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REVERSE LOGISTICS AND OPERATIONAL PERFORMANCE: THE MODERATING EFFECT OF PROCESS INNOVATION AMONG MANUFACTURING FIRMS IN KENYA

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Abstract

In the present day, countries and manufacturing establishments worldwide are concerned with environmental sustenance. Implementation of reverse logistics has been regarded as a feasible option to diminish the harmful environmental effects of manufacturing. However the question has been whether reverse logistics generates operational performance gains. Similarly, literature has opined that process innovation results in improved operational performance. The study objective was to determine the moderating effect of process innovation on the association between reverse logistics and operational performance. Using correlation cross-sectional survey design, primary data was collected from 151, Kenya Association of Manufacturers (KAM) registered firms. Covariance-based, Structural Equation Modeling (SEM) was used to test the hypothesis. Results revealed the relationship linking reverse logistics and gaining internal operational competency was significantly moderated by process innovation. It further confirmed that there are factors that hinder or accelerate the diffusion of innovation rate depending on how resources are mobilized. Policymakers within the manufacturing sector in Kenya should improve the regulatory framework to upscale application of reverse logistics strategies in a manner that also creates opportunities for improved process innovation. The research identified replication of the study using direct measures for all variables and in other contexts as possible future research streams.

Keywords: Reverse Logistics, Process Innovation, Diffusion of Innovation Theory, Covariance-based SEM, Manufacturing firms in Kenya

INTRODUCTION

As a consequence of ensuring environmental sustainability, manufacturing firms today are redesigning their systems to achieve both profitability and environmental sustenance. (Govindan, Soleimani & Kannan, 2015; Prakash, Barua & Pandya, 2015). As a way of addressing the repercussions of climate change, the emphasis of the United Nations (UN) has been for countries and businesses alike to reexamine their value chains in order to devise new and sustainable business models that create sustainable supply chains (United Nations Environment Programme (UNEP), 2016). Today, it has become a requirement for manufacturers to consider, reuse, recycling or safe disposal as part of the effort to conserve the environment (Sheth, Sethia & Srinivas, 2011). The movement of “end-of-useful life” products from consumers to manufacturers such that processes of recapturing value or environmentally acceptable disposal is undertaken is the primary concern of reverse logistics (Stock, 1992). While managing the product returns, firms also focus on operational performance improvements

(Stock, Speh & Shear, 2006). Similarly, the introduction of process innovation in managing reverse logistics helps firms to create and execute strategies that result in efficient and effective business models (Barney, 1991). While infusing innovations within a business model, the diffusion of innovation theory creates a foundation for explaining factors obstructing or facilitating the diffusion of innovations (Rogers, 2003).

Reverse logistics is a set of processes requiring manufacturing entities to reuse, recycle or remanufacture “end-of-useful-life” products in an environmentally responsible manner or ensure sustainably friendly disposal (Stock, 1992). Reverse logistics is a managerial activity that facilitates movement of “end-of-useful-life” products back to the remanufacturing entities for the purpose of value recapturing or apt disposal. It also includes value recapturing for products found not to be useful by the end consumer (Rogers & Tibben-Lembke, 1999). The major reasons leading to the emergence of reverse logistic are poor product quality, increased used of environmental conscious policies among manufacturing firms, product variety causing rapid shift in consumer tastes and preferences, more products being purchased over the internet and shortened product life cycles (Bernon & Cullen, 2007; Ravi & Shankar, 2015). Reverse logistics implementation approaches include outsourcing, collaborations, adopting green strategies or using a product-life cycle perspective to implement reverse logistics. Outsourcing encourages firms to remain focused on their core competencies. It also allows firms to share risks with third parties and improve flexibility (He & Wang, 2005; Moghaddam, 2015; Hsu, Tan & Mohamad-Zailani, 2016). Collaborations facilitate reverse logistics integration among supply chain members in an industry through associations or consortia (Hung-Lau & Wang, 2009). Green strategies encourage manufacturing firms to adopt environmentally sustainable manufacturing policies and processes (Rogers & Tibben-Lembke, 2001; Rao & Holt, 2005). Finally, the product-life cycle perspective to implementing reverse logistics facilitates value recreation through the closed-loop supply chain (Closs, Speier & Meacham, 2011; Govindan et al., 2015; Sangwan, 2017).

Operational performance refers to how preplanned objectives of a firm are achieved through processes that assess attributes of products and services (Shaw, 2003). Operational performance establishes a criterion such that the firm’s processes are related to performance using identifiable and measurable attributes. Operational performance monitors and takes corrective action in attaining companywide goals efficiently and effectively (Carter, Kale & Grimm, 2000). Studies have demonstrated the key operational performance indicators include cost, time/speed, operations flexibility, dependability and quality (Carter et al., 2000; Brah & Ying-Lim, 2006; Slack, Chambers & Johnston, 2010; De Souza & Brito, 2011; Chavez, Gimenez, Fynes, Wiengarten & Yu, 2013) These indicators can further be operationalized using proxy indicators that include per unit variable cost of production, average leadtime, diversity of product line, downtime, order fill rate and the number of customer complaints (Brah and Ying-Lim, 2006; De Souza and Brito, 2011; Chavez et al., 2013).

Davenport (2013) notes that process innovation involves the radical development of new services, products and production systems in a creative manner. This improves equipment, production techniques or software. Keeley, Walters, Pikkel and Quinn (2013) classified innovations into an offering, configuration and experience linked processes. Schumpeter (1934) identified process innovation as consisting of new production approaches and new sources of manufacturing inputs, semi-finished products or components. Adopting process innovation in a multidimensional manner through process reengineering, value chain restructuring, resource deployment, product redesign, and implementing information systems should guide organization strategy (Jayaraman & Luo, 2007). Process reengineering involves an examination and redesign of business processes to significantly improve on critical performance indicators (Armbruster, Bikfalvi, Kinkel & Lay, 2008); Value chain restructuring involves an analysis of internal organizational activities to develop and upgrade the value of products or processes (Porter, 2008); Resource deployment is the way in which the organization methodologically introduces programs, processes, and activities (Jayaraman & Luo, 2007). Product redesign involves generating and developing ideas to improve the existing product(s) (Porter, 2008). Information systems involves the use of computer and telecommunication systems to monitor supply network activities, achieve visibility, and improve collaboration among supply chain partners (Morgan, Richey Jr. & Autry, 2016). Further, interaction with suppliers, customers and competitors together with the establishing of innovation systems are characteristic of innovative organizations (Inauen & Schenker-Wicki, 2012).

Reverse logistics strategies have been presumed to hold present generations environmentally accountable and thereby encourage environmental sustenance for future generations (Sheth et al, 2011; Dias & Braga Jr., 2016; Sangwan, 2017). Research has demonstrated that if these strategies are innovatively implemented, they create processes that utilize a firm’s resources optimally which results to sanctioning negative environmental effects on planet earth at a micro- level and generating operational performance gains at a macro-level (Closs et al., 2011; Ravi & Shankar 2015). Although reverse logistics has been argued to potentially create sustainable competitive capabilities research in supply chain has not given it considerable attention until recently (Zhikang, 2017). Similarly the uptake of reverse logistics programs by firms has been slow due to the challenges associated with implementation (Huscroft, Skipper, Hazen, Hanna & Hall, 2013).

Research linking reverse logistics, process innovation and operational performance has been exploratory (Hart, 2005: Armbruster et al., 2008; Jack, Powers & Skinner, 2010; Huang & Yang, 2014). According to Christmann (2000) process innovation is essential for reverse logistics since reverse logistical flows are distinct from forward logistics. Reverse logistics also requires additional resources because of the uniqueness of handling systems (Zhikang, 2017). Glenn-Richey, Genchev and Daugherty (2005) suggested that the strategy guiding resource utilization in the firm should be based on building innovative competencies to handling product returns. Despite the relative importance of how process innovation influences reverse logistics and achieving internal operational proficiency, few studies have sought to examine the nature of this relationship.

Despite the increasing cognizance of the importance of environmental protection at a worldwide scale, adoption of approaches such as reverse logistics which focus on curbing the negative environmental impact has experienced hindarances (Hung-Lau & Wang, 2009). This is because practitioners and academicians alike have focused on developing efficient and effective forward logistics information systems while reverse logistics systems have lagged at infancy. Further, asset value recovery systems have not been substantially developed (Dekker, Fleischmann, Inderfurth & van Wassenhove, 2013). In addition firms are not willing to invest additional resources for the implementation of reverse logistics programs as these are considered unnecessary additional cost on infrastructure which includes additional storage facilities, equipment, labour and transportation (Rogers, Banasiak, Brokman, Johnson & Tibben-Lembke, 2002). The other challenge has been forecasting demand for reverse logistics flow. This requires more sophisticated algorithms to accurately predict flows in reverse compared to forward flows. Again many firms are inclined to control product return processes individually and not collectively as a supply chain. Finally, product return increases have enormously surpassed firm capacity at the business unit level (Genchev, Glenn-Richey & Gabler, 2011).

Manufacturing firms in Kenya in their quest to protect the environment have not harnessed the potential of reverse logistics programming. Key challenges have been cost associated with reverse logistics programming and difficulties in developing accurate reverse logistics forecasts (Rogers et al., 2002). Further an inadequate government policy framework has hindered the development of asset recovery programs and processes (Dekker et al., 2013). Only until recently have we seen the development of initiatives such as Kenya Green Economy Strategy and Implementation Plan (K-GESIP) to increase uptake of environmental protection (World Bank, 2016). Research on reverse logistics in the African context has also been sparse (Somuyiwa & Adebayo, 2014; Kwateng, Debrah, Parker, Owusu & Prempeh, 2014; Meyer, Niemann, Mackenzie & Lombaard, 2017). To account for differences across contexts and due to the prominence of developing economies in global business more research on reverse logistics needs to be done in Africa.

LITERATURE REVIEW

This research was anchored on the diffusion of innovation theory that recognizes in a societal system, innovations are spread widely within a certain time interval to members using varying avenues at several levels of influence (Rogers, 2003). The theory is guided by certain key tenets. First, innovations are spread using information streams founded on communication network attributes established by the interconnectedness of individuals. Second, innovation disseminators in their position as opinion leaders or seekers dictate how innovations will disseminate in the network. Third, innovation characterisitcs namely relative advantage, compatibility, simplicity, trialability and observability together with the innovation's perceived attributes, influence diffusion rate (Shoham & Ruvio, 2008). Relative advantage examines the extent to which current process innovations are perceived to be better than those used previously or those used by our competitors (M'Chirgui & Chanel, 2008). Compatibility examines the extent to which current process innovations are deduced to be accordant with prevailing values and the requirements of possible adopters. Simplicity determines the extent to which current processes are discerned as easy to learn, apprehend and use (Shoham & Ruvio, 2008). Trialability looks at the extent to which current processes can be explored or tested on a restricted basis. Finally, observability looks at how current processes are visible to potential adopters (Rogers, 2003). The theory was useful in testing the extent to which adoption variations in process interventions affect innovation spread. Adoption variations were established by measuring the degree to which innovation attributes influence diffusion rate. Therefore, the theory advanced a basis to illustrate and forecast factors that accelerate or hinder innovations spread in understanding how process innovation influences reverse logistics and operational performance.

Hart (2005) observed that firms need to reposition current assets to gain innovative capabilities in order to have higher operational performance and generate sustainability creating processes at a strategic, tactical and operational level. Armbruster et al. (2008) opined that innovations affect operational performance with regard to flexibility, dependability, productivity and quality. Process innovation is useful in reverse logistical flows because they are distinct from forward logistics operations (Christmann, 2000; Sangwan, 2017). Huang and Yang (2014) observed that reverse logistics innovation positively influences firm performance. Glenn-Richey et al. (2005) and Hsu et al. (2016) argued that developing innovative reverse logistics capabilities using resources is important for improving operational performance and competitiveness. Yet, until recently, research linking reverse logistics, process innovation and operational performance has been scarce (Jack et al., 2010). Morgan et al. (2016) posited that innovations in information technology moderate the relationship between collaboration and level of reverse logistics capabilities. These studies have shown process innovation is a necessary driver for the improved performance of a firm. However, the nature of the relationship among reverses logistics, process innovation and operational performance remains unexplored. Based on these the researcher posited the following: Process innovation has no significant moderating influence on the association linking reverse logistics and operational performance. Figure 1 below provides the specific path diagram for the relationship between the latent constructs of reverse logistics, process innovation and operational performance.

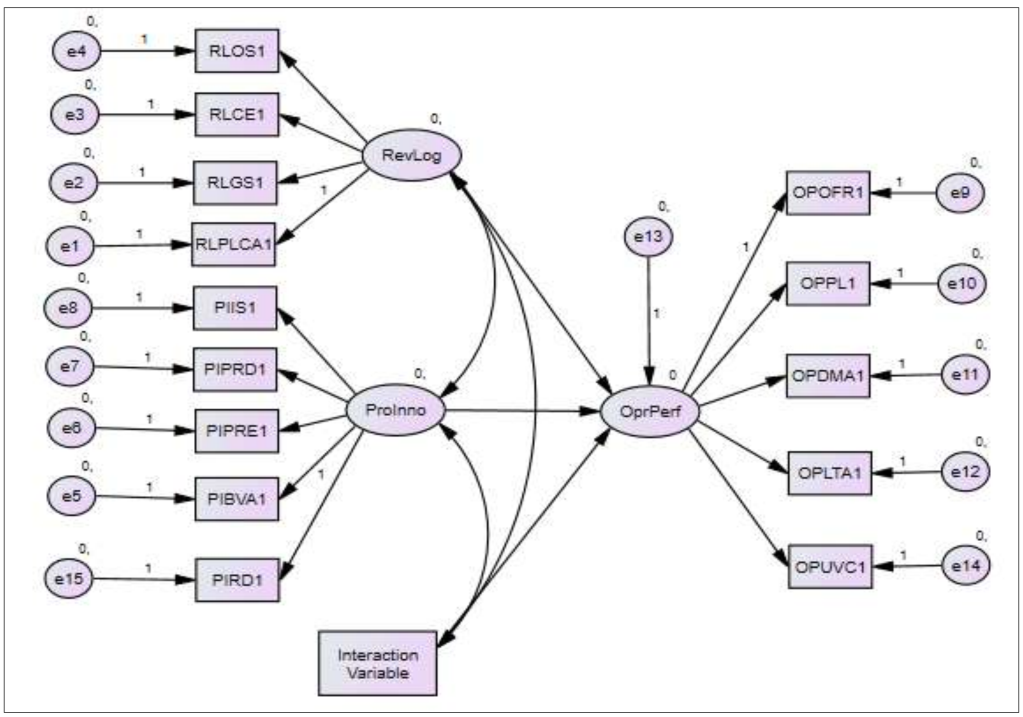

Figure 1 Path Diagram linking Reverse Logistics, Process Innovation and Operational Performance

Figure 1 suggested that process innovation moderates the relationship between reverse logistics with operational performance. Reverse logistics represented in the diagram as RevLog had outsourcing, collaborative enterprising, green strategies and the product life cycle each of these represented by the rectangular nodes RLOS1, RLCE1, RLGS1 and RLPLCA1 respectively in the diagram. Process innovation represented as ProInno was measured using information systems, product redesign, process reengineering, business value chain and resource deployment. These were diagrammatically represented using the rectangular nodes PIIS1, PIPRD1, PIPRE1, PIBVA1 and PIRD1 respectively. Operational performance represented in the diagram as OprPerf was operationalized using per unit variable cost, order fill rate, number of product lines, machine availability and leadtime represented as rectangular nodes labeled, OPUVC1, OPOFR1, OPPL1, OPDMA1 and OPLTA1 respectively.

RESEARCH METHODOLOGY

The study applied correlation cross-sectional survey. Correlation research focuses on indicating the direction, extent and nature of observed relationships (Zikmund, Babin, Carr & Griffin, 2013). The study was cross-sectional because data was collected over a specific time duration. Secondly, cross-sectional research also permitted the creation of homogenous population strata in understanding the underlying strata attributes.

As at 30th June 2018 there were 903 firms registered as KAM members that formed the target population of this study. KAM had the most comprehensive listing of manufacturing firms in Kenya. Further KAM membership was considered appropriate for this study because the association encourages members to have a reuse, reduce and recycling policy. The association also encourages partner organizations to work closely with National Environmental Management Authority (NEMA). Further KAM has an annual Energy Management Award (EMA) that recognizes firms' efforts towards energy conservation. These efforts reflect on efforts towards implementation of reverse logistics practices. The sample size was 340 manufacturing firms in Kenya after taking into account a non-response factor of 0.8 based on similar studies (Mellat-Parast & Spillan, 2014; O'Cass & Viet, 2007). The study sought to use proportionate stratified random sampling based on the manufacturing sub-sectors in the KAM directory and the number of firms in each sub-sector. Proportionate stratified random sampling minimizes sampling bias where the researcher can mutually exclusively classify members of the population.

A total of 151 questionnaires were completed and returned. This represented a response rate of 44.4%. Although high response rates (> 70%) are preferable Mugenda and Mugenda (1999) scholars have demonstrated that no statistically significant difference exists between studies with high response rates and results from studies with response rates as low as 20% (Keeter, Kennedy, Dimock, Best & Craighill, 2006: Curtin, Presser & Singer, 2000). Kaiser-Meyer-Olkin (KMO) and Bartlett tests were conducted using the latent constructs of reverse logistics, process innovation and operational performance. The KMO test yielded a value of 0.950 which is > 0.7. Sphericity test gave a p-value of 0.000 which is < 0.05.This means that conducting Confirmatory Factor Analysis (CFA) will produce statistically reliable factors and results. It also means that it is possible to conduct dimension reduction for both the measured and structured model with reverse logistics, process innovation and operational performance. Table 1 below provides details of the Cronbach's alpha measuring the internal reliability of the questionnaire items for reverse logistics and process innovation. These were expected to be above 0.7.

Table 1 Cronbach Alpha Test Results Measuring Internal Reliability of Questionnaire Items for Reverse Logistics and Process Innovation

	Variables	Cronbach Alpha
1	Outsourcing	0.708
2	Collaborative Enterprise	0.716
3	Green Strategies	0.729
4	Product Life Cycle Approach	0.707
5	Information Systems	0.704
6	Resource Deployment	0.744
7	Product Redesign	0.732
8	Process Reengineering	0.723
9	Business Value Chain	0.709

Based on table 1 above the Cronbach alpha coefficient to check whether the questionnaire items were actually measuring the latent constructs for reverse logistics and process innovation ranged between 0.707 and 0.744. Communality coefficient were checked using Principal Component Analysis (PCA) and ranged between 0.307 to 0.889. This means that the undeleted questionnaire items explained between 30.7% and 88.9 % of the variance of the respective latent construct. Since these values were > 0.3 it indicated that latent constructs have sufficient explanatory power on the latent variables (Field, 2013). Cronbach alpha coefficient to check whether the latent constructs were actually measuring the latent variables ranged between 0.908 and 0.972. These indicate sufficient internal consistency between the latent constructs and the latent variables. The standardized factor loadings for all the latent constructs of reverse logistics, process innovation and operational performance were > 0.5 except for the latent constructs PIRD1 and OPUVC1. For this reason they were deleted from the model. To confirm convergent validity Average Variance Extraction (AVE) method was used as shown in table 2 below.

Table 2 Average Variance Extraction results for Reverse Logistics, Process Innovation and Operational Performance

Factor	<---	Component	Loadings	Squared Loadings	AVE
RLPLCA1	<---	RevLog	0.631	0.398	0.844
RLGS1	<---	RevLog	0.997	0.994	
RLCE1	<---	RevLog	0.995	0.990	
RLOS1	<---	RevLog	0.996	0.992	
PIBVA1	<---	ProInno	0.969	0.939	0.782
PIPRE1	<---	ProInno	0.457	0.209	
PIPRD1	<---	ProInno	0.996	0.992	
PIIS1	<---	ProInno	0.994	0.988	
OPLTA1	<---	OprPerf	0.918	0.843	0.852
OPDMA1	<---	OprPerf	0.933	0.870	
OPPL1	<---	OprPerf	0.925	0.856	
OPOFR1	<---	OprPerf	0.916	0.839	

Since the AVE values for reverse logistics, process innovation and operational performance were > 0.5, this indicated good convergent validity. To check for discriminant validity a comparison between AVE and the Maximum Shared Variance (MSV) was made. Table 3 below summarized the MSV squared loadings.

Table 3 Maximum Shared Variance results for Reverse Logistics, Process Innovation and Operational Performance

Component	<-->	Component	Loadings	Squared Loadings
RevLog	<-->	ProInno	0.835	0.698
RevLog	<-->	OprPerf	0.682	0.465
ProInno	<-->	OprPerf	0.690	0.476

Based on table 3 above, the square correlation between reverse logistics and process innovation latent variable was 0.698. This value was < the AVE of reverse logistics and process innovation latent variables with coefficient of 0.841 and 0.782 respectively (Table 2). The square correlation linking reverse logistics with operational performance latent variables was 0.465. This value was < the AVE of reverse logistics and operational performance latent variables (Table 2). The square correlation between process innovation and operational performance latent variables was 0.476. This value was < the AVE of process innovation and operational performance latent variables. This means that there was evidence to suggest discriminant validity. The study used Statistical Product and Services Solution – Analysis of Moment Structures (SPSS-AMOS) version 21 for SEM testing.

RESULTS

Descriptive statistics for reverse logistics indicated outsourcing as the most prevalent reverse logistics strategy among manufacturing firms in Kenya with a mean of 3.63 and a standard deviation (Std.Dev = 0.51). Green strategies was the second most prevalent (Mean = 3.56, Std.Dev = 0.41). Product life cycle approach and collaborative enterprise both had a mean of 3.51 and (Std.Dev = 0.58 and 0.60 respectively). These generally indicated that the respondents generally concurred with the statements to a large extent. The z-skewness scores were between -0.06 and 0.11. The z-kurtosis scores were between -1.56 and -0.78. These showed the distributions were fairly symmetrical and mesokurtic. For process innovation, process reengineering and information systems were regarded as the most prevalent approaches with a mean of 3.68 and 3.67 (Std.Dev = 0.43 and 0.43 respectively). The least rated was business value chain (Mean = 3.26, Std.Dev = 0.37). These indicated respondents agreed with the statements to a fairly large extent. Z-skewness scores were between -0.06 and 0.32. Z-kurtosis scores were between -1.00 and -0.85. These suggested that the distributions formed by the latent constructs of process innovation were symmetrical and mesokurtic. For operational performance the order fill rate was 95.20% with a Coefficient of Variation (CV) of 2.0%. The average number of product-lines among manufacturing firms was 9.47 (CV = 36.6%). The capacity utilization rate was 91.26% (CV = 1.3%). Lead-time was 10.50 days (CV = 33.7%). Z-skewness scores were between 0.01 and 0.33 showing symmetry. Z-kurtosis scores ranged from - 1.33 to - 0.74, showing a fairly mesokurtic distribution.

The results of the Kolmogorov-Smirnov and Shapiro-Wilk test ranged between 0.058 and > 0.200 and between 0.069 and 0.348 respectively. Because the p-values were > 0.05 then normality was presumed (Field, 2013). Durbin-Watson test statistic (D) was used to test for autocorrelation of the first order. The Durbin-Watson calculated statistics values ranged from 1.848 to 2.148, with an acceptance region of 1.788 to 2.212 meaning there was no serial autocorrelation. The Variance Inflation Factor (VIF) values for the latent constructs of reverse logistics and operational performance were between 1.082 and 5.597. The corresponding tolerance values ranged between 0.179 to 0.924. Since the VIF coefficients were < 10 this indicated the latent variables were not multicollinearily associated. Statistical heteroscedasticity was tested using the Koenker test. For this test if the p-value is > 0.05 then heteroscedasticity is not present and homoscedasticity is assumed (Hair, Black, Babin & Anderson, 2014). The Koenker calculated test statistics value ranged from 0.055 to 0.702. Since these p-values were > 0.05, homoscedasticity was presumed.

The number of iterations taken by AMOS to achieve model minimization was 27. The overall model fit of the measured models was assessed through the absolute, incremental and parsimonious model fitness tests as summarized in table 4 below. From the results absolute fitness was assessed using chi-square value, p-value, Root Mean Square Error of Approximation (RMSEA) and Goodness of Fit Index (GFI). Because these were all within the decision criteria it indicated the models had good absolute fit. Incremental model fitness was assessed using Adjusted Goodness of Fit Index (AGFI), Comparative Fit Index (CFI), Normed Fit Index (NFI) and Tuker Lewis Index (TLI). Based on the decision criteria, these values indicated that all the measured models had good incremental fit.

Table 4 Overall Model Fit Results for the Measured Model

Test	**Decision Criteria**	**Model Result**		
		RevLog	**ProInno**	**OprPerf**
Chi-Square		0.319	0.253	5.050
Degrees of Freedom		1	2	2
p-value	> 0.05	0.572	0.881	0.08
GFI	> 0.90	0.999	0.999	0.983
CFI	> 0.90	1.000	1.000	0.995
AGFI	> 0.90	0.989	0.996	0.916
NFI	0.8 < NFI < 1.00	1.000	1.000	0.993
TLI	> 0.90	1.003	1.005	0.986
RMSEA	< 0.08	0.000	0.000	0.101
CMIN/DF	< 5	0.319	0.126	2.525

Finally, Chi-square/Degrees of Freedom (CMIN/DF) values ranged between 0.126 and 2.525. These indicated good parsimonious fit. Table 5 below summarizes model fitness results for the structured model.

Table 5 Overall Model Fit Results for the Structured Model

Test	Decision Criteria	Model Result
Chi-Square		183.970
Degrees of Freedom		58
GFI	>0.90	0.848
CFI	>0.90	0.970
AGFI	>0.90	0.761
NFI	0.8<NFI<1.00	0.957
TLI	>0.90	0.960
RMSEA	<0.08	0.120
CMIN/DF	<5	3.172

For the structured model, the chi-square value was 183.970, RMSEA was 0.120 which is > 0.08 but sufficiently low to consider the model for analysis. The GFI of 0.848 was not significantly < 0.90. This reveals that the model does have a fairly good absolute fit. AGFI, CFI, NFI and TLI had coefficients of 0.761, 0.970, 0.957 and 0.960. NFI was within the range between 0.80 and 1.00. CFI and TLI were > 0.9. Despite the low AGFI (0.761) this model exhibited a fairly good incremental fit. Parsimonious model fitness was assessed using CMIN/DF which was 3.172. This suggests a good parsimonious fit. In conclusion the model had a fairly good overall fit. Figure 2 below revealed the overall structure of the CFA model.

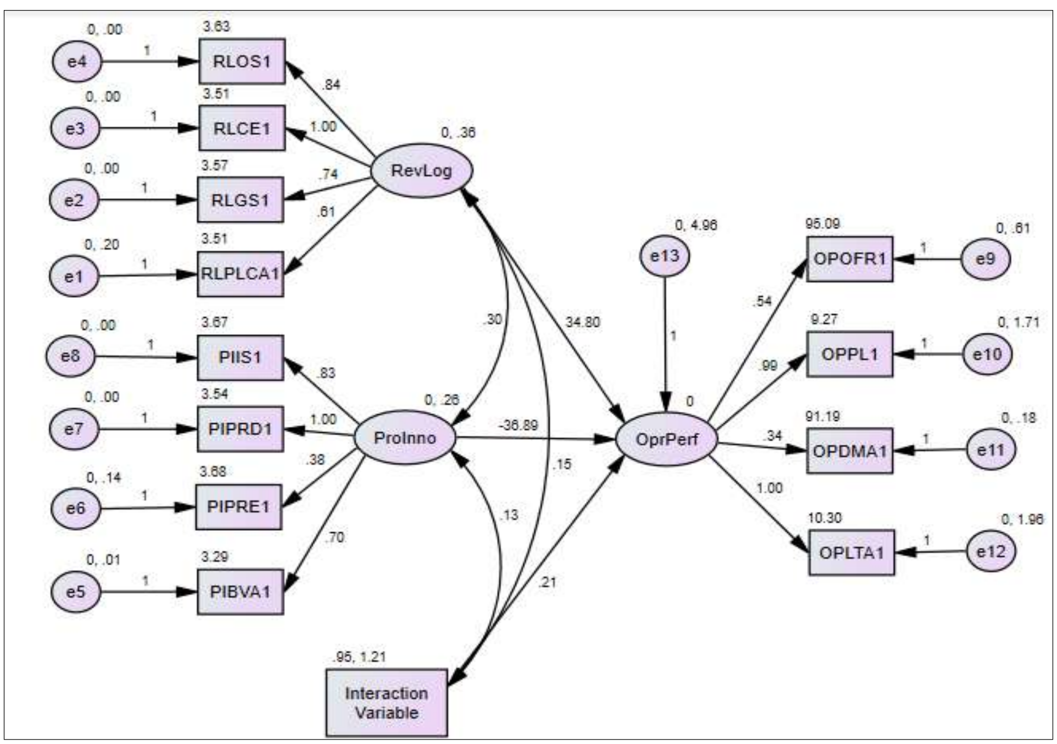

Figure 2 Unstandardized Structural Equation Model for Reverse Logistics, Process Innovation and Operational Performance

The standard error of the estimates of the unstandardized factor loading and p-values were calculated to assess statistical significance. The p-values were < 0.05 indicating statistical significance of factor loadings. The least standardized factor loading was 0.631 and highest 0.997. This therefore meant that the factors explain the components to a large extent. To check whether a statistically significant association among the latent variables of the structured model was present, calculations of the standard error of the estimates and p-values were performed. The p-values were < 0.05 indicating that the factor loadings were statistically significant. This meant that the latent variables of the structured model had statistically significant relationship. For the hypothesis test the study concluded that process innovation moderates the relationship between reverse logistics and operational performance. The Common Method Variance (CMV) which is supposed to be <0.5 was 0.0009 for each of the variables. This meant that the model was not affected by spurious correlations.

DISCUSSION

This study sought to examine the relationships among reverse logistics, process innovation, and operational performance among manufacturing firms in Kenya. This research concluded that process innovation has significant moderating effect on the relationship between reverse logistics and operational performance. According to Hart (2005) firms should reposition current assets to gain innovative potentials in order to have higher operational performance and improve sustainability. According to Armbruster et al. (2008), innovations influence operational performance dimensions such as flexibility, dependability, productivity and quality. This study, revealed that by innovatively developing reverse logistics competences from resources was going to improve operational performance and sustainability (Huang and Yang, 2014; Glenn-Richey et al., 2005; Hsu et al., 2016).

The findings also suggested that the manner in which process innovations were shared is affected by communication network characteristics such as compatibility, relative advantage, simplicity, observability and trialability and the innovation’s perceived attributes formed by the interconnection of individuals (Shoham & Ruvio, 2008). This could either imply current process innovations are deduced to be in harmony with prevailing values and the requirements of possible adopters or current process innovations could be perceived to be better than those used previously or those used by competitors (M’Chirgui & Chanel, 2008). It further could imply current processes are perceived as easy to learn, understand and use (Shoham & Ruvio, 2008). It could also be interpreted to mean current processes could be explored or tested or they had visibility to potential adopters (Rogers, 2003).

The findings further agreed with conclusions made by Rogers (1976) that not all innovations yield positive results and should not be wholesomely adopted. They further concured that explaining the diffusion rate is arduous because of environmental dynamics and power play among various business partners. These are brought about by the complexity of understanding the difference between the effect individual characteristics have on a system and the effect the system structure has on diffusion (Rogers, 2003). Therefore, the diffusion of innovation theory provided the basis to describe and predict factors that accelerated or hindered innovation spread.

SUMMARY AND CONCLUSION

The research observed that the effect of reverse logistics on operational performance is dependent on process innovation. Developing innovative reverse logistics capabilities using resources improved operational performance and competitiveness (Hart, 2005; Ambruster et al., 2008; Huang and Yang, 2014; Glenn-Richey et al., 2005; Hsu et al., 2016). This could either imply current process innovations may be consistent with prevailing objectives and requirements of manufacturers in Kenya in so far as implementation of reverse logistics is concerned. It could also imply that current process innovations could be perceived to be better than those used previously or those used by competitors of manufacturing firms. Manufacturers in Kenya could also be perceiving current process innovations as easy to implement within and among supply chain partners.

From a diffusion of innovations theory this research contributed to the findings of Rogers (1976) that not all innovations generate positive results and should not be adopted in totality. Further it contributed to the proposition that explaining the diffusion rate is challenging as a result of the complexity of understanding the difference between the effect individual characteristics have on a system and the effect the system structure has on diffusion (Rogers, 2003).

IMPLICATIONS

These research findings directly impact policy and practice. The study provided a framework for regulating policy in the implementation of reverse logistics in achieving operational performance. The study suggested that by implementing reverse logistics as an integrated intervention this would lead to firms' improving on cost management, product quality, delivery speed and product variety. Policy makers and practitioners through this study can understand the strategic significance reverse logistics has both at a micro and macro-economic level to the economy of Kenya. The study also demonstrated that while striving to gain economic benefits, through reverse logistics also contribute to social and environmental benefits creating a triple bottom line effect.

The study observed that the effect of reverse logistics on operational performance was dependent on process innovation. Previous studies have shown that developing process innovations while implementing reverse logistics was likely to improve operational performance and competitiveness (Hart, 2005; Ambruster et al., 2008; Huang and Yang, 2014; Glenn-Richey et al., 2005; Hsu et al., 2016). This is attributed to the fact that process innovations remove the requirement for disposal and associated costs thereof thereby improving the organization's image and its profitability. It also encourages reuse and remanufacture. These practices reduce negative environmental impact apart from improving competitiveness and profitability for the firm. Policy makers within the manufacturing sector in Kenya should therefore improve the regulatory framework to enable firms to implement reverse logistics strategies. Such a framework should encourage awareness creation on the significance of reverse logistics both at the micro and macro-economic level. This would increase the use of remanufactured/refurbished products. The end result is that it will have a triple bottom line effect that is it will have social, environmental and organizational benefits.

LIMITATIONS AND FURTHER RESEARCH

The constructs used to measure reverse logistics namely; outsourcing, collaborative enterprising, green strategies and closed-loop supply chain were not exhaustive. A more in-depth review of reverse logistics literature would uncover additional strategies or approaches to the implementation of reverse logistics. These additional approaches or strategies could augment generalizability and validity of the results of the study models and variables.

Reverse logistics and process innovation were measured using the Likert-type scale. Direct measures remain consistent over a given time period and sectoral inconsistencies are more controllable in the models. These make the models have better explanatory power. Future researchers should consider using direct measures among the variables in hypothesized relationships and more specifically when using covariance-based SEM in analyzing data.

Increased attention of research in the service sector requires future research to aim at generalizing the results beyond the context of manufacturing. This research could also be replicated in other industries or countries with different cultural backgrounds. Similarly intra-industry or intra-sectoral comparison of results could also be undertaken as a research stream. These would require larger samples per industry or sector.

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