating that the comparison results were acceptable. AHP consistency can be calculated using the following equation from (Taherdoost, 2017).

Measurement of DMU efficiency and benchmarking using the DEA

The DEA model used in this study considers the priority weights of each input and output (w_i) obtained from the AHP method. The weights obtained were used to multiply the input and output values. If x_{ij} was the number of weighted inputs used by the jth DMU and y_{rj} was the number of weighted outputs produced by the jth DMU; a_{ij} was the number of actual inputs used by the jth DMU and a_{rj} was the number of actual outputs produced by the jth DMU; and ${w_i}^{AHP}$ was the weight of input and output, then the equation can be obtained (Dania et al., 2019):

$$x_{ij} = a_{ij} \,.\, {w_i}^{AHP} \text{ .... } (9)$$

$$y_{rj} = a_{rj} \,.\, {w_i}^{AHP} \text{ .... } (10)$$

The characteristics of the available data determine the DEA model used in the efficiency measurement. This study assumed that a change in the input does not change the output proportionally. In other words, adding two more inputs can result in a less or more than two times increase in output. Therefore, in this study, the DEA VRS model was used. In addition, the VRS model was preferable if all DMUs cannot operate optimally and consist of various scales and sizes (Banker et al., 1984; Dania et al., 2019). The output used in this study was considered easier to modify and control than the input. Therefore, the DEA model in this study used output orientation to maximize output by maintaining inputs to achieve efficiency.

This study used two types of output, desirable and undesirable. CO_2 emissions were included in the group of undesirable outputs. Based on that case, DEA can accommodate these calculations to produce eco-efficiency. In the basic DEA model, the output can only move towards increasing or decreasing simultaneously to describe the efficiency level. Therefore, it is necessary to modify the DEA equation to accommodate the desirable and undesirable outputs in the same model. Adding positive scalars (β) was considered most suitable for the DEA VRS model and can maintain a positive value of undesirable output (Dania et al., 2019; Halkos and Petrou, 2019). Thus, with the modification of the basic DEA formula based on undesirable output, the DEA VRS model in the form of a dual multiplier can be described as follows (Dania et al., 2019):

$$\min \textstyle\sum_{i=1}^{m} u_i x_{i0} - \xi \text{ .... } (11)$$

Subject to:

$$\sum_{i=1}^{m} u_i x_{ij} - \sum_{r}^{s} v_r^* y_{rj}^{d} - \left[\sum_{s+1}^{t} v_r^* y_{rj}^{u} + \beta\right] - \xi \geq 0, j = 1, \dots, n,$$
$$\sum_{r}^{s} v_r^* y_{r0}^{d} - \left[\sum_{s+1}^{t} v_r^* y_{r0}^{u} + \beta\right] = 1$$
$$u_i, v_r \geq \varepsilon \ \ \forall i, r, \xi$$

Where u_i and v_r was the weight assigned to the input i and output r. The purpose of the equation was to generate a weight vector (u_i, v_r), which can maximize the efficiency of the rated DMU. u_i^*, v_r^* and ξ^* were the optimal set of weights, which ξ indicates the type of return-to-scale. An increasing return-to-scale can only occur if $\xi^* < 0$, a decreasing ξ^* return-to-scale can only occur if > 0 and a constant return-to-scale can only occur if $\xi^* = 0$. In output-oriented DEA, the constraints can make the return-to-scale tend to be of decreasing type, which prevents the negative cross-efficiency that can occur in input-oriented DEA. (Dania et al., 2019; Zhu, 2015).

The DMU in this study consisted of potato chips MSMEs, which were very diverse in size and type of company, so the operational performance level of several DMUs would also vary. This can cause the input and output values obtained from several DMUs to have different ranges. Normalization needed to be done so that every MSME can be compared with an equal position in the DEA. One of the normalization methods that can be applied is rescaling, changing the value to a scale of 0-1 by considering the maximum and minimum values (Dania et al., 2019). The rescaling normalization equation can be described as follows:

$$y_{rj}' = \frac{y_{rj} - \min(y_{rj})}{\max(y_{rj}) - \min(y_{rj})} \qquad (12)$$

By considering the normalization and efficient frontier, Eq. 11 can be modified to:

$$\min \sum_{i=1}^{m} u_i x_{i0} - \xi \qquad (13)$$

Subject to:

$$\sum_{i=1}^{m} u_i \hat{x}_{ij} - \sum_{r}^{s} v_r^* \hat{y}_{rj}^d - \left[\sum_{s+1}^{t} v_r^* \hat{y}_{rj}^u + \beta\right] - \xi \geq 0, j = 1, \ldots, n,$$

$$\sum_{i=1}^{m} u_i \left(\frac{\hat{x}_{ij} - \min(\hat{x}_{ij})}{\max(\hat{x}_{ij}) - \min(\hat{x}_{ij})}\right) - \sum_{r=1}^{s} v_r \left(\frac{\hat{y}_{rj}^d - \min(\hat{y}_{rj}^d)}{\max(\hat{y}_{rj}^d) - \min(\hat{y}_{rj}^d)}\right) - \left[\sum_{s+1}^{t} v_r \left(\frac{\hat{y}_{rj}^u - \min(\hat{y}_{rj}^u)}{\max(\hat{y}_{rj}^u) - \min(\hat{y}_{rj}^u)}\right) + \beta\right] - \xi \geq 0, \ j = 1, \ldots, n$$

$$\sum_{r=1}^{s} v_r \left(\frac{\hat{y}_{r0}^d - \min(\hat{y}_{r0}^d)}{\max(\hat{y}_{r0}^d) - \min(\hat{y}_{r0}^d)}\right) - \left[\sum_{s+1}^{t} v_r \left(\frac{\hat{y}_{r0}^u - \min(\hat{y}_{r0}^u)}{\max(\hat{y}_{r0}^u) - \min(\hat{y}_{r0}^u)}\right) + \beta\right] = 1$$

Several factors (such as economic conditions, demographics, and other social factors) can influence the determination of efficiency in the future. PERT is a method used to adapt to the uncertainty of a situation, where the situation is expressed in three forms, namely "most likely", "optimistic," and "pessimistic" (Shabani and Saen, 2015). PERT was used to estimate the input ($\tilde{x}_{ij}$) and output ($\tilde{y}_{rj}$) values instead of the current input ($\hat{x}_{ij}$) and current output ($\hat{y}_{rj}$) values. Thus, the parameters and equations used to estimate the input and output values of the DMU in the future are as follows:

a. "Most likely" estimates for input (ML_{ij}) and output (ML_{rj});
b. "Optimistic" estimates for input (OP_{ij}) and output (OP_{rj});
c. "Pessimistic" estimates for input (PE_{ij}) and output (PE_{rj});

The conversion of the input and output value estimations can be obtained from the following equation,

$$\tilde{x}_{ij} = \frac{(OP_{ij} + 4ML_{ij} + PE_{ij})}{6} \qquad (14)$$

$$\tilde{y}_{rj} = \frac{(OP_{rj} + 4ML_{rj} + PE_{rj})}{6} \qquad (15)$$

Thus, Eq. 11 can be modified to:

$$\min \sum_{i=1}^{m} u_i x_{i0} - \xi \qquad (16)$$

Subject to:

$$\sum_{i=1}^{m} u_i \tilde{x}_{ij} - \sum_{r=1}^{s} v_r^* \tilde{y}_{rj}^d - \left[\sum_{s+1}^{t} v_r^* \tilde{y}_{rj}^u + \beta\right] - \xi \geq 0, j = 1, \ldots, n,$$

$$\sum_{i=1}^{m} u_i \left(\frac{\tilde{x}_{ij} - \min(\tilde{x}_{ij})}{\max(\tilde{x}_{ij}) - \min(\tilde{x}_{ij})}\right) - \sum_{r=1}^{s} v_r \left(\frac{\tilde{y}_{rj}^d - \min(\tilde{y}_{rj}^d)}{\max(\tilde{y}_{rj}^d) - \min(\tilde{y}_{rj}^d)}\right) - \left[\sum_{s+1}^{t} v_r \left(\frac{\tilde{y}_{rj}^u - \min(\tilde{y}_{rj}^u)}{\max(\tilde{y}_{rj}^u) - \min(\tilde{y}_{rj}^u)}\right) + \beta\right] - \xi \geq 0, \ j = 1, \ldots, n$$

$$\sum_{r=1}^{s} v_r \left(\frac{\tilde{y}_{r0}^d - \min(\tilde{y}_{r0}^d)}{\max(\tilde{y}_{r0}^d) - \min(\tilde{y}_{r0}^d)}\right) - \left[\sum_{s+1}^{t} v_r \left(\frac{\tilde{y}_{r0}^u - \min(\tilde{y}_{r0}^u)}{\max(\tilde{y}_{r0}^u) - \min(\tilde{y}_{r0}^u)}\right) + \beta\right] = 1$$

Table 3. Characteristics of decision making unit (DMU)

DMU	Labor (person)	Production Volume (kg/year)	Downstream Supply Chain Reach	Type of Business Entity	DMU's Age (Years)
DMU1	2	218.4	Prod – Cons	home	5
DMU2	3	1,800	Prod – Cons	home	10
DMU3	10	4,800	Prod – Ret – Cons	CV	12
DMU4	5	4,800	Prod – Ret – Cons	SP	8
DMU5	17	33,600	Prod – Ret – Cons	CV	11
DMU6	15	7,800	Prod – Ret – Cons	CV	15
DMU7	3	3,650	Prod – Ret – Cons	SP	12
DMU8	4	7,300	Prod – Ret – Cons	SP	10
DMU9	1	2,760	Prod – Cons	home	4
DMU10	1	1,560	Prod – Ret – Cons	home	8
DMU11	8	9,250	Prod – Ret – Cons	SP	12
DMU12	1	7,488	Prod – Ret – Cons	home	12
DMU13	2	8,190	Prod – Ret – Cons	home	8
DMU14	2	1,440	Prod – Cons	home	8
DMU1 5	4	3,650	Prod – Ret – Cons	home	10
DMU16	10	1,200	Prod – Ret – Cons	CV	15
DMU17	3	7,200	Prod – Cons	home	7
DMU18	6	3,600	Prod – Ret – Cons	SP	9
DMU19	1	720	Prod – Cons	home	11
DMU20	5	1,100	Prod – Ret – Cons	home	11

Prod: Producer, Ret: Retailer, Cons: Consumer

Results and Discussion

Description of DMU characteristics

The characteristics of DMU are shown in Table 3. The type of business entity of the DMU is closely related to the business process mechanism and affects production capacity. 4 of the 20 DMUs in this study are potato chips MSMEs with a smaller production capacity due to limited human resources and equipment. Based on Table 3, home industry DMU has the most significant number, namely 55%, followed by SP (*Sole Proprietorship*) of 25%, and CV (*Commanditaire Venootshcap*) of 20%. Those data indicate that 9 of the 20 DMUs are home industries, which, based on the survey, cannot maintain stability and business conditions due to weather conditions and other operational issues. Moreover, because this research was conducted shortly after the COVID-19 pandemic, extraordinary conditions like this also significantly impact on the sustainability of potato chips MSMEs, especially in terms of adjusting human resources (Khomah et al., 2021). Also, Esubalew and Raghurama (2021) revealed that the larger the company size, the greater its recognition from the surrounding environment, so sustainability is essential for the company. Companies can maintain their stability by improving their performance.

Experience for an organization or company can be determined by how long it has existed. The longer a company operates, the more information can be received by the surrounding environment, which leads to increased consumer and partner trust if the company has a good performance (Backes-Gellner and Veen, 2013). Table 3 shows that the highest frequency is 60%, or 12 DMUs have been established for 10-15 years. Thus, respondents are expected to have understood the mechanism of the supply chain of potato chip products thoroughly based on their experience. The subsequent highest frequency is 35%, or 7 DMUs have existed for 5-10 years. 1 DMU has been established for less than 5 years or by 5%. According to Sable and Dave (2020), the longer a company can survive, the more excellent the opportunity for the company to return its investment due to the considerable amount of experience gained. Companies that have been around for a long time will find gaining consumer confidence in their products easier.

Table 3 shows that regarding the number of workers, all DMUs are classified as home and small industries since they do not involve more than 20 workers. Based on the classification of industrial companies from Statistics Indonesia (2022), companies are classified as home industries if they involve less than 5 workers and small industries if they involve 5-19 workers. The classification does not consider the type of machinery and equipment used and the amount of capital employed. In terms of supply chain flow, this research is limited to only observing the downstream supply chain flow of each DMU, where most of the DMUs have used a minimal distribution channel through the presence of retailers before finally reaching consumers. This indicates that most DMUs have tried to expand their market reach further and make it easier for end consumers to obtain their products.

Analysis of variable weighting results using AHP

The weight calculation of the DEA inputs and outputs helps to know how the relative importance of applying a variable is compared to other variables in a DMU. Before calculating priority weights, all existing variables were considered to have the same importance and priority in their application. DMUs in the form of MSMEs can only apply some of the input and output variables to supply chain operations, especially from a sustainability point of view. With the weighting, the implications of improving between aspects of SSCM in MSMEs can be carried out on target and following the predetermined priority weights.

The preparation of the pairwise comparison matrix is based on the expert's judgment. Determination of each variable's relative weight or level of importance of each variable begins with the normalization process based on the pairwise comparison matrix table to know the average value of each row (each variable), which shows how much priority level is obtained. Based on the normalization results, the average value of each row can be determined to produce variable priority, as shown in Table 4.

The consistency ratio (CR) calculation needs to be done to ensure that the results of expert assessments are consistent and accurate. It is being done both for the input and output variables. Based on the calculations, the CR value for the input variable matrix is 0.044, and the output variable is 0.05. The two consistency obtained met the requirements seen from the CR value, which should not be more than 0.1. This indicates that the comparison results have been consistent between decision-makers and have been valid (Taherdoost, 2017). With this consistency, the results of expert respondents' assessment of the importance of variables can describe the actual conditions.

Based on Table 4, energy use is the input variable with the highest priority weight (X1=0.23). Several types of energy sources used in the operation of the potato chips supply chain by MSMEs are fuel (stationary and non-stationary) and electrical energy. Good energy management will encourage MSMEs to survive long-term because using energy for operations is directly related to the supply chain cost efficiency. According to Lakuma et al. (2019), the paradigm regarding the benefits obtained by a business entity, which previously had a lot to do with efficient manufacturing processes, shifted to efficient use/management of energy required by the equipment. Pelz et al. (2021) revealed that energy use is closely related to supply and demand, where MSMEs can make conservation efforts from the demand side to realize efficient use.

As an output variable, total sales (Y2) have the highest priority, with the value of 0.49. The high priority score of the sales variable shows that the main focus of achieving potato chips SMEs is increasing total sales. Potato chips SMEs tend to emphasize resource and cost efficiency, which will determine the total sales earned. In addition, MSMEs sales will evaluate the business's sustainability because it is related to efforts to maintain a stable cash flow. According to Wuttke et al. (2013), the financial flow will also facilitate the material flow, which needs to be coordinated to ensure a smooth supply chain among its members. As a result, an explicit agreement is needed on the payment system from the downstream sector.

DEA model analysis

The calculation of DMU Technical Efficiency (TE) was carried out on 20 MSMEs of potato chips based on several sustainability criteria, including energy use, the volume of solid waste, CO_2 emissions, raw material costs, production volume, total sales, LER, collaboration with other business units and improving the welfare of workers. The data sets are obtained from the actual data processing of the sustainability practices of 20 potato chips MSMEs. The data from internal energy sources is calculated by Eq. 2 to produce data on energy use in Terra Joules. The same is applied to CO_2 emissions using Eq. 1 and 2; also LER using Eq. 4.

a. Current DMU efficiency

Based on the current efficiency calculation, Table 5 shows that there are three DMUs classified as marginally efficient, namely DMU5 (0.965), DMU7 (0.955), and DMU8 (0.995). In this study, improvements to the sustainability aspect assessed in the DEA are carried out with an output orientation so that inputs will be maintained at the same level and outputs will be increased as much as possible. Outputs that have the potential for improvement include CO_2 emission levels, total sales, and labor welfare improvement. The improvement suggestions are provided in the next section.

Table 4. Results of variables weighting

Variable	Variable Weight	Rating
Energy Usage (x1)	**0.23**	**1**
Solid Waste Volume (x2)	0.19	2
Raw Material Cost (x3)	0.18	3
Production Volume (x4)	0.12	5
Labor Absorption (x5)	0.12	5
Collaboration Efforts (x6)	0.15	4
CO2 emissions (y1)	0.08	3
Total Revenue (y2)	**0.49**	**1**
Labor Welfare (y3)	0.43	2

Table 5. Current output efficiency scores

DMU	Output									TE
	Carbon Emissions (kg CO_2)			Total Sales (USD)			Labor Welfare Improvement (Likert)			
	Original	Projected	%	Original	Projected	%	Original	Projected	%	
…	…	…	…	…	…	…	…	…	…	…
DMU5	10,048,792.41	17,460.09	99.83	66206.9	69383.4	4.58	3.5	5	54.03	0.975
DMU7	12,428,713	424,897.41	96.58	57931.0	61607.4	5.97	4	5	50.06	0.97
DMU8	18,578,567.57	1,647,209.37	91.13	45517.2	47499.4	4.17	4.3	5	48.06	0.998
…	…	…	…	…	…	…	…	…	…	…

From the environmental aspect, DMU5, with the current efficiency level of 0.965, can turn efficient by reducing the CO_2 emission level by 99.83%. The emission level is an aspect that is lowered because it is classified as undesirable output. From the economic and social aspects, DMU5 should increase its sales by 12.94% and the workforce's welfare by 54.17% to achieve efficiency. Several things cause DMU5 still cannot achieve efficiency. DMU5 has a large production capacity, so it impacts the resulting CO_2 emissions. DMU5 is one of the DMUs with a medium scale that consistently produces potato chips, leading to a high distribution rate. The distribution process also contributes significant emissions to DMU5. According to Tortoe et al. (2023), as much as 50% of energy consumption in the world is used for industrial purposes, where management in terms of energy sources and energy use costs must be considered to achieve good efficiency. DEA calculations show that DMU5 has a small ratio between raw material costs and total sales. Thus, total sales should continue to be increased, as well as the welfare of the workforce on the social aspect. Such condition shows that there is no significant change in terms of labor welfare from before and after work in that place.

DMU7, with an efficiency score of 0.955, can also be efficient by optimizing some aspects of its output. In the environmental aspect, DMU7 needs to reduce CO_2 emissions by 96.58%, increase sales by 34.37% and improve the welfare of its workforce by 50.38%. DMU7 has the lowest level of efficiency compared to other DMUs. DMU7 also produces significant CO_2 emissions that are not proportional to the production volume. In addition, the energy consumption of DMU7 is considered high compared to other DMUs, which indicates a lack of efficiency in production and distribution operations, resulting in increased energy use and CO_2 emissions. This shows that DMU7 cannot implement cleaner production, where this method is vital for any business level. Production efficiency can reduce pollution figures and operational costs (Naik and Mallur, 2018). From the social aspect, the welfare of the DMU7 workforce is good because it reaches the maximum Likert scale.

DMU8, with an efficiency score of 0.995, can be efficient by reducing CO_2 emissions by 91.13%, increasing its sales by 17.65%, and increasing the welfare of its workforce by 48.35%. Compared to other DMUs, DMU8 has a low production volume but produces very high CO_2 emissions. One of the reasons is the use of energy sources in the form of LPG in the drying process through the oven when there are unfavorable weather conditions. On the other hand, as long as appropriately managed, using LPG as fuel for cabinet dryers is ideal for producers (i.e., MSMEs) as it can increase value addition and reduce post-harvest losses (Tortoe et al., 2023). This has resulted in DMU8 tending to be unbalanced in using existing resources. The costs incurred for raw materials are also high, so the sales need to be increased to increase the ratio between sales and expenditure. From the social aspect, the welfare of the DMU8 labor is also good.

Table 6. Future output efficiency scores

DMU	Output									TE
	Carbon Emissions (kg CO_2)			Total Sales (USD)			Labor Welfare Improvement (Likert)			
	Original	Projected	%	Original	Projected	%	Original	Projected	%	
…	…	…	…	…	…	…	…	…	…	…
DMU5	53,558,379.7	53,558,379.7	0.00	64137.9	64137.9	0.00	3.58	3.58	0.00	1
DMU7	62,173,305.4	54,421,758.50	12.47	58620.7	58620.7	0.00	4	5	49.89	0.996
DMU8	105,574,959.6	2,269,059.59	97.85	42758.6	42758.6	0.00	4.37	5	47.84	0.980
…	…	…	…	…	…	…	…	…	…	…

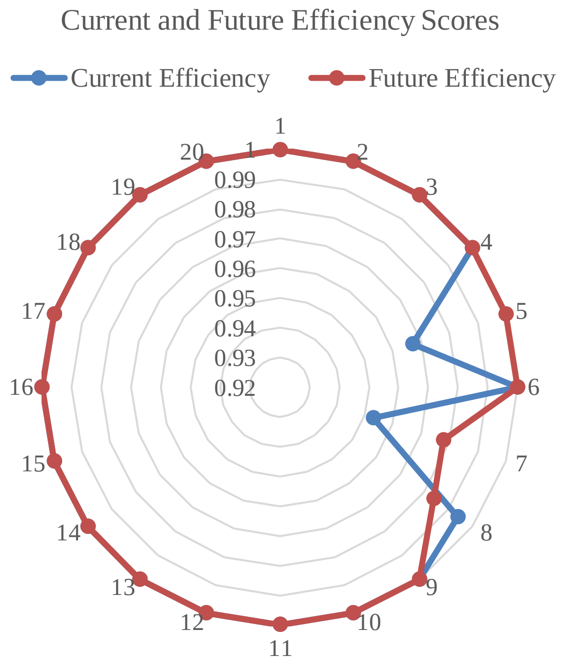

Figure 1. Comparison between current and future efficiency

b. Future estimates of DMU efficiency using PERT

The influence of internal (DMU's operational condition) and external conditions (market, consumer preferences, extraordinary conditions) in the future can affect the efficiency level of each DMU. PERT estimates the input and output of each DMU based on the influence of internal and external conditions in the future. Based on the DEA calculation modified with the PERT mathematical formula (Table 6), there is a slight difference in the DMU efficiency level. DMU5, initially classified as marginally efficient, has achieved efficiency with future estimates through the PERT method. DMU7 and DMU8 remain marginally efficient, with efficiency scores of 0.978 and 0.984, respectively. From the environmental aspect, DMU7 needs to reduce CO_2 emissions by 12.47% and improve the welfare of its workforce by 49.97%. DMU8 must significantly reduce CO_2 emissions by 97.85% and increase labor welfare by 48.02%. From the economic aspect, DMU7 and DMU8 have good efficiency in total revenue, so there is no need to increase significantly. The efficiency level of DMU7 and DMU8 has not reached the best point because, with a relatively moderate production volume compared to other DMUs, DMU7 and DMU8 produce high CO_2 emissions. DMU7 uses a stationary fuel source in the form of 12 kg LPG for a short period of usage, so it is less efficient when compared to the use of 3 kg LPG. While DMU8 uses a lot of LPG for the drying process through the oven if unfavorable weather condition exist. On the social aspect, both DMUs have a good score on the welfare of the workforce but still need improvement towards the maximum scale. According to Shabani and Saen (2015), analysis of future DMU efficiency is considered essential to develop because it can include long-term planning, where the input and output of a system are influenced by external factors such as economic, social, and environmental conditions.

Figure 1 shows a comparison between the results of the current DMU efficiency score and its estimation in the future using PERT calculations. Using the OP, ML, and PE scenarios, some DMUs obtained different efficiency scores than the current ones. DMU5 experienced a change in efficiency score from 0.965 to 1 (efficient). This result indicates that the internal and external constraints that DMU5 will face in the future have no significant effect on DMU5's operations, even making DMU5 produce much better efficiency. DMU7 and DMU8 did not experience substantial changes in technical efficiency. DMU7, which has a current efficiency score of 0.955, increased to 0.978 based on the PERT estimation method, while DMU8 experienced a slight decrease in efficiency from 0.995 today to 0.984 in the future. This indicates that the constraints of internal and external factors in the future on DMU7 have no significant effect but result in a slight increase in efficiency scores. On the other hand, future internal and external factors experienced by DMU8 resulted in a slight decline in technical efficiency. Based on that comparison, Dotoli et al. (2016) stated that PERT is a good project management stochastic method for dealing with uncertainty from expert judgment. This method can help DMU determine its future efficiency level using the three estimation scenarios given.

PERT can lead some inefficient DMUs to improve technical efficiency, even though some DMUs do not reach the maximum efficiency level. However, it should be underlined that the efficiency level of DMU7 and DMU8 is still limited to a marginally efficient level. So, there is still a need for an overall improvement effort on SSCM practices for efficient and inefficient DMUs that can be done through several managerial implications that can still be easily applied to potato chips SMEs.

Sensitivity analysis

The term sensitivity in DEA refers to the stability and reliability of the data used in the calculations. The sensitivity analysis aims to identify the effect of DMU efficiency if there are changes in the parameters used in the model (Huguenin, 2012; Zhu, 2015). The concept of sensitivity analysis has evolved from initially focusing on input and output analysis for a single DMU to evaluating DEA results when inputs and outputs are varied simultaneously across DMUs (Cooper et al., 2011). There are several ways to apply DEA sensitivity analysis, among others, by adding or subtracting DMU in the DEA model to modify/variating the input and output values to determine the maximum data variation that can affect the efficiency status of the DMU (Huguenin, 2012). In this study, sensitivity analysis was carried out by modifying the current input and output values on one of the inefficient DMUs to become efficient (efficiency score 1) according to the projected value obtained.

Sensitivity analysis is carried out by modifying the actual value of input and output in the current DMU7 data set (lowest efficiency score) to be the same as the projected value *in* the previous calculation. This change only affects the efficiency score of DMU7 but does not change anything from other DMUs. DMU5 and DMU8, as two inefficient DMUs, still get the same efficiency score after going through sensitivity analysis and efficient DMUs. This indicates that from the sensitivity point of view, the DEA model used in this study has good stability in overcoming the variation of the data used, as evidenced by the absence of significant changes if there is a modification of the DMU data that is inefficient to other DMUs. A stable term is achieved because DMUs in the efficient frontier remain in the same range after some data changes. Arabjazi et al. (2021) stated that DEA is a data-based performance appraisal method. Therefore, it is essential to test the possibility of a change in input/output data (data perturbation) from a DMU to produce a consistent efficiency classification. In this case, sensitivity analysis is very beneficial in showing how far the tolerance for data changes can be made to determine DEA efficiency.

Managerial Implications

The calculation results of the DEA method can be used as a reference for formulating an improvement strategy for each DMU in the form of potato chips SMEs to achieve better efficiency. The proposed improvement of SSCM practices also pays indirect attention to the stakeholders involved, especially in the downstream supply chain of potato chips products. Since the DEA in this study is output-oriented, the output variables emphasize the improvements.

a. Total sales

As one part of the economic dimension in SSCM, sales is the aspect with the highest concern among potato chips MSMEs. Potato chips MSMEs consider sales as the main objective in their operations, which determines the sustainability of their business. The amount of sales earned by all MSMEs is very diverse because it is also determined by consistency, production volume, and sales volume. One factor that affects the efficiency of total sales is the ratio of sales and expenditure of each MSME, as well as maximizing the use of existing resources such as raw materials, energy, and labor (Purwanto et al., 2014). The environmental, economic, and social aspects must be optimized to maximize total sales. From the environmental aspect, utilizing potato peel waste as animal feed can increase MSME sales as an alternative solution to high animal feed prices (Gebrechristos and Chen, 2018).

From an economic point of view, it is necessary to look for alternatives from sources of the most significant cost components, such as raw materials. MSMEs can bring in potato raw materials from suppliers who provide lower and more stable prices, such as directly from farmers in the highest potato-producing areas like the Greater Malang. In the downstream sector, it is essential to pay attention to marketing techniques to optimize sales volume and increase customer awareness of the product. With the help of internet technology, online marketing can improve the sustainability of related MSMEs in terms of sales due to the higher consumer awareness of their products (Rahman et al., 2016).

Regarding social aspects, potato chips MSMEs can also consider empowering workers in the surrounding environment to minimize the cost of labor mobility to come to production sites to reduce labor wages further. On the other hand, total revenue can also be increased by maximizing sales by expanding the structural collaboration of the downstream supply chain network (increasing the number of distributors/retailers), maintaining production consistency, and increasing promotional efforts of its products. According to (Björnfot and Torjussen, 2012), the flexibility of horizontal collaboration in the MSME supply chain can encourage regional economic growth and benefit all business entities involved.

b. Labor welfare

Welfare is an aspect of the social dimension of SSCM, which is the second highest priority for potato chips SMEs. According to Rani and Kumar (2020), the workforce's socio-economic conditions significantly influence the development of MSMEs. The impact of a good level of welfare is that the workforce will have a positive attitude, high self-confidence, and utmost dedication. Potato chips producers as MSMEs should pay attention to the balance between improving the welfare of their workforce and maintaining good operational stability, especially the operating cost. MSMEs have to ensure that they have sufficient labor welfare because it is one of the essential sustainability indicators. Also, due to the trend,most potential laborers tend to decide to work in other places that provide a higher salary. One way to improve the welfare of the workforce is to provide financial and non-financial facilities, such as by providing allowances for transportation and food. That approach is likelyl to be applied since some MSMEs in this study already used it. In addition, concerning the workforce involved in MSMEs being unskilled labor and managed with a simple labor hierarchy, efforts to achieve prosperity can also be made by creating a supportive work environment and good flexibility for the workforce. Those efforts can be easily implemented by small industries, which are still far from the reach of the law governing the workforce. Thus, the workforce producing potato chips is expected to work more optimally.

c. CO_2 emissions

The impact of environmental degradation as a result of MSME operations in large quantities needs special attention. The high number of emissions produced by MSMEs indicates the low efficiency of using energy sources, both stationary and non-stationary. In this regard, MSMEs need to improve efficiency from the environmental aspect and reduce emission levels to avoid climate change. Moreover, controlling climate change by MSMEs can be a primary 'budgeting' effort to address the high costs of using energy and carbon costs directly or indirectly (Hendrichs and Busch, 2012).

In contrast to large companies, MSMEs require more straightforward guidelines to be applied in their daily operations to control CO_2 emissions. The first thing that can be done is to look for alternative energy sources from currently used stationary fuels (LPG), such as biogas and solar energy for electrical energy. Investment in renewable energy is beneficial for MSMEs to anticipate unpredictable events such as power outages, which can be done by installing simple power-generating sets (Anaba and Olubusoye, 2021). More than that, using alternative energy sources with low carbon emissions can be a long-term investment for MSMEs in developing countries to reduce operational energy costs and dependence on fossil fuels (Murshed et al., 2021). Drying potato slices can be combined with direct sunlight and oven equipment to balance energy use and production consistency that is not affected by weather conditions. The current situation shows that the transportation system for MSMEs distribution is inefficient, thus affecting the total cost. Regarding non-stationary fuels (petrol, diesel), CO_2 emissions can be minimized by distributing potato chips to different places in one trip and larger volumes. This, of course, requires consideration of changing the mode of transportation that can accommodate a large volume of distribution (> 1 ton capacity). Several types of transportation modes that can be used are closed box cars with a maximum carrying capacity of 700 kg (box dimensions of 237x155x129 cm) and ankle trucks with a maximum carrying capacity of 2.2 tons (box dimensions of 310x170x170 cm).

Conclusions

Motivation to promote SSCM practices among potato chips MSMEs is vital to support their competitive advantage. 17 DMUs in this study have achieved the best efficiency, except for DMU5, DMU7, and DMU8, which are classified as marginally efficient through current efficiency calculations. In the analysis of future efficiency, it is known that DMU5 experienced a change in efficiency score from 0.965 to 1 (efficient), while DMU7 and DMU8 remained marginally efficient. Improving the SSCM practice in each potato chips MSME is necessary to improve efficiency. In total sales, improvements can be made by identifying alternatives from existing cost sources so that total expenses can be further suppressed. In improving the welfare of the workforce, it is possible to provide measurable financial and non-financial facilities for the unskilled labor involved. In the aspect of CO_2 emissions, improvements can be made by finding alternative sources of stationary fuel and redesigning the distribution system to the downstream sector. Findings from this paper can be beneficial for further research related to SSCM. Comparing the DMU's perspective from the different regions may be able to describe significant differences supported by variations in geographic and demographic conditions. This paper only evaluates the SSCM practice in one agricultural product with a similar producer level. Thus, more extensive and diverse samples are needed for a comprehensive analysis. There is a potential to develop the model or the result of DEA and assign it to a machine learning algorithm to analyze a trend or make a future prediction.

Declarations

Conflict of interests The authors declare no competing interests.

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