

# Sustainable Reverse Logistics Implementation with Triple Bottom Line Approach

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## Abstract

To explore reverse logistics in the context of the Indonesian food and beverage manufacturing industry and examine the effect of the effectiveness of reverse logistics activity on TBL. Performance and operational performance. By applying the method of Structural Equation Modeling based on Partial Least Square (SEM-PLS). Recommendations are made to improve the implementation of sustainable reverse logistics. The hypothesis related to the effectiveness of reverse logistics activity, TBL performance, and operational performance is developed. Based on data collection, as many as 123 respondents were involved in collecting data by distributing online questionnaires to company stakeholders. Findings based on the results obtained show that internal factor capability has no significant effect on the effectiveness of reverse logistics activity, while external factor capability has a significant effect on the effectiveness of reverse logistics activity. The effectiveness of reverse logistics activity has a significant impact on economic performance, environmental performance and social performance. In contrast, the effectiveness of reverse logistics activity does not have a significant impact on operational performance. However, economic performance and environmental performance have a significant influence on operational performance. Therefore, the implications of the research results can be input for companies to continue to improve the implementation of reverse logistics in companies.

## 1. Introduction

Producers are parties that have activities to produce output, both in goods and services, but in the process and finished goods will generate waste in packaging, therefore producers have a big responsibility in solving packaging waste made of plastic they produce as stated in the regulation. Reverse *logistics* as a related process, starting from the point of consumption to the point of origin with the aim of creating value or proper disposal of products/goods in a cost-effective manner includes planning, implementing and controlling efficiently the flow of raw materials, goods in process, finished goods, and information. Environmental concerns form the basis for legal pressures, and environmental regulations that steer companies towards sustainable *reverse logistics management*. But it requires practices that are environmentally and socially sensitive. Moreover, environmental applications include investment in pollution control and prevention as well as the implementation of environmental management systems. Previous researchers said to address this increasing global concern, Gaustad, (2018) that economic policy can be considered as an effective solution that allows by leveraging a circular economy consisting of end-of-life management of a product only so that the product can be brought back into the supply chain by a mechanism that once it has completed its functional life, instead of being considered waste.

This research also considers the factor of *reverse logistics activities* as a main objective, which analyzes what is interfering with the wider adoption of *reverse logistics among manufacturers in the Nigerian manufacturing sector* (U-Dominic et al. 2021) . Research in Bangladesh that reviews perspectives and barriers to adopting green supply chain management practices in the textile context (Tumpa et al. 2019) . Meanwhile in Thailand addressing performance bottlenecks by focusing on identifying and ranking solutions on *reverse logistics adoption* in the palm oil industry using a *fuzzy multi-criteria decision making method* (Phochanikorn et al. 2020) . Research aimed at implementing *reverse logistics* in finding solutions for the Thai electronics industry using *structural equation modeling* (SEM) (P Sirisawat 2019) . SEM is also used to measure the effects of the three pillars of the *triple bottom line* (TBL) which include: economic, environmental and social by identifying the antecedents of sustainable product innovation performance (Muñoz-Pascual et al. 2019) .

Previous researchers Saurabh Agrawal & Singh (2019) have modeled external and internal factors considered in disposition decisions affect the effectiveness of disposition decisions on TBL performance. Agarwal et al. (2018) tested internal and external factors for their impact on the adoption of *green supply chain management* (GSCM). Afum et al. (2021) in his research aims to determine the effect of the relationship between external factors on the adoption of *reverse logistics* in the pharmaceutical industry. Chileshe et al. (2018) measured the effect of known drivers on *reverse logistics*, thereby identifying action items with the greatest potential to positively enhance *reverse logistics outcomes by hypothesizing a positive relationship between economic, environmental, and social drives on reverse logistics implementation*. Saurabh Agrawal & Singh (2020) conducted a test between the economic, environmental and social performance of *outsourcing* and *reverse logistics*. Meanwhile, according to Masa'deh et al. (2017) by developing a hypothetical model that aims to determine the effect of the relationship between *economic performance* and *operational performance* in *green implementation supply chain management on hotels*. Permana & Soediantono (2022) also developed a hypothetical model that aims to determine the effect of the relationship between *environment performance* and *operational performance* in the industrial *supply chain management sector* in Indonesia. Based on some of the literature, it has strengthened several contexts, decisions in the effectiveness of *reverse logistics* encountered from several cases. Therefore, to obtain the expected model in Indonesia by identifying the effectiveness of implementing *reverse logistics activities* in the food and beverage industry that uses plastic-based packaging on the relationship with TBL *performance* and *operational performance*.

## **2. Literature Reviews**

### **2.1 Reverse Logistics In The Plastics Industries**

Research has been carried out to increase understanding of plastic recycling such as by designing a sustainable *reverse logistics network* for efficient plastic recycling, through the development of a *reverse logistics network model*. Bing (2014) made a choice between source separation, post-separation collecting *polyethylene terephthalate* (PET) bottles separately or not and if separately, whether or not to include PET bottles of all sizes in this channel. Regarding *reverse logistics* in the plastics sector, there have been many studies conducted, including by analyzing the results of an exploratory study on *reverse logistics practices* in the plastics sector in Colombia (Halabi 2013). While in Iran the researcher chose the PET bottle *reverse logistics network*, a brief review published in the last decade according to which some of the models under consideration are solved using numerical examples whereas other models use real case studies and solve real world problems (Paydar 2018). This research proves that *reverse logistics* plays an important role in dealing with environmental issues, especially plastic by evaluating studies related to plastic waste recycling and analyzing the available frameworks for using *reverse logistics* as a strategic tool (Tesfaye 2020). Meanwhile, in Indonesia, several have conducted ongoing research, especially discussing *the reverse logistics* of plastic waste. Suryana (2017) in the *reverse logistics system* in Indonesia is one of the best alternatives that can be considered to reduce the limited resources of raw materials, so conduct research that aims to develop a plastic waste recycling model, especially Low Density Polyethylene (LDPE) and High Density plastics. *Polyethylene* (HDPE).

### **2.2 Hypotheses Development**

#### **a. Internal and External Factor**

Adoption of *green supply chain management* (GSCM) is broader in scope than *reverse logistics*. According to Agarwal et al. (2018) in addition to regulatory, market, and supplier drivers, we suggest that internal drive, indicating internal organizational motivation and managerial commitment to environmental sustainability, is the main driver of GSCM adoption. Furthermore, external forces have also been studied for their impact on *effectiveness by using reverse logistics with the auto-parts industry in Thailand* (Charoensuk, 2018). Research conducted by Afum et al. (2021) aims to determine the effect of the relationship between external factors on the adoption of *reverse logistics* in the pharmaceutical industry. The findings reveal that all external variables including stakeholder (top management support) and customer pressure, except environmental regulations, have a strong influence on adoption. This means that RL activities shorten lead times and reduce procurement of new raw materials needed for production. Thus, with the implementation of RL, companies can rely on product returns as a secondary source of materials rather than a source of new raw materials. This ultimately leads to reduced operating costs, increased company competitiveness and increased profits.

**H1** : *internal factor capability* does not have a significant effect on *the effectiveness of reverse logistics activity*

The external pressures referred to include: regulations, markets and suppliers related to higher adoption of GSCM (Agarwal et al. 2018) . External and internal factors are also used in research, Agrawal & Singh (2019) which considers each disposition decision to influence the effectiveness of disposition decisions in *reverse logistics activities* by analyzing the relationship between internal and external factors, and their impact on the effectiveness of disposition decisions, and their relationship to performance economic, environmental, and social in *reverse logistics* , including indicators including internal factors: *environmental mission, quality of returned products, reverse logistics costs* , and *the volume of returned products*. While the external factors consist of: *consumer behavior, business environment* , and *government rules and regulations*. Another indicator that is included in internal barriers is *support for reverse logistics practices* (Govindan & Soleimani 2017; Prakash et al. 2015; Pornwasil Sirisawat & Kiatcharoenpol 2019) . This can run according to the procedure if it is supported by commitment from *top management* (S Agrawal 2019; Piyachat, 2017; Waqas et al., 2018) . Meanwhile, external barriers require an efficient and effective system to monitor returns and withdrawals (Jindal & Sangwan 2011; Kiatcharoenpol 2020) . With infrastructure facilities to support the implementation of *reverse logistics* (S Agrawal 2019; Kiatcharoenpol 2020) . Research conducted by Charoensuk (2018) aims to determine the effect of external factor relationships on the effectiveness of *reverse logistics* in the auto parts industry. Based on this research, it results that if a company can manage external barriers, *reverse logistics management* will be successful. When a company is successful with *reverse logistics management* , their costs and time are reduced and they can gain more reliability.

**H2** : *external factor capability* has a significant influence on *the effectiveness of reverse logistics activity*

#### **b. Reverse Logistics Activities**

According to Hazen et al. (2012) extrapolated the components of dispositional decisions in determining what alternative to decide on from *reverse logistics activities* , the aim is to identify the critical components of the decision-making process and suggest alternative decision frameworks that can guide future investigations and practices. According to Roger (2002); Saurabh Agrawal et al. (2015); Saurabh Agrawal & Singh (2019); Hazen et al. (2012) in the alternative decisions of *reverse logistics activities* most frequently used in the literature there are four including: reuse, material recovery, product improvement, and waste management. So that in measuring the effectiveness of *reverse logistics management* of industrial companies using three dimensions, the results reveal the factors of cost assignment, time assignment, and reliability assignment. Where the variables that represent *costs* include *customer service costs, transportation costs, remanufacturing, recycling costs* and *inventory carrying costs* (Saurabh Agrawal & Singh 2019; Charoensuk, 2018; Hazen et al. 2012) . According to Afum et al. (2021) explained that these activities include return, salvage, stockpiling, remanufacturing, disposal, reuse, recycling, repair and repackaging. Agrawal & Singh (2019) , proposed a model of the mechanism of influence of *internal factors and internal factors* on *TBL performance* through mediating *effectiveness of disposition decisions in reverse logistics activities* which include: *reuse, repair, remanufacturing* and *recycling* . Aparecida et al. (2020) , determine the effect of the relationship between *reverse logistics competence* on economic performance and environmental performance in the manufacturing sector in Brazil . positively, namely economic and environmental performance.

**H3** : *The effectiveness of reverse logistics activity* has a significant influence on *economic performance*

**H4** : *effectiveness of reverse logistics activity* does not have a significant effect on *operational performance*

**H5** : *The effectiveness of reverse logistics activity* has a significant influence on *environmental performance*

**H6** : *The effectiveness of reverse logistics activity* has a significant influence on *social performance*

#### **c. Economies performances**

Economic performance is the company's ability to reduce the cost of purchasing goods, waste disposal, waste treatment, energy consumption, and fines for environmental accidents. According to Jindal & Sangwan (2011) the implementation obstacles faced in implementing *reverse logistics* will outweigh the economic benefits because apart from the benefits that can be obtained by implementing *reverse logistics* , many organizations are still reluctant to implement *reverse logistics* in a simple way. *high investments and less return-on-investments* are the reasons companies are reluctant to implement *reverse logistics* in an economic context (Saurabh Agrawal & Singh 2019; Lau & Wang 2009; Tan & Hosie 2010; Waqas et al. 2018) . Meanwhile, research that is constrained by the high cost of

*reverse logistics* is an obstacle that many companies experience (MD Abdulrahman 2014; Jindal & Sangwan 2011; Sarkis 2010; Waqas et al. 2018) . Company efficiency in carrying out recycling processes with *cost optimization activities* (Saurabh Agrawal & Singh, 2019) . Higher production costs are one reason for *remanufacturing* or low value products are generally preferred for material recovery in recycling, but product value is an important factor in the decision. Consumers choose recycled products or may prefer new products so that they are used as indicators of *annual sales of remanufactured products* (Saurabh Agrawal & Singh 2019; Chung & Wee 2011; Sharma et al. 2016) . The obstacle to the sustainability of *reverse logistics* in economic factors is due to the lack of realization of economic benefits (Saurabh Agrawal & Singh 2019; Jindal & Sangwan 2011; Waqas et al. 2018) . So it requires a positive impact on operational performance. Masa'deh et al. (2017) in this study developed a hypothetical model that aims to determine the effect of the relationship between *economic performance* and *operational performance* in the *supply chain management sector on hotels* .

**H7** : *economics performance* has a significant influence on *operational performance*

#### **d. Environmental Performances**

The industry is generally not aware of *reverse logistics practices*, as support and knowledge that cares for the environment while increasing the company's economy. Therefore it requires awareness from the company or the consumer itself. Many researchers and practitioners have used *key indicators* as parameters to improve or analyze barriers including *environmental law awareness indicators* due to the company's lack of concern for the environment caused by producers (Bouzon et al. 2016, 2018; Govindan et al. 2014; Mudgal et al. 2009; Waqas et al. 2018) . *Waste management* and *waste reduction* are waste management practices, where companies are responsible for or reduce the impact caused by their products (Muhammad D Abdulrahman et al. 2014; Saurabh Agrawal & Singh 2019; Bouzon et al. 2018) . Furthermore a lack of *Eco-literacy* among members of the Industry's supply chain (Govindan et al., 2014; Mudgal et al. 2009) . So that the number of actions that are less effective on environmental performance. Manufacturers also sometimes neglect the use of efficient packaging both from the ease of packaging damage and the efficiency of use, resulting in performance to reduce packaging usage (Saurabh Agrawal & Singh 2019) . The complexity in measuring and monitoring suppliers still applies *environmental practices* (Govindan et al. 2014; Waqas et al. 2018) . *Monitoring and end-of-life management* are important for companies to pay attention to ( de Campos et al. 2021). So researchers want to prove that environmental performance can have a significant effect on *operational performance* . Based on research conducted by (Fernando & Tew, 2016) who developed a hypothetical model that aims to determine the effect of the relationship between *reverse logistics activity*, *economics performance* on *operational performance* in the Malaysian manufacturing industry *supply chain management sector*.

**H8** : *environment performance* has a significant influence on *operational performance*

### **3. Methods**

#### **3.1 Research Design**

This research uses *descriptive research* because the researcher wants to examine the phenomenon that occurs with the relationship between the variables that the researcher has determined. In terms of data collection, this research includes *a cross-sectional* design because researchers collect data in only one group, namely, departmental representatives related to *reverse logistics* from companies that produce and distribute food and beverage products that use plastic packaging.

#### **3.2 Conceptual Models**

According to the literature review, there are 2 independent constructs namely, internal factor capability (IFC) and external factor capability (EFC). Then 5 dependent constructs namely, effectiveness reverse logistics activity (ERL), economics performance (ECP), environment performance (EVP), social performance (SCP) and operational performance have been used to build the SEM model can be seen in Figure 1 depicting the SEM conceptual model that used in this study showed a variety of predictors and outcome variables. The conceptual model built in this study works to examine the relationship between the seven variables. Thus, the following seven hypotheses (H1, H2, H3, H4, H5, H6, H7 and H8) are also proposed to test the degree of association between various variables in food and beverage companies that use plastic packaging. Hypothesis testing consists of four groups that are directly and indirectly related.

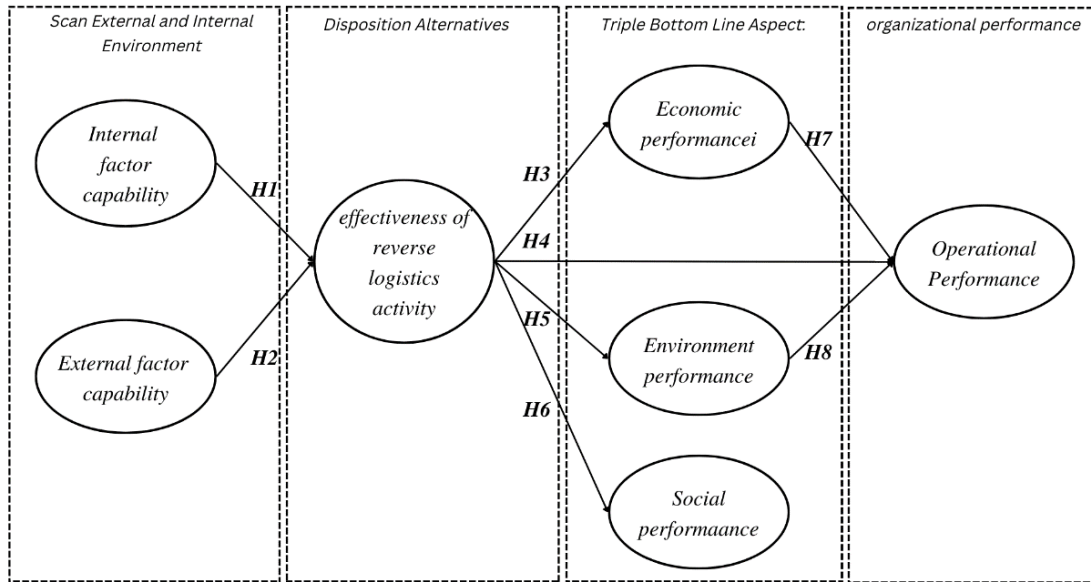


Figure 1. Conceptual model

Based on the framework and population in this study, it is limited to beverage and food companies that use plastic packaging in South Sulawesi, Indonesia. The hypothesis is tested after accessing the suitability of the data through a measurement model. The complexity of the relationship is studied using the Partial Least Squares Path Modeling (PLSPM) approach, a structural equation model that takes into account the causal relationship between latent variables. PLSPM was used in this study because it can solve a sample with a small size. Although PLSPM is an old technique it has been used in the field of logistics management by researchers such as.

### Sampling

This Sampling Frame consists of a series of instructions to identify the target population Malhotra and Birks (2007). Respondents who participated in the survey represented various levels of management including top positions for mid-level and executive employees and most belonged to the logistics, marketing & sales, corporate strategy, *quality control* and human resources departments. Based on the company that includes *reverse logistics* include: *manufacturing, third party logistics, and wholesalers*. In this study, researchers used a non-probability sampling technique with a judgmental sampling method because respondents were selected according to the criteria, namely, respondents who have criteria as stakeholders in beverage and food companies and are related to forward and reverse *logistics* operations Determining sample size by Hair et al. (2017) in PLS-SEM using *the minimum R-squared method* Furthermore, detecting the minimum value of *R - square* in the previous literature model is 0.327 (Saurabh Agrawal & Singh, 2019) . Based on the r-square value, it is determined by the closest value and the range in the table (Hair et al. 2016), which is a minimum R-square of 0.25, with a 5% probability of error. *the minimum R-square method* is used to determine the number of samples that must be obtained for analysis using the SEM -PLS technique using the smartPLS application. So that the minimum number of samples that must be obtained is 84 data. So, the amount of data needed for processing is more than enough. The designed questionnaire is based on the variables that have been used in the research

### Stages testing PLS- SEM

After the data is collected and meets the minimum amount, the next step is to test the model that has been made. Testing was carried out using the SEM-PLS method by using *software* called SMART-PLS. Tests were carried out to find out whether the model created was consistent and matched the data collected. According to , Hair et al. (2017) there are stages in testing PLS-SEM includes: *measurement mode* and *structural model*. The test uses several criteria If the model does not match the data, it is necessary to modify the model in order to obtain a better match. Testing on SEM consists of testing *the measurement model* and *structural model* as follows

#### a. Model Testing Measurement ( *OuterModel* )\_

Model \_ measuring is a model that defines how an indicator can relate to latent variables. In measure or interpret measurement models, by looking at *convergent validity*, *discriminant validity*, and *reliability*. Stages in Hair et al. (2017) testing the measurement model is as follows.

1. *Convergent validity* useful for measuring the amount of *outer loading* and *average variance extracted (AVE)* for every variable latent. Mark *outer loading* Which recommended that is above 0.7 but the value of 0.6 is still understandable if the model is in the development stage. The recommended dam *average variance extracted is AVE > 0.5*
2. *Discriminant Validity* ) is useful for assessing whether a variable has sufficient *discriminant validity*. To find out the *discriminant validity* value i have sufficient ie with compare correlation indicator with construct Which must aim more big If compared with the correlation with the construct other. To find out the correlation value between other constructs can be seen by value *fornell-lacker criterion*. By looking at the *fornell-lacker value criteria* or AVE must be higher than the correlation between each latent construct
3. *reliability* indicates consistency from every indicator in variable latent Which measure these variables. The value when the variable has a good level of consistency can be measured with mark *cronbach's alpha > 0.6 - 0.7*, *composite reliability*, And  $\rho_A$  accepted is  $> 0.7$

**b. Model Testing Structural ( InnerModel ) \_**

The structural model is a model that serves to examine the relationship between latent variables. The inner model can show that there are *direct effects*, *indirect effects*, and *moderating effects* of the variables studied. According to Ghozali (20 08 ) for the structural model begins by looking at the *R-square value* for each latent variable, then the *f-square*, *q-square* and *t-statistic values* as predictive power. Stages in Hair et al. (2017) testing the structural model is as follows:

1.  $R^2$  (*coefficient of determination*) is the outcome measure of the modification of the coefficient of determination that calculates the number of independent variables Which enter into the similarities and sizes sample. It means  $R^2$  states how much influence the independent variable has on the dependent variable.
2.  $Q^2$  (*cross validated redundancy*) According to Ghozali (20 08 )  $Q^2$  is a means to assess the predictive relevance of the inner model.
3.  $f^2$  (*effect size*) is the effect size for each path determined by calculating  $f^2$ . Based on literature how to calculate  $f^2$  is to see the change in  $R^2$  when the construct is removed from the model. The level of *effect* will be high when exogenous variables contribute to endogenous variables.  $f$  value  $^2$  divided into three power tests in cohen (1998)
4. *T-Statistics* serves to test how significant the hypothesis is in research by means of a *bootstrapping process*. This study uses an *alpha level* of 5% which makes the critical value for this research is 1.65. If obtain mark on prone to  $-1.65 < t$ -statis so test which done stated No significant. If mark *t-statistics* is at on vulnerable  $< -1.65$  or  $> 1.65$  so test Which done stated significant. In addition, by looking at the *p-value*  $< 0.05$ .

**4. Data Collection**

Based on the questionnaire that has been distributed, data is obtained regarding the characteristics of the respondents contained in the study. The general description of the respondents includes : distribution of age, education, gender, employee position, and type of company. Respondents who participated in the survey represented various levels of management including positions for mid-level employees and executives namely; *managers, supervisors, unit heads, and staff*

Table 1. Research demographics

Age	20 - 30 years	53	43.09%
	31 - 40 years	61	49.59%
	41 - 50 years	9	7.32%
	> 50 years	0	0.00%
Education	Strata 2 (S2)	3	2.44%
	Undergraduate (S1)	112	91.06%
	Diploma (D3)	6	4.88%
	Senior Hih school	2	1.63%
Position	manager	14	11.38%
	Supervisors	22	17.89%
	head unit	22	17.89%
	staff	65	52.85%
Company	Manufacturing Units	36	29.27%

	<i>third party logistics</i>	18	14.63%
	<i>wholesalers</i>	69	56.10%

Furthermore, based on the companies involved, it includes the supply chain, namely: *manufacturing*, *third party logistics*, and *wholesalers* with food and beverage products . Data collection begins on the 3rd October 2022 to 10 December 2022. This response can be seen from how the respondents replied to *the email* sent by the researcher . Delivery process via *direct message* and *whatsapp* to the respondents. During that period, 131 data were obtained response received . Then 8 were eliminated because they did not meet the criteria or were incomplete so that there were 123 respondents .

## 5. Results and Discussion

### 5.1 Evaluation of Measurement Models

In the PLSPM technique of the measurement equation model, all relationships between constructs related to testing the hypothesis of the developed model are analyzed. The model is analyzed using the PLSPM approach with the help of Smart-PLS software. The relationship between internal and external factors, as well as their impact on the effectiveness of disposition decisions, and their relationship to the economic, environmental and social performance of RLs are considered in the model. The individual reliability of each item is accessed by standard factor loading. As shown in Table 1, the factor loadings for all items ranged from 0.618 to 0.931, which is greater than the threshold value of 0.7, suggested by Hair et al. except for the 6th external factor which is EF6: Government rules and regulations. The value of this factor is 0.24 which is smaller than the threshold value. Therefore, these factors were removed from the study and again factor weights were calculated. The final loading values are shown in Table 1 which meet the minimum threshold criteria for individual reliability of each construct. Internal consistency for each construct is accessed by the CR Value, which must have a minimum value of 0.7 for acceptance (Nunnally, 1978). CR values for all constructs are greater than the minimum threshold values as shown in Table 1. AVE analyzes convergent validity for all constructs. The values for all constructs are higher than the minimum threshold value of 0.5 which meets the requirements of convergent validity. The correlation between the constructs and the AVE square root for each construct was analyzed to access the discriminant validity of the model.

Table 2. Statistical results of the measurement model

Latent Variable	Indicator	Loading factor	Cronbach's alpha	Composite reliability	AVE
<b>Internal factor capability (IFC)</b>	Compliance rate volume of products returned	0.802	0.785	0.861	0.61
	Corporate environmental mission level	0.735			
	The importance of the business advantages of reverse logistics	0.756			
	Budget value allocated by top management/Top management commitment	0.549			
<b>External factor capability (ECP)</b>	Level of fulfillment/requirements for environmentally friendly products	0.672	0.75	0.856	0.666
	Government pressure and regulation	0.806			
	Level of environmental friendly technology mastery from suppliers	0.785			
	<i>green strategy</i> comparison for the same product	0.786			
<b>Effectiveness of reverse logistics (ERL)</b>	Product packaging reuse rate	0.8	0.746	0.855	0.663
	Packaging waste processing level	0.622			
	The effectiveness of recycled products	0.824			
	Product remanufacturing/repackaging/repair effectiveness	0.716			
<b>Economic performance (ECP)</b>	Appropriate rate of disposal of returned product	0.56	0.732	0.832	0.553
	Rate of return on Investment from returned products	0.836			
	Sales levels of remanufactured/repackaged products	0.852			
	<i>Reverse logistics</i> cost optimization total cost of disposal of waste ( <i>disposal cost</i> )	0.717			
<b>Environmental Performance (EVP)</b>	Percentage reduction in consumption of rare materials/non-renewable energy	0.75	0.731	0.848	0.65
	Reduction rate of packaging used	0.722			
	Waste reduction rate with the use of recycled materials	0.793			

	Number of infrastructure facilities to support RL implementation	0.708			
<b>Social Performance (SCP)</b>	Level of consumer complaints	0.557	0.825	0.613	0.613
	Consumer health and safety level	0.779			
	Number of environmental certifications/awards achieved	0.775			
	Job stability level	0.624			
<b>operational performance (OPP)</b>	Responsiveness is significant in the lead time of <i>reverse logistics operations</i>	0.578	0.838	0.72	0.72
	Level of capacity utilization and supply chain integration	0.726			
	Significant product quality improvement	0.736			
	<i>scarp</i> rate is decreasing	0.836			

The results shown in table 3 show that the square root of the AVE value in all cases is greater than the corresponding off-diagonal value in the correlation matrix which supports the discriminatory validity condition. *Discriminant* validity testing relates that the gauges (manifest variables) are different and should not be highly correlated. Includes how to compare the AVE square root for each latent variable with the correlation value in the model (Fornell Larcker, 1981; Chin., 2010; Hair et al., 2019).

Table 3 . Discriminant Validity via Fronell-Larcker

Latent Variable	ECP	EFC	ERL	EVP	IFC	OPP	SCP
<i>Economics performance</i>	<b>0.781</b>						
<i>External factor capability</i>	0.75	<b>0.816</b>					
<i>Effectiveness of reverse logistics</i>	0.642	0.589	<b>0.814</b>				
<i>Environmental Performance</i>	0.688	0.603	0.576	<b>0.744</b>			
<i>internal factor capability</i>	0.492	0.476	0.62	0.486	<b>0.806</b>		
<i>operational performance</i>	0.724	0.64	0.674	0.693	0.575	<b>0.783</b>	
<i>Social Performance</i>	0.515	0.442	0.541	0.511	0.349	0.584	<b>0.849</b>

## 5.2 Structural Model Evaluation

Evaluation of the structural model (inner model) is used to evaluate the influence relationship between latent variables. The size used to evaluate the structural model in this study is to use the *R-square* ( $R^2$ ) and *Q-square* ( $Q^2$ ) values,

Table 4. *R-square* ( $R^2$ ) and *Q-square* ( $q^2$ ) values

hypothesis	R-square	q-square
<i>Effectiveness of reverse logistics</i>	0.367	0.317
<i>Economics performance</i>	0.562	0.356
<i>Environmental Performance</i>	0.364	0.283
<i>Social Performance</i>	0.195	0.187
<i>operational performance</i>	0.607	0.36

The ability of exogenous latent variables can explain variations in exogenous variables. It was found that the R-square of the endogenous *ERL latent variable* was 36.7%. This means that the variation can be explained by the *IFC* and *EFC latent variables*, while the other 63.3% is influenced by other variables outside the model. The R-square value on the ECP latent variable is 56.2%, the EVP latent variable is 36.4%, and the SCP is 19.5%. which means that it can be explained by the ERL, while for the percentage difference in the ECP latent variable of 43.8%, EVP of 63.7%, and SCP of 80.5% the other variables are influenced by other variables outside the model. Finally, the R-square value for the OPP latent variable is 60.7%, which means that it can be explained by the ECP and EVP variables. while the other 39.3% is explained by other variables outside the model. Based on table 4.21 above, it shows that the Q-square value of each ERL endogenous latent variable is worth 31.7%, meaning it has a moderate effect, ECP is 35.6%, it means it has a strong effect, EVP is 28.3%, it has a moderate effect, SCP is 18.7%, it has a moderate effect, and OPP is 36. % has a strong influence.

The values  $f^2$  shown in Table 3 are within the limits as discussed in the method section regarding testing the structural model by looking at reference  $f^2$ . Shows the value  $f^2$  of each latent variable *IFC* on *ERL* is worth  $0.032 > 0.02$  meaning that the effect is weak, *EFC* on *ERL* is worth  $0.221 > 0.15$  meaning the effect is moderate, *ERL* on *ECP* is worth  $1.286 > 0.35$  meaning it has a very strong effect, *ERL* on *OPP* is worth  $0.025 > 0.02$  weak effect, *ERL* on *EVP* is



worth  $0.572 > 0.35$  strong influence, *ERL* on *SCP* is worth  $0.243 > 0.15$  moderate effect, and *ECP* on *OPP* has value  $0.123 > 0.02$  weak effect. *EVP* against *OPP* is worth  $0.155 > 0.15$ , meaning that it has a moderate effect.

### Hypotheses Testing

The next step is to look at the path coefficient. The value of the path coefficient or path model shows the level of significance in testing the hypothesis in this study. Hypothesis (H1) predicts that *IFC* affects *ERL* and Hypothesis (H2) *EFC* affects *ERL* in RL. The results obtained from the Smart-PLS software are shown in Table 5 and Figure 1. The path coefficient for the internal factor is 0.18 and the t-statistics value of the *IFC* latent variable on *ERL* is 1.330 which is smaller than the t-table which is 1.96. So it can be concluded that these variables have no significant effect. External factors show that the path coefficient is 0.18 with the t-statistics value of the *EFC* latent variable on *ERL* having a value of 3.194 which is greater than the t-table which is 1.96. So it can be concluded that the effect is significant or *EFC* has a positive effect on *ERL*.

Table 5. Statistical results of the measurement model

hypothesis	Latent variable	original samples	T-statistics	P-values	f-square	Information
H1	IFC -> ERLs	0.18	1.33	0.184	0.032	Rejected
H2	EFC -> ERLs	0.477	3,194	0.001	0.221	Accepted
H3	ERL -> ECP	0.75	15,443	0	1,286	Accepted
H4	ERL -> OPP	0.153	1,578	0.115	0.572	Rejected
H5	ERL -> EVP	0.603	8,483	0	0.025	Accepted
H6	ERL -> SCP	0.442	4,355	0	0.243	Accepted
H7	ECP->OPP	0.371	3,531	0	0.123	Accepted
H8	EVP->OPP	0.346	4.145	0	0.155	Accepted

Hypothesis (H3) has a t-statistics value of the *ERL* latent variable to *ECP* of 15,443 which is greater than the t-table, which is 1.96. So it can be concluded that the effect is significant or *ERL* has a positive effect on *ECP* and the magnitude of the effect is 0.750. Hypothesis (H4) The t-statistics value of the *ERL* latent variable on *OPP* is 1,578 which is smaller than the t-table, which is 1.96. So it can be concluded that this variable has no significant effect. Hypothesis (H5) the t-statistics value of the *ERL* latent variable on *EVP* is 8,483 which is greater than the t-table, which is 1.96. So it can be concluded that the effect is significant or *ERL* has a positive effect on *EVP* and the magnitude of the effect is 0.603. Hypothesis (H5) The t-statistics value of the *ERL* latent variable on *SCP* is 4,355 which is greater than the t-table, which is 1.96. So it can be concluded that the effect is significant or *ERL* has a positive effect on *SCP* and the magnitude of the effect is 0.442. Hypothesis (H7) The t-statistics value of the *ECP* latent variable on *OPP* is 3,531 which is greater than the t-table, which is 1.96. So it can be concluded that the effect is significant or *EVP* has a positive effect on *OPP* and the magnitude of the effect is 0.371. Hypothesis (H8) the t-statistics value of the latent variable *EVP* to *OPP* is 4.145 which is greater than the t-table which is 1.96. So it can be concluded that the effect is significant or *EVP* has a positive effect on *OPP* and the magnitude of the effect is 0.346.

This study analyzes the factors that affect *ERL* and its relationship with *TBL* and *OPP* performance. Hypothesis (H1) in predicting internal factors has no influence on the effectiveness of dispositional decisions in RL. In contrast, Agarwal's research (2018) states that with greater managerial motivation for green supply chain management (GSCM) is translated into a strong internal drive because the company's mission statement, corporate strategy, and organizational policies are a reflection of the beliefs and values managers in seeing the impact on the company. This can happen when suppliers are more concerned with the affordability of the manufacturing process in order to maintain the quality of the company's products. Chileshe et al. (2018) stated that the affordability of original products without remanufacturing processes is still more competitive than recycled materials. While based on the results of the hypothesis (H2) it can be concluded that *EFC* can affect *ERL* in companies. That is, with the encouragement of the level of technological mastery regarding reverse logistics from suppliers or third parties, the level of fulfillment of customer pressure and competitor pressure related to the company's green strategy regarding its products will have a significant effect on *ERL*.

The hypotheses (H3, H4, H5 & H6) show a significant relationship to the *ECP*, *EVP* and *SCP* hypotheses except *OPP*. It is clear that *ERL* is significantly influenced by *EFC* and not significantly by *IFC* in reverse logistics activities that can effectively increase *OPP* reverse logistics through mediation or the intervention of *EVP* and *ECP* variables. Based on table 6, this shows that there is no direct relationship to *OPP* variables. Further studies analyzing Fernando & Tew (2016) Increase in *OPP* should also be considered in supply chain performance. Thus, this study has achieved its

objectives and provided empirical justification for a positive and significant relationship between EVP and OPP, with ERL mediating the relationship in manufacturing companies. In this study it was found that a significant relationship between EVP and OPP obtained a higher t-value than significant relationship between ERL and OPP. Yu et al. (2018) in Pakistani context research and found that the ECP of companies can be improved by adopting recycling, remanufacturing activities, which are part of the reverse logistics operations. Huang et al. (2010) stated that in addition companies can increase their profitability in terms of ECP and productivity by reducing costs and investing in inventory. The company also avoids the pressure of caring for the environment and environmental regulations. Because the essence of reverse logistics is to reduce harmful effects on the environment and use recycling and remanufacturing techniques, which not only reduces solid waste but also increases process efficiency Fleischmann et al. (2000) the relationship to social performance is pressure to handle product returns at the end of their useful life due to government rules and regulations, environmental concerns, and corporate social responsibility. One way to deal with both types of returns is to adapt and implement reverse logistics practices (Agrawal 2019).

Hypotheses (H7, & H8) show a significant relationship to the hypothesis of economic performance and environmental performance to operational performance. This means that the more companies manage waste or manufacturing scrap or repairs produced by the company will have an impact on operational performance. But operational responsiveness in lead time and capacity utilization decreases when implementing *reverse logistics*. Masa'deh et al. (2017) stated that ECP significant effect on *OPP*. This is associated with several context-specific factors that are very important for *reverse logistics*, namely labor costs, disposal costs, the market value of the goods or products salvaged. Based on these results, it can be concluded that. This study found variables with high relative importance but performance scores below other variables in the model. Previous studies had the same conditions as these indicators (Agarwal et al. 2018; Fernando & Tew, 2016; Yu et al. 2018).

## **6. Conclusion**

Based on the data processing and analysis that has been done previously, the conclusions that can be drawn are in accordance with the research objectives set at the beginning that the research aims to test the hypothesis. In the research model developed using 7 variables, namely: IFC, EFC, ERL, ECP, EVP, SCP, and OPPs. The 7 variables of the research model produce the 8 research hypotheses that are tested. In this study, recommendations were obtained as an effort to improve companies that can be carried out by companies by increasing the company's reward system for implementing reverse logistics. This study explores that EFC heavily influences ERL. Factor This identified will help managers and academics in decision making. This study relates the TBL aspect where ERL has the highest influence on ECP after EVP and SCP. OPP is not significantly influenced by ERL variables so it must be mediated by ECP variables and EVP variables. It can be concluded that the variables that can drive operational performance in implementing reverse logistics in companies are ECP and EVP.

Based on an analysis of reverse logistics activities using the TBL approach, researchers found that there were hypotheses that were not significantly different from previous studies. Researchers found that the IFC hypothesis on ERL has no significant relationship. In contrast to previous studies stating that IFC has a significant relationship to ERL. Researchers found that the ERL hypothesis against OPP has no significant relationship. In contrast to previous studies stating that the ERL variable has a significant relationship to OPP which can be a driving force for improving reverse logistics in companies. This study incorporates the conceptual model from previous studies. But there is no conceptual model or hypothesis directly or indirectly linking IFC and EFC to OPP. Based on the results of the study, it has indirectly linked EFC and IFC to OPP. The results, researchers found that there was a significant indirect relationship to OPP mediated by the ERL and ECP and EVP latent variables. While IFC does not have a significant relationship indirectly.

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