Implementation of sustainable manufacturing in Indonesia paint industry based on triple bottom line

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Abstract

The manufacturing industry is currently faced with many challenges both from competitors and from stakeholders. The paint industry is one of the manufacturing industries that has received a lot of attention so that it can become a sustainable manufacturing industry. The implementation of triple bottom-based sustainable manufacturing can be a solution to these sustainability challenges. The purpose of this study was to analyze the implementation of green manufacturing and its effect on the sustainability of the decorative paint industry using the SEM-PLS method. The PLS SEM method was chosen because it works efficiently for small sample sizes and complex models. The results of triple bottom line modeling using SEM PLS show that the input category indicator has a negative effect on the economic dimension and does not affect the social dimension. Operations and output category indicators have a positive effect on the social dimension. Prediction accuracy is moderate for the social dimension and high for the relevance value for the social dimension. This shows that environmentally friendly products can increase social trust for both employees, customers and the surrounding community but are perceived to have a negative impact on the economy from the use of environmentally friendly input materials.

Keywords: decorative paint, green manufacturing, sustainable manufacturing, SEM-PLS.

1. Introduction

Sustainable manufacturing is currently a very important issue for governments and industries around the world (Seliger et al., 2008). Achieving sustainability in manufacturing activities has been recognized as a critical need due to the reduction of non-renewable resources, strict regulations relating to the environment and work safety, and increasing consumer preference for environmentally friendly products (Jayal et al., 2010). Resolving environmental, social and economic challenges early in governance will contribute to ongoing process improvements (Hussain, Rigoni, & Orij, 2018). The sustainability measurement infrastructure provides a foundation for decision making and is expected to be tightly integrated into the company's business strategy development process (Feng, Joung, & Li, 2010).

Manufacturing performance is critical to the success of many companies. Superior performance leads to competitiveness. In order to stay competitive, a manufacturing company must regularly evaluate its performance. Thus, it is very important for manufacturing companies to identify and ensure good performance in global competition (Amrina & Yusof, 2011; Ikatrinasari et al., 2018). Sustainable manufacturing is the creation of manufactured products that minimize negative environmental impacts, save energy and natural resources, are safe for employees, communities and consumers and are economically healthy (US Department of Commerce, 2009). The general principle of sustainable manufacturing is to reduce the intensity of material use, energy consumption, emissions, and the creation of unwanted byproducts while maintaining, or increasing, the value of products to society and organizations (OECD, 2009).

One of the growing industries is the paint industry. This causes very tight competition between industries to market their respective products. One way to win the competition that occurs is that the quality of the products produced must be good (Gunawan, 2013). Paints are used to decorate, protect and extend the life of natural and synthetic materials, and act as a barrier against environmental conditions. Paints can be broadly classified into decorative paints, applied to decorate and protect buildings and other objects, and industrial coatings applied in factories to finish manufactured goods such as automobiles (CIEC Promoting Science, 2013).

Increased regulatory pressure and increased public awareness of environmental and health concerns have created a greater demand for low volatile organic compound (VOC) paints and coatings in recent years, leading to the development of a new generation of low solvent free or low-solvent decorative paints in the Malaysian and Indonesian markets. Myanmar's investment commission currently requires submitting a provisional environmental impact assessment before a ban on paints and coatings that are harmful (high VOC) to the environment or human health (Singh, 2017).

2. Literature Review

A review of the indicators of sustainable manufacturing has been conducted and summarized based on the triple bottom line. Sustainability includes 3 parts, namely economic, social and environmental. The relationship between social, environment and economy is part of the sustainability industry (Rosen & Kishawy, 2012). The three parts then consist of related aspects as shown in Figure 1.

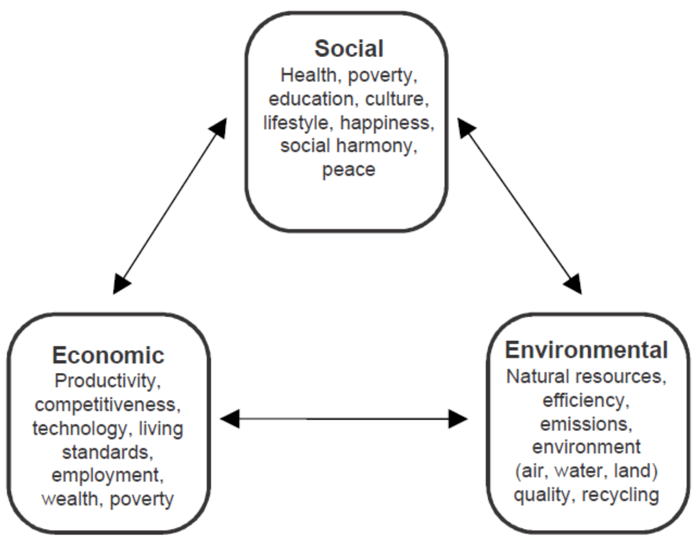

Figure 1 Relationship of social, environmental and economic sustainability.

Sustainability is defined as the level of human consumption and activity, which can continue into the future, so that the system that provides goods and services to humans continues indefinitely (Rachuri, Sriram, & Sarkar, 2009). Sustainable manufacturing is not just about the manufacturing process or the products that are produced, but a multi-level approach to products, processes, companies and supply chains needs to be considered (Jayal et al., 2010).

Experts have agreed on 12 environmental indicators that can be used in green manufacturing in the paint industry. The 12 indicators are divided into 3 sub-categories, namely: input, operations and products (Purnama, Hasibuan, & Ikatrinasari, 2020). Social indicators measure the social impact of the manufacturing process and manufactured products. Employees, customers and the surrounding community are all directly and indirectly affected by the organization's actions and considerations of these important impacts to ensure a socially sustainable operation and overall sustainability (Joung et al., 2012). Performance evaluation can be carried out in several stages with adequate analytical tools. A common example of evaluation is for indicators that have a relationship with their business information such as costs and profits (Feng & Joung, 2009). All triple bottom line indicators are presented in Table 1.

Table 1 Indicator triple bottom line

Variable		Indicator	
Environment	**Input**	Intensity of forbidden substance	I.2
		Recycled content	I.3
	Operations	Water intensity	O.1
		Energy intensity	O.2
		Greenhouse gas intensity	O.4
		Residue / waste intensity	O.5
		Air release intensity	O.6
		Water release intensity	O.7
	Product	Recycled / reused content	P.1
		Recycling	P.2
		Prohibited substance	P.5
		The intensity of greenhouse gas emissions	P.7
Economy		Profit	E.1
		Cost	E.2
Social		Employee	S.1
		Customer	S.2
		Community	S.3

3. Method

PLS-SEM is the preferred method when the research objective is theory development and variance explanation (construct-construct prediction). For this reason, PLS-SEM is considered a variance-based approach to SEM. PLS-SEM works efficiently with small sample sizes and complex models and makes practically no assumptions about the underlying data. In addition, the PLS-SEM can easily handle both reflective and formative measurement models, as well as single-item constructions, without identification problems. Therefore it can be applied in a wide variety of research situations. When implementing PLS-SEM, researchers also benefit from high efficiency in parameter estimation, which is manifested in the method's greater statistical power. The greater statistical power means that PLS-SEM is more likely to make a specific, significant relationship when it is actually significant in the population (Hair et al., 2014).

In Structural Equation Modeling (SEM) there are two forms of images, namely ovals and squares, and arrows. The oval shape is indicating variable latency, square is observed variable and arrows from oval to oval indicate causal relationship, while arrows from oval to square indicate the variable manifestation relationship formed. From the picture above, area A is a measurement model which means that the model where all measurement results are inputted can be seen the validity and reliability of the measurement results. This area is divided into A1, namely the measurement for exogenous latent variables and A2, namely the measurement model for endogenous latent variables. Whereas area B is the area of the relationship between latent variables which is also called the structural model (Kurniawan, 2015).

SEM appears to overcome the various problems above, namely by involving errors in measurement, latent indicators and variables at the same time in one analysis execution. Before SEM was widely known to see the causal relationship in the picture above, it was commonly used regression analysis or path analysis, of course, latent variable scores or data were obtained by adding up all the results in the indicators. So that the process of validation and indicator reliability is done separately, besides that, by adding up each indicator in the latent variable as if it considers 100% that the latent variable is only measured by existing indicators so that the element of measurement error or error in determining the variable is not accommodated. In turn the resulting regression or path analysis will contain a large error so that in the end the resulting conclusions will be biased and may even be wrong in concept or oddities in the research results (Kurniawan, 2015). Figure 2 shows the concept scheme for understanding the concept of Structural Equation Modeling (SEM) which will be used in the research.

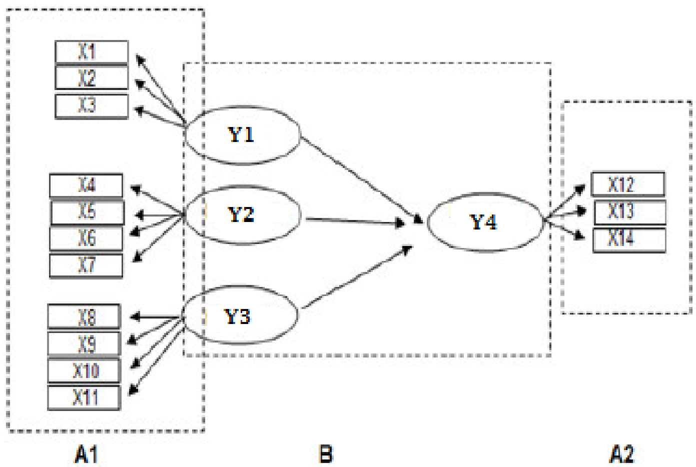

Figure 2 SEM concept.

This study aims to determine whether there is an influence of environmental factors (Product Input, Operations and Paint Products) on economic and social factors. In this study, hypothesis testing used the Partial Least Square (PLS) analysis technique with the SmartPLS 3.0 program. Figure 3 is a schematic of the PLS program model tested in the study.

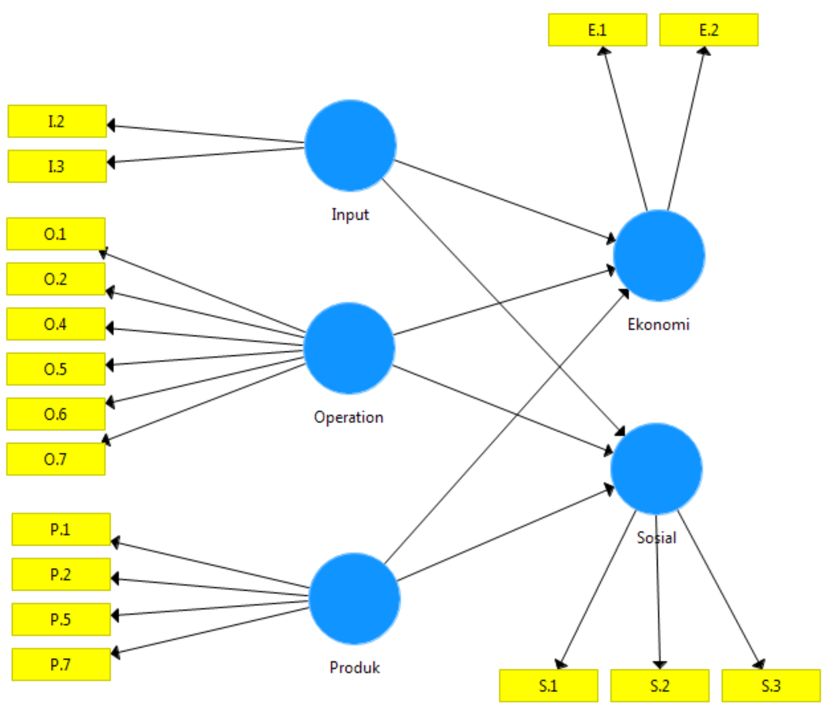

Figure 3 SEM PLS triple bottom line schematic.

Data collection techniques are the most strategic step in research, because the main purpose of research is to obtain data (Sugiyono, 2013) while data collection instruments are tools that are selected and used by researchers in data collection activities so that these activities become systematic and simplified (Arikunto , 2006). The population is a research subject that is considered important. Population is a generalization area consisting of objects/subjects that have certain qualities and characteristics that are determined by researchers to study and then draw conclusions (Sugiyono, 2013). The population in this study was paint companies in Indonesia. The sample is part or representative of the population under study (Arikunto, 2006). The samples taken in this study came from several paint companies in Indonesia. SEM-PLS works efficiently for small sample sizes and complex models. For an experiment, the minimum sample that can be recommended is 30 or more samples (Hair et al., 2014). The population in this study were paint companies in Indonesia, while the samples taken in this study came from several companies as the market leader in decorative paint in Indonesia.

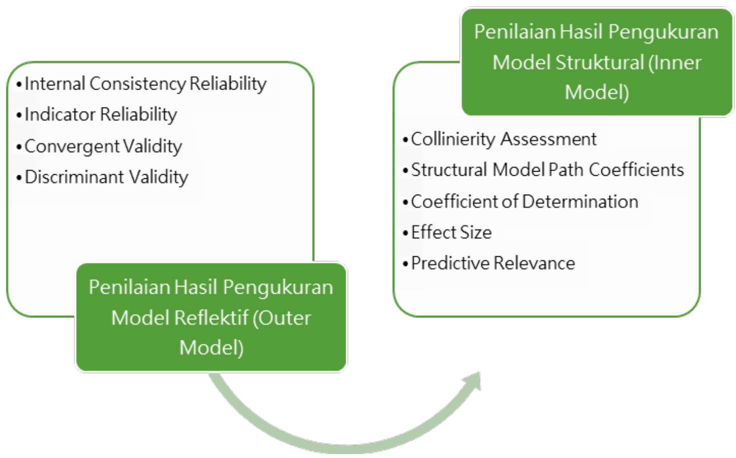

Figure 4 SEM PLS analysis flow chart.

The flow chart of the PLS SEM analysis results can be seen in Figure 4. This study the outer model is only reflective, so the assessment of the outer model is only based on the measurement results of the reflective model. There are 4 stages of inspection, namely Internal Consistency Reliability using CR, Indicator Reliability using Outer Loading, Convergent Validity using AVE and Discriminant Validity using the Former Larcker Criterion. After the examination of the outer model is complete, it is followed by an assessment of the measurement results of the structural model (inner model). There are 5 stages Collinierity Assessment using VIF, Structural Model Path Coefficients using the t test or p test, Coefficient of Determination using R2, Effect Size using f2 and Predictive Relevance using Q2 (Hair et al., 2014).

4. Result

4.1 Internal Consistency Reliability

Internal consistency reliability can be measured by composite reliability (CR). In order to meet the criteria, the CR value must be greater than 0.7. Based on Table 2, it can be seen that all latent variables have a CR value above 0.7, which means that all variables have met the criteria for internal consistency reliability (Hair et al., 2014).

Table 2 CR & AVE

Variable	CR	AVE
Economy	0.919	0.850
Input	0.952	0.909
Operation	0.925	0.673
Product	0.904	0.702
Social	0.917	0.786

Table 3 Outer Loading

Indicator	Economy	Input	Operation	Product	Social
E.1	0.909				
E.2	0.934				
I.2		0.966			
I.3		0.940			
O.1			0.886		
O.2			0.781		
O.4			0.877		
O.5			0.770		
O.6			0.760		
O.7			0.839		
P.1				0.877	
P.2				0.907	
P.5				0.770	
P.7				0.789	
S.1					0.865
S.2					0.874
S.3					0.919

Table 4 Fornell-Larcker Criterion

Variable	Economy	Input	Operation	Product	Social
Economy	0.922				
Input	-0.230	0.953			
Operation	-0.061	0.800	0.820		
Product	0.076	0.521	0.524	0.838	
Social	-0.005	0.623	0.659	0.767	0.886

4.2 Indicator Reliability
Indicator reliability can be measured by looking at the value of outer loading, if outer loading is greater than 0.7 then the indicator is used. If there is an outer loading between 0.4 to 0.7, it is necessary to re-run it with the removal of indicators that are not suitable, this is done to see the effect of indicator removal on AVE and CR. If AVE and CR increase above the threshold then the indicator with an outer loading between 0.4 to 0.7 needs to be discarded, otherwise it is still used. If outer loading <0.4, the indicator is immediately discarded. Based on Table 3, it can be seen that all outer loading is> 0.7 which means the reliability indicator has been fulfilled (Hair et al., 2014).

4.3 Convergent Validity
Convergent validity can be measured using AVE. If the AVE value is> 0.5 then the convergent validity criteria are met. Based on Table 2, it can be seen that all AVE values of each latent variable are> 0.5, so that they meet the convergent validity criteria (Hair et al., 2014).

4.4 Discriminate Validity
Discriminant Validity can be measured using the Fornell-Larcker Criterion. A latent variable shares more variance with the underlying indicator than with other latent variables. This is what underlies the Fornell-Larcker Criterion. The AVE root value must be greater than all values either to the left or down. Based on Table 4, it can be seen that

all the diagonal matrices are greater than all values both to the left and downward so that it can be said to have met the criteria for discriminant validity (Hair et al., 2014).

4.5 Collinearity Assessment

Based on the results in Table 5, it can be seen that the VIF value is less than 5, which means that there is no multicollinearity in all predictors of all responses, so that it can be continued for the next stage (Hair et al., 2014). The results of data analysis from respondents were processed by the SEM-PLS method using the SmartPLS software. From the results of the analysis, there is no multicollinearity in all predictor indicators for all responses, so it can be interpreted that the agreed indicators do not influence each other.

4.6 Structural Model Path Coefficient

Structural model coefficient analysis is used to determine which relationship has a significant effect. The results of the structural model coefficient analysis can be seen in Figure 5 and Table 6. If the p-value <α (0.05) then the relationship is significant, conversely if the p-value ≥ α (0.05) then the relationship is not significant (Hair et al., 2014). Based on the results of Table 6, it can be seen that almost all variables have a positive influence on the Economy and Social Affairs, only Input variables have a negative effect on the economy. But of all these things, what has a significant effect is the effect of product on social, while other variables have an effect but not significant.

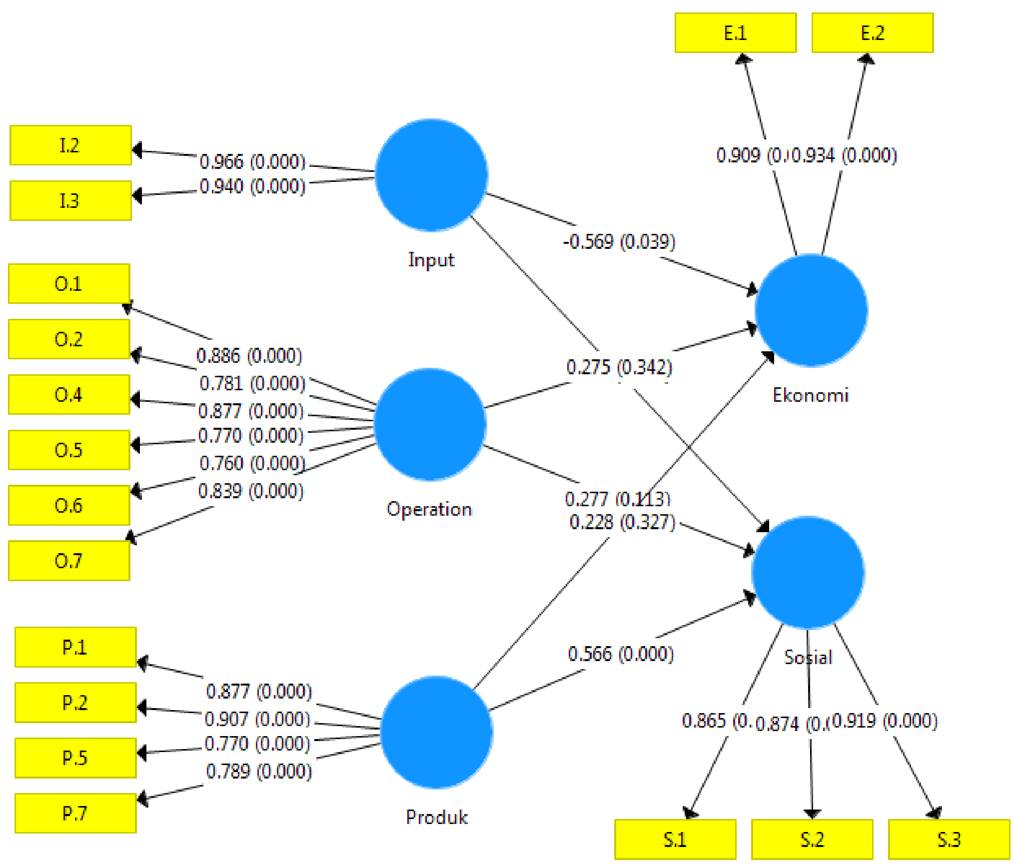

Figure 5 Results of the structural model coefficient analysis.

4.7 Coefficient of Determination

The coefficient of determination is used to measure the accuracy of the estimation. The results of the coefficient of determination can be seen in Table 7. In general, the R^2 value of 0.75 is considered to have great prediction accuracy, the R^2 value of 0.50 is considered to have moderate prediction accuracy, and the R^2 value of 0.25 is considered to have weak estimation accuracy (Hair et al., 2014). Based on the results of Table 7, it can be seen that the accuracy of Economic estimation is in the weak category while Social is in the medium category because it has a value between 0.5 to 0.75.

Table 5 VIF Inner Model

Indicator	VIF
E.1	1.971
E.2	1.971
I.2	3.056
I.3	3.056
O.1	3.671
O.2	2.076
O.4	3.074
O.5	2.015
O.6	2.010
O.7	2.620
P.1	2.451
P.2	2.953
P.5	2.420
P.7	2.390
S.1	1.958
S.2	2.395
S.3	2.569

Table 6 Coefficients and Testing the Influence of Structural Models

	Coefficient	T Statistics	P Values
Input --> Economy	-0.569	1.953	0.051
Input --> Social	0.107	0.603	0.547
Operation --> Economy	0.275	0.853	0.394
Operation --> Social	0.277	1.672	0.095
Product --> Economy	0.228	0.942	0.347
Product --> Social	0.566	4.222	0.000

4.8 Effect Size

In addition to evaluating the R^2 value of all endogenous variables we can use f^2. The difference between f^2 and R^2 is that f^2 is more specific for each exogenous variable. The results of the f^2 test can be seen in Table 8. In general, the value of 0.02 is considered to have a small effect size, 0.15 has a medium effect size and 0.35 has a large effect size (Hair et al., 2014). Based on the f^2 value in Table 8, it can be seen that almost all variables have a moderate effect size except for the Input variable on Social which has a small effect size and the Product on Social variable which has a large effect size.

Table 7. Coefficient of Determination

Variable	R^2
Economy	0.132
Social	0.683

Table 8. Effect Size

f^2	Economy	Social
Input	0.129	0.012
Operation	0.030	0.083
Product	0.042	0.702

Table 9. Preductive Relevance

Variable	Q^2
Economy	0.021
Social	0.456

4.9 Predictive Relevance

In addition to evaluating the value of R^2 as a criterion for predictive accuracy, researchers can use the Stone-Geissers (Q^2) value. The value of Q^2 was obtained using a blindfolding procedure. As a relative measure of predictive relevance, a value of 0.02 is considered to have small predictive relevance, 0.15 has moderate predictive relevance and 0.35 has large predictive relevance (Hair et al., 2014). The results of predictive relevance (Q^2) can be seen in Table 9. Based on the results in Table 9, it can be seen that the predictive relevance for the economy is classified as small but for the social predictive relevance is large.

5. Conclusions

Input variables have a negative influence on the economy, but have a positive influence on social. Operation and Product variables have a positive influence on the Economy and Social Affairs. The variable that has a significant effect is product on social, while other variables have an effect but not significant. The accuracy of economic estimation is in the weak category while Social is in the medium category. Input variables to the Economy, Operations on the Economy and Social Affairs and Products on the Economy have a moderate effect size. Input variables on Social have a small effect size and Product variables on Social have a large effect size. Predictive relevance for Economy is small, but for Social predictive relevance is large. The negative effect of input on the economy is very likely to occur, because to make environmentally friendly paint requires a special material at a high enough cost so that industrially it has a negative effect on the company economy, but from the customer side, employees and society will feel the economic benefits.

In assessing the effect of green manufacturing on sustainability manufacturing (Environmental, Economic and Social), actual data on company achievement can be used, not only survey data for respondents, so that they can provide an assessment of the effect that is closer to the real condition of the company.

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